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DOCTORAL THESIS

Development of Methods for Real-time In-step Anomaly Detection in Gait Analysis

Jakob Rostovski

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for any academic degree elsewhere.

Jakob Rostovski ______________________
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Reaalajaliste meetodite arendus sammusiseste kõrvalkallete tuvastamiseks kõnnianalüüsis

JAKOB ROSTOVSKI

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Contents

List of Publications

The present Ph.D. thesis is based on the following publications, articles under review and patent application that are referred to in the text by Roman numbers.

Publications

I J. Rostovski, A. Krivošei, A. Kuusik, U. Ahmadov, and M. M. Alam. SVM time series classification of selected gait abnormalities. In *Body Area Networks. Smart IoT and Big Data for Intelligent Health Management*, pages 195–209, Cham, 2022. Springer International Publishing

II J. Rostovski, A. Krivošei, A. Kuusik, M. M. Alam, and U. Ahmadov. Real-time gait anomaly detection using SVM time series classification. In *2023 International Wireless Communications and Mobile Computing (IWCMC)*, pages 1389–1394, 2023

III J. Rostovski, M. H. Ahmadilivani, A. Krivošei, A. Kuusik, and M. M. Alam. Real-time gait anomaly detection using 1D-CNN and LSTM. In M. Särestöniemi, P. Keikhosrokiani, D. Singh, E. Harjula, A. Tiulpin, M. Jansson, M. Isomursu, M. van Gils, S. Saarakkala, and J. Reponen, editors, *Digital Health and Wireless Solutions*, pages 260–278, Cham, 2024. Springer Nature Switzerland

IV B. Gerazov, E. Hadzieva, A. Krivošei, F. I. Soto Sanchez, J. Rostovski, A. Kuusik, and M. Alam. Matrix profile based anomaly detection in streaming gait data for fall prevention. In *2023 30th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pages 1–5, 2023

Article Under review

V J. Rostovski, A. Krivošei, A. Kuusik, Y. Le Moullec, I. K. Niazi, and M. M. Alam. Signal shape tracking algorithm for real-time in-step gait anomaly detection. *IEEE Access*, 12 2024

Patent Application

VI A. Krivošei, A. Kuusik, J. Rostovski, and M. M. Alam. Real-time motion abnormality detection method and device, 2024. PCT Patent No: PCT/IB2024/055807

Author’s Contributions to the Publications

I Publication I (Appendix 1): In this paper I am the first author. I provided an overview of the state-of-the-art methods in gait analysis for fall detection and fall prevention, as well as anomaly detection. I proposed the data collection campaign protocol used to evaluate the gait anomaly detection methods. I supervised the data collection campaign, evaluated the quality of the data and adjusted the settings of the data collection device. I supervised the data labeling procedure and examined the labeling quality. I wrote the code for the data preprocessing and classification performance estimation. I prepared the figures, tables and analyzed the achieved results by accuracy and F1 scores. I wrote the manuscript under the guidance of my supervisors, and revised it based on the reviewers’ comments.

II Publication II (Appendix 2): In this paper I am the first author. I provided an overview of the state-of-the-art methods in gait analysis for real-time anomaly detection methods. I proposed a method for real-time in-step anomaly detection, the real-time tslearn support vector machine anomaly detection (RTtsSVM-AD) algorithm. I wrote the code for pre-processing the data and developed the real-time in-step anomaly detection algorithm. I conducted the experiments and analyzed the results by F1 scores, "earliness", true positive rate and false positive rate. I prepared the tables and figures. I wrote the manuscript under the guidance of my supervisors, and revised it based on the reviewers’ comments.

III Publication III (Appendix 3): In this paper I am the first author, I presented the overview of state-of-the-art on the gait anomaly detection, wearable sensors and real-time algorithms. I provided extended dataset for the real-time in-step anomaly detection, to validate the achieved results from Publication II. I supervised the extended data collection campaign, evaluated the quality of the data and adjusted the settings of the data collection device. I supervised the data labeling procedure and examined the labeling quality. I utilized the one dimensional-convolutonal neural network (1D-CNN) and long short-term memory (LSTM) algorithms for real-time in-step anomaly detection. I wrote the code for data pre-processing and the algorithms, performed the experiments, and optimized the neural networks hyperparameters. I analyzed the results in terms of accuracy, F1 scores, "earliness" and real-time factor (RTF). I prepared the figures and tables. I wrote the manuscript under the guidance of my supervisors, and revised it based on the reviewers’ comments.

IV Publication IV (Appendix 4): This work was done in collaboration with Prof. Elena Hadzieva from University of Information Science and Technology "St. Paul the Apostole" and Assoc. Prof. Branislav Gerazov from University “Ss. Cyril and Methodius”. Primarily I provided the dataset and consultation about the content of the dataset. The consultation included data cleaning steps, labeling, data collection methodology.

V Publication V (Appendix 5): In this paper I am the first author. I presented the overview of state-of-the-art on some consequences of neurological diseases on the gait quality, the use cases of Inertial Measurement Units (IMUs) and functional electrical stimulation (FES) in gait analysis, and existing real-time algorithms in gait analysis. I proposed the one class support vector machine (OCSVM) algorithm. I proposed novel signal shape tracking anomaly detection (SST-AD) algorithm with Senior Researcher Andrei Krivošei. I wrote the code for data preprocessing and the algorithms. I conducted the experiments and analyzed the results in terms of accuracy, F1 scores, "earliness", recall, precision and RTF. I prepared the tables and figures. I wrote the manuscript under the guidance of my supervisors, and revised it based on the reviewers' comments.

VI Patent application VI (Not appended): The patent application is filled and is based on selected results from Publications II and V. It contains the idea of in-step anomaly detection algorithms and description of the RTtsSVM-AD and SST-AD algorithms working principle. The patent extends the possible applications of the RTtsSVM-AD and SST-AD algorithms to similar signal processing topics.

Abbreviations

AFO	Ankle-Foot Orthosis
CNN	Convolutional Neural Network
CNN-LSTM	Convolutional Long Short-Term Memory Neural Network
EMG	Electromyography
FES	Functional Electrical Stimulation
FSM	Finite State Machine
HO	Heel-Off
HS	Heel-Strike
IMU	Inertial Measurement Unit
LSTM	Long Short-Term Memory
ML	Machine Learning
MP	Matrix Profile
MS	Multiple Sclerosis
OCSVM	One Class Support Vector Machine
1D-CNN	One Dimensional-Convolutonal Neural Network
PD	Parkinson's Disease
RF	Radio Frequency
RNN	Recurrent Neural Network
RSVM	Reduced Support Vector Machine
RTtsSVM-AD	Real-time tslearn Support Vector Machine Anomaly Detection
RTF	Real-Time Factor
sEMG	Surface Electromyography
SVM	Support Vector Machine
SST-AD	Signal Shape Tracking Anomaly Detection
TO	Toe-Off
TS	Toe-Strike
tsSVM	Time-Series Support Vector Machines

1 Introduction

1.1 Background and Motivation

Walking is a fundamental aspect of daily life. The wide availability of smart wearable devices and smartphones has made it easy and popular to monitor walking patterns, including the speeds and gait modes. As a result, people are more engaged in tracking their physical activities [9]. Over the years, advancements in activity detection technology have significantly improved both its affordability and accuracy [91]. Modern smartwatches and sensors enable real-time exercise tracking, which is widely utilized for analyzing professional athletes' training and technique. Such data-driven insights contribute to performance optimization and injury prevention [52, 86]. Gait phase detection plays a critical role in identifying step initiation and termination, providing essential information on step count and phase duration [24]. Additionally, knowing the shape of individual steps aids in activity recognition and facilitates accurate classification of different gait modes, such as walking, running, stair ascent, and descent [93]. Gait phase and pattern analysis have practical applications beyond athletics. For instance, such data can be leveraged to develop assistive devices for workers handling heavy equipment, enhancing their safety and efficiency [22]. Additionally, walking patterns are unique to each individual, making them suitable for biometric identification. Similar to recognizing a person by their gait, personalized walking patterns can serve as a means of authentication [64].

One of the fast evolving motion and gait analysis technologies is motion capture. Success from research and wide usage in cinematography have improved the quality and usability of technology in medical applications as well [18], i.e. it is used to evaluate gait parameters. Gait parameters change with age of the person [55]. To understand the changes, musculoskeletal analysis is performed, which can be done with various techniques like motion capture or inertial sensors [8]. Another significant topic is the study of electrical signals traveling through the body, their interaction with specific muscles, and the signal pathways. This research can contribute to the development of an effective electrical map of the human body [65].

Gait, an integral aspect of human life, often goes unnoticed by individuals who can walk without any problem. However, even minor injuries can significantly diminish quality of life by restricting mobility [95]. While many injuries can heal relatively quickly, age-related changes can lead to a decline in gait quality and overall well-being [36]. In particular neurological diseases are a primary cause of reduced quality of daily living, affecting millions of individuals worldwide [2]. These diseases range from migraines to neurodegenerative conditions such as Multiple Sclerosis (MS), Parkinson's disease, stroke, epilepsy, and others. These diseases can affect gait patterns and change the locomotion to abnormal. Gait patterns can be used for the diagnosis of the diseases, identification of the stage of disability and can help to tailor individual treatment plan for the patient [23]. Changes in gait should be tracked during the treatment process for analysis of the treatment efficacy [36].

Gait impairments can be treated in different ways, depending on the type of the disease and its severity. The first common treatment option is to use medication, which can help with some of the symptoms of the disease (i.e. anti-inflammatory drugs for arthritis or dopaminergic medications for Parkinson's disease) [20]. The second common treatment option is physical therapy, which aims at strengthening the muscles, can help the person to adapt to the impairment and regain as much gait stability and balance as possible. This is achieved through specialized exercises, training to maintain balance, and education on fall prevention techniques. Another common treatment option involves the

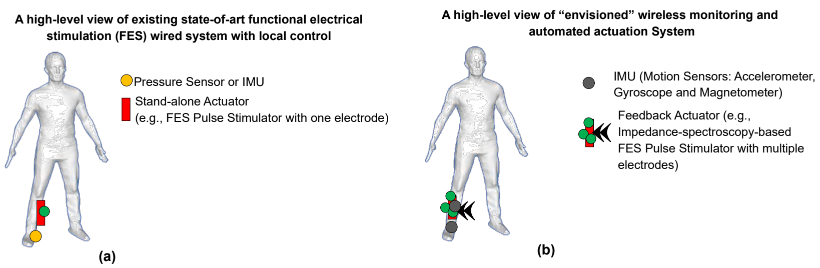

Figure 1: Neurodegenerative Disease Monitoring and Actuation for Assistive Living

use of assistive and orthopedic devices, ranging from customized braces or shoe inserts to canes, walkers, or crutches. Some individuals may also benefit from active assistive devices, such as exoskeletons [98] and Functional Electrical Stimulation (FES) devices [57].

Gait assistive devices can be categorized as either active, such as devices utilizing FES [65] (Fig. 1), active exoskeletons [22], and audio or haptic feedback devices [88], or passive, such as Ankle-Foot Orthoses (AFOs) [97], passive exoskeletons [7], walkers, and canes [48]. The current market trends favor exoskeletons and audio or haptic feedback devices; however, their efficacy and comfort remain inconsistent and often unreliable. These devices are typically tested for conditions like Parkinson's disease in research settings, but they may not effectively address other motion disorders.

The above emphasizes the need for more comprehensive research in gait assistive technologies [56]. To summarize, each patient has specific target areas for improvement. The help from professionals combined with regular exercises remains one of the most effective approaches for adapting daily activities to new conditions.

1.2 Data and Methods in Gait Analysis

Depending on the research topic in gait analysis, various types of gait data are collected and analyzed. One common topic is the study of the kinematics of a person's gait, which involves examining key parameters such as step length, stride duration, swing phase duration, stance phase duration, and related metrics [62]. Biomechanical data, on the other hand, is used to understand how the body functions, by analyzing factors such as the movement of the center of mass, knee angles, ground reaction forces, and muscular work [60].

Data for gait analysis can be collected by various sensors and methods. Some of the most popular sensors are: inertial measurement units (IMUs), which contain accelerometer, gyroscope and magnetometer [83], pressure and force sensors [60], electromyography (EMG) [50], radio frequency sensors [31], cameras which are used with and without markers (by leveraging image processing) [100], etc.

Often, the research involving data collection requires controlled environments. Typically, it is laboratories which are equipped with various systems such as cameras, controlled lighting, pressure sensors, and treadmills [37]. The controlled setup ensures repeatability during the data collection and facilitates the collection of high quality datasets to derive meaningful insights. However, camera-based systems have limited usability outside the laboratory environment, making them impractical for real-world applications [24].

This limitation has contributed to the growing popularity of data collection devices based on IMUs [24]. IMUs are widely used in gait analysis due to their minimal operational requirements compared to camera-based systems, resulting in significantly lower costs [31]. Additionally, IMUs are compact, commonly found in motion sensors, and integrated into commercially available gait correction systems. These attributes make IMUs suitable for use in real life environments. IMU data supports various research topics, including gait phase analysis [24], gait mode analysis [59], and gait-based identification [64].

Another widely used sensor type is pressure sensor, which can also be utilized in uncontrolled environments. Pressure sensors are typically embedded in specialized insoles for footwear but can also be deployed as force pads in laboratory settings [60, 86].

Recently, radio frequency (RF) sensors have emerged as a novel addition to gait analysis technologies. These sensors detect changes in radio fields, enabling the detection of movements and even movement intentions [31]. This can provide meaningful input to the gait analysis systems by using the modern connectivity possibilities of devices and widespread use of radio technology in households.

In addition to sensor advancements, the progress has been made in data analysis, in particular, deep learning techniques have been increasingly applied in gait analysis. When combined with motion capture or camera systems, these techniques can extract reliable and precise kinematic data without requiring body markers [100]. Using video data alongside pose estimation and Q-learning methods, researchers can extract movement information and accurately estimate poses [100].

Gait data is complex and can be used for many applications, as shown above. Sophisticated algorithms and methods are used in research to find the desired information. Some of the most popular methods used in gait analysis, like in this thesis are: support vector machines (SVM) (Publication II), convolutional neural networks (CNN), recurrent neural networks (RNN) (Publication III) and heuristic algorithms (Publication V).

1.3 Challenges in Gait Analysis

Gait analysis presents several challenges, primarily driven by the need for technological advancements and a deeper understanding of human gait. This section reviews some of the key challenges in the field:

1. The first challenge is **data acquisition and feature extraction**. Every research effort in gait analysis relies on data collection, with specific topics requiring tailored datasets to support their objectives. Data labeling and feature extraction still often requires manual labor. To speed up the data processing, various tools have been developed to facilitate the extraction of gait features [106, 6], as discussed in the previous section, wearable and non-wearable solutions, including vision-based, environment-based, and Radio Frequency (RF)-based technologies, have been proposed to address this need. However, further advancements are needed in automatic data labeling techniques for faster deployment of Machine-Learning (ML) methods

2. The second challenge is **marker-less analysis**. Developing a gait analysis system capable of extracting reliable and precise kinematic data in a standard and unobtrusive manner remains an open problem. Most widely used gait analysis systems today rely on markers, imposing constraints such as the need for controlled environments and extended processing durations, which limit their practicality and usability [100].

3. The third challenge is **achieving high accuracy and robustness**. Many areas within gait analysis still face difficulties in meeting these requirements. For example, fall

detection and fall prevention systems must improve their accuracy and robustness to noise in the data, to detect falls earlier [40] or prevent them in real-time, as discussed in Publication I.

4. The fourth challenge is connected to the **complexity of human gait**. From the perspective of analysis, human gait is among one of the most complex phenomena [21]. Gait is the result of combined effort of the brain, nerves, and muscles. Any deviation from healthy walking ability can significantly reduce the quality of life. The analysis of such complex signals as gait patterns is a challenging task [46], due to high variability in gait signals and changes of gait modes and speeds.

5. The final reviewed challenge is **technological advancement**. With technological advancement, human gait analysis can now be done objectively and empirically [43]. However, this also brings challenges in terms of handling and analyzing the large amount of collected data [74].

1.4 Problem statement and Formulation of Research Questions

One of the important topics in gait analysis is fall detection. Falls can be caused by various gait disorders [92]. Some of the primary reasons of gait disorders are neurodegenerative diseases. Unfortunately, many neurologic conditions cannot be fully treated, resulting in varying degrees of permanent disability. Individuals affected by these conditions are particularly prone to falls and subsequent injuries [58, 27]. Fall detection can help to retrieve the information about how a fall has happened, how severe it is and what help should be provided [40]. Various methods for detecting falls have been investigated, utilizing motion sensors, including those found in smartphones and wearable devices. Understanding the manner in which a fall occurs can provide insight into its severity and potential consequences.

The optimal approach in addressing gait disturbances is to develop methods that prevent falls entirely. For example, in conditions like MS, where neuronal and muscular connection impairments lead to muscle-specific issues, training and rehabilitation options remain limited [19]. Gait disturbances are a major concern, and various solutions aim to improve gait quality. Common approaches include rigidly fixing the leg in the correct position with devices like AFOs [12] or stimulating muscles using FES [65].

However, despite their potential, these methods face several challenges. Fixation devices, such as AFOs, may reduce muscle activity and lead to muscle degradation over time [97]. FES, on the other hand, requires precise and effective stimulation to achieve positive outcomes [25]. Current assistive devices often rely on phase detection methods to identify the start and end of a step, which serve as the trigger points for FES activation. Such devices are predominantly used during rehabilitation processes [67]. On the other hand, constant electrical stimulation may lead to overstimulation of muscles and skin irritation, with prolonged adaptation periods, which significantly limit their usability and patient compliance [63]. Addressing these issues is crucial for advancing the development and adoption of effective gait assistive technologies.

In the view of the above, current state-of-the-art methods have several gaps. These are combined to the problem statement:

1. **PS1** Assistive devices used after rehabilitation to maintain gait quality use uncomfortable predetermined periodic FES, which lack gait deviation detection and personalization, leading to preliminary fatigue.

2. **PS2** The state-of-the-art lack methods and algorithms for detection of in-step anomalies in real-time.
3. **PS3** Available datasets do not combine normal and abnormal steps in one gait recording from one person and thus make it challenging to develop integrated anomaly detection algorithms.

Approaching the above problems, lead to the following research questions:

1. **RQ1** How to develop a methodology for dataset collection that would be suitable for the development of the real-time in-step anomaly detection algorithms? (**PS3**)
2. **RQ2** How to adapt benchmark methods and develop new algorithms which are capable of in-step abnormality detection in real-time? (**PS2**)
3. **RQ3** How to compare the benchmark methods and the proposed real-time in-step anomaly detection algorithms performance? (**PS2**)
4. **RQ4** What are the key elements of personalized and comfortable gait assistive device with efficient FES? (**PS1**, **PS2**)

1.5 Contributions

This thesis presents the following contributions:

1. A new dataset collected on volunteers, containing normal and abnormal steps in one gait recording, which can be used for different classification purposes, including in-step anomaly detection (**Publications I and III**).
2. New benchmark methods and an evaluation framework to estimate the performance of real-time in-step anomaly detection algorithms (**Publication II, III, IV, V and VI**).
3. The new in-step anomaly detection methods for real-time in-step anomaly detection. These methods are 1) real-time tslearn support vector machine anomaly detection (RTtsSVM-AD), 2) one class support vector machine (OCSVM), 3) one dimensional-convolutonal neural network (1D-CNN), 4)long short-term memory (LSTM) and 5) matrix profile (MP) algorithms (**Publication II, III, IV and V**).
4. A new advanced heuristic method that, overcomes the limitations of the state-of-the-art methods for real-time in-step anomaly detection, which is called signal shape tracking anomaly detection (SST-AD) (**Publication V**).
5. Evaluation of the resistance to the changes in gait speed for 1D-CNN and SST-AD algorithms. Preliminary efforts for the development of the prototype device have been taken, which are considering the real-time in-step anomaly detection (**Publication VI and unpublished results, see Appendix 6**).

1.6 Thesis organization

Thesis is organized as follows: first the state-of-the-art solutions in gait analysis are described in Chapter 2, which is followed by a summary of the publications in Chapter 3. Finally, the thesis is concluded in Chapter 4. Appendices 1-5 are publications I to V. Appendix 6 presents with preliminary efforts towards the gait assistive device and resistance of the algorithms to the changes in gait speed.

2 State-of-the-art

2.1 Research on Gait Analysis

Some of the most widely researched topics in gait analysis are gait phases detection, gait modes detection, electrical and musculoskeletal analysis of the body, and gait assistive devices. Gait phase detection plays a crucial role in identifying the start and end of a step, as well as key events within the step cycle [49]. Similarly, gait mode detection provides insights into walking activities and transitions between different terrains, such as shifting from overground walking to stair ascent [59].

Each research topic in gait analysis necessitates data collection, which can be achieved using various methods, including camera systems, IMUs, and force plates. Additionally, electrical and musculoskeletal analyses are used to study how muscle stimulation is processed by the body. These analyses are instrumental in tracking muscle activities, identifying stimulation points, and determining appropriate stimulation methods, as well as understanding joint movements.

Gait assistive devices serve multiple purposes, including treatment, maintaining gait quality, and providing assistance during physically demanding tasks. Collected gait datasets not only support the optimization of existing algorithms but also offer opportunities to derive new insights, driving advancements in the field of gait analysis.

One of the primary beneficiaries of advancements in gait analysis are medical professionals, physiotherapists, and their patients. State-of-the-art tools enable more efficient analysis of patients' gait and provide valuable insights into musculoskeletal properties and other critical parameters [108]. Traditionally, gait analysis for a single patient can take several hours or even days. To evaluate gait parameters such as joint angles and ground reaction forces, medical professionals use a wide range of tools, including movement analysis systems, posturography, various types of dynamometers, and kinesiologic electromyography [34].

Gait analysis subtopics are instrumental in detecting gait phases, classifying gait patterns, identifying anomalies, and developing tailored treatment plans or advanced assistive devices. Currently, most state-of-the-art methods rely on laboratory environments for data collection. Collected data often requires extensive preprocessing to extract features and label data before insights can be derived. However, there is a pressing need to condense this process into easy-to-use tools that do not yet exist, although progress is being made in this direction.

Such tools would significantly benefit medical professionals by enabling faster data acquisition, automating gait feature analysis, and aiding in the classification of disability levels and types. Emerging platforms which help to evaluate gait quality and symmetry, such as those mentioned in [28], aim to help personalize rehabilitation programs based on individual needs.

In parallel, physical assistive devices are increasingly being used to support physiotherapists' work. Devices such as exoskeletons [89] and FES systems [67] are actively employed in rehabilitation settings. These devices assist in providing physical support and training muscles involved in walking, contributing to improved outcomes for patients.

2.1.1 Data Collection Techniques

Depending on the gait analysis topic, different data collection techniques should be used. In case of tracking the movement of the body, vision based systems (Fig. 2) as well as IMUs (Fig. 3) are the most widely used tools. Vision based systems use cameras to collect images. The obtained images can be used to extract gait parameters and to track movement of the persons. Vision based systems are used for detection of freezing of gait [41], identification [42, 26], for fall detection [77, 75], etc. The main limitation of vision based systems is that they commonly require a controlled environment. IMUs on the other hand can be used in free living environment. IMUs are used for fall detection [17], for gait phases and modes detection [109], activity recognition [15], etc. Downsides of the IMUs are that they are sensitive to calibration errors and can experience gyroscope drift. Other types of sensors like pressure sensors and EMG sensors are often used in combination with vision based sensors or IMUs. Pressure sensors are used to detect gait events like step start and end events [60], for fall detection [1], etc. The limitations of the pressure sensors are that they typically require significant amount of power to operate, are sensitive to temperature changes, and require specialized or modified footwear for gait data collection. EMG sensors are used to track muscle activity, to extract gait features [43], to recognize gait phases [50], etc. Limitations of the EMG sensors is noisy signal, requiring extensive filtration techniques to extract useful information.

Figure 2: Modern gait analysis laboratory. Cameras are located for 3-dimensional capture of kinematic and temporal-spatial data. Also uses force plates in walkways.

One of the emerging topics in data collection is using radio frequency sensors, which are implemented for fall detection [75]. However, they are in the early phases of development and are sensitive to the signal interference and the detection is limited to one person.

Finally, depending on the goal of the study, different sensors or combination of sensors can be used.

2.1.2 Electrical and Musculoskeletal Analysis

Analyzing the electrical paths and musculoskeletal properties can provide significant insights about the health of a person. The full body could be analyzed to see how a person is walking and what is in target range and what should be treated. It is crucial to select cor-

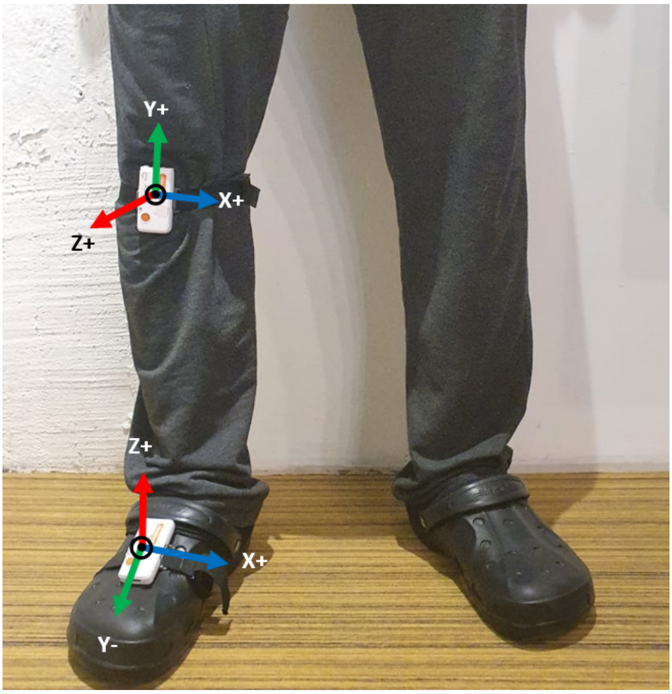

Figure 3: Some of the most popular placement of IMU

rect placement of the surface EMG (sEMG) sensors and the electrodes for FES to generate the desired muscle contraction [54]. This would provide correction in desired manner and provide necessary assistance. sEMG can be used to study the difference in the electrical signals between healthy persons and persons with neurological diseases [104] to analyze how the muscles are reacting after the electrical stimulation. This helps to determine the affected areas of the body and for instance to adjust the FES parameters to accommodate the patients needs.

2.1.3 Gait Phases Detection

Phase detection is a central topic in gait analysis, which holds significance across numerous applications. This ranges from identifying the initiation of the walking and transition from the stance phase to the swing phase of a step, to the development of assistive devices aimed at treating patients and improving their gait quality.

Gait phases can be gathered from motion data, with IMUs being one of the most popular sensors for this purpose. Various methods, i.e. SVM are used for gait phase detection. Such methods can achieve a classification accuracy of over 90%, and they can successfully identify the heel-strike (HS), toe-off (TO), and stance or swing phases. Such information can be applied to determine various forms of locomotion, including running and hopping [107].

Existing real-time algorithms are used for the detection of initial contact and terminal contact gait events, achieving a sensitivity and precision of 100% using a heuristic algorithm in conjunction with IMU and pressure insoles [60]. Furthermore, real-time algorithms are utilized for the detection of gait events like heel-strike and toe-off across various demographics, including healthy young and elderly individuals, stroke patients, and those with Parkinson's disease [99]. Research delves into the real-time detection of gait phases during free-living locomotion, utilizing SVM, reduced support vector machine (RSVM), and finite state machine (FSM) algorithms to identify heel-off, toe-off, and heel-strike events [103].

In the context of children with cerebral palsy, gait phase detection in real-time is explored in [49]. Five gait phases, including HS, toe-strike (TS), heel-off (HO), TO, and swing midpoint, are identified using SVM in real-time [109]. Such detection is required to effectively control the assistive devices in the adaptive and tailored manner. This involves the utilization of heuristic algorithms and foot-mounted IMUs for the detection of gait events such as toe-off and heel strike [71].

2.1.4 Gait Modes Detection

Regular everyday walking includes overground walking on a flat terrain and changes in elevation, which might require to use the stairs, etc. Gait in such situation is different from regular overground walking, and thus gait phases can deviate in comparison to the overground walking. In context of assistive devices, i.e. exoskeletons, it is crucial to know the intended movement for correct assistance. Gait speed can affect the length of the step, and gait mode would affect the form and amount of required assistance. Even walking on the soft or hard surfaces differ and should be taken into account.

Different gait modes, such as overground walking, stair ascend or descend, walking on treadmill and stationary, can be detected using various methods. Real-time algorithms, such as convolutional long short-term memory neural network (CNN-LSTM) can classify such modes using time-series data from IMU (Fig. 4) [59]. Other approach is to use heuristic algorithms, which use certain gait characteristics visible on IMU signal [90]. Exoskeletons can achieve better results in mixed gait and reduce delay using real-time gait trajectory prediction by multi-head-CNN algorithm [105].

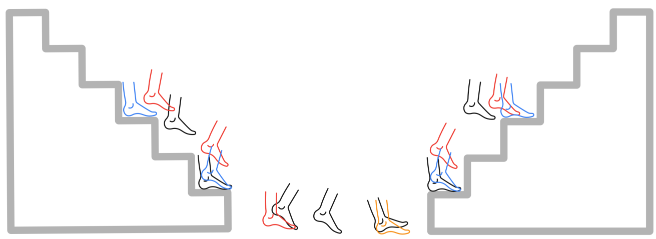

Figure 4: Examples of gait modes like walking on level ground and stair ascend and decent.

2.1.5 Gait Assistive Devices

The most common devices to assist gait are passive devices like canes and crutches. Such devices can help people who are experiencing mild balance disorders [48]. Other type of passive assistive devices is prosthetic devices, which help individuals with limb loss to restore mobility [68]. Exoskeletons are gaining attention and popularity. They can be used for assistance i.e. while handling heavy loads, enhancing stability and reducing load on joints while walking [22, 3].

There are a number of devices, which are using audio, visual or haptic feedback to correct movement patterns. Real-time haptic biofeedback devices are implemented to correct toe-in or toe-out during walking [88].

2.1.6 Available Datasets for Gait Analysis

It is observed in state-of-the-art datasets that they often contain data collected from individuals with normal gait patterns. These datasets are typically used for research topics such as gait phase detection, gait mode classification, identification, and similar studies. Examples of such datasets can be found in Table 1. These datasets were collected from healthy participants of varying ages, using a range of sensors and methods. For instance, in [11], data was collected using 12 cameras and force plates, while in [37], data was collected solely with force plates. In contrast, [53] utilized IMUs and sEMG for data collection.

In these studies, the starting gait speed was either self-selected by the participants [37] or predetermined by the experimenters to target a range of normal, slow, and fast walking speeds [11], with some studies incorporating walking on a treadmill at a fixed speed [53].

Table 1: Available datasets with normal walking data from healthy participants

Authors	Number of Participants	Data Collection System	Types of Walking	Number of Recordings
Bauer C. et al. [11]	100	3D-high-speed camera system with 12 cameras and two force plates	Slow and fast walking speed	1000
Horst F. et al. [37]	350	Force plates for ground reaction force and center of pressure	Self-selected walking speed	8819
Loose H. et al. [53]	108	IMUs and sEMG	Treadmill, Slow, normal, and fast walking speed	3479

This subsection described the most popular gait analysis topics and focused on the key elements, i.e., how the gait data is collected, which are the most popular methods for this; how the musculoskeletal analysis is performed and what it can give to the medical professionals; how gait phases are detected and how it is used in assistive devices; how gait modes are detected and how they would be beneficial for exoskeletons as well as for assistive devices; and concluded this section with available gait datasets and what data they contain.

2.2 Anomaly Detection in Human Gait

Neurodegenerative diseases are affecting person's gait quality, reducing possible movement in limbs, as well as limiting the muscles' responsiveness. This leads to reduced mobility and can change the gait pattern to abnormal, which should be treated. During the rehabilitation, the severity of gait disability is determined to tailor the rehabilitation methods for the patient. One of the effective treatment and post-treatment methods is to use active gait assistive devices [38]. Modern active gait assistive devices use FES and rely on gait phases detection. The other option for gait treatment and post-treatment is to use passive assistive devices, like AFO [12], which can fix the leg in the desired position, and thus improving gait quality.

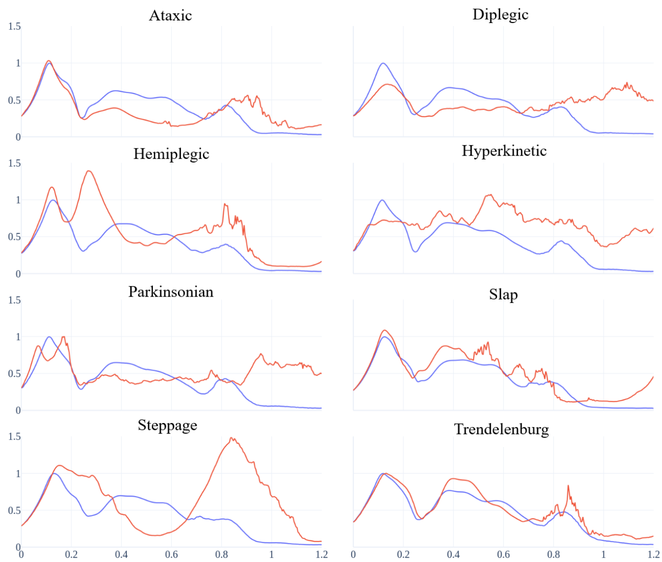

Figure 5: Example of ensemble averaged characteristic step for each gait type, compared to ensemble averaged normal one. The blue lines correspond to a normal step and the red lines correspond to an abnormal step. On the X-axis there is time in seconds while Y-axis is normalized by maximum normal step gyroscope vector magnitude.

Abnormality detection in state-of-the-art is focusing on classification between normal gait patterns and abnormal gait patterns in offline classification process. This is used to understand the features of the patient's gait and to determine the severity of the disease.

2.2.1 Abnormal Gait Types

Neurodegenerative diseases can affect gait quality and change its locomotion cycle to abnormal [47]. The most frequent gait abnormalities, which can be treated using FES, are shown in Fig. 5 and are described in the list below.

Ataxic gait – characterized by uncoordinated body movements and impaired balance, resulting from disruptions in the brain-muscle connection [13].

Diplegic gait – a distinct subtype of motion disorders commonly associated with cerebral palsy [84].

Hemiplegic gait – involves restricted natural swing at the hip and knee, accompanied by leg circumduction. The pelvis is often elevated on the affected side to enable adequate circumduction [94, 25].

Hyperkinetic gait – associated with basal ganglia disorders such as Sydenham's chorea, Huntington's disease, and other conditions like chorea, athetosis, or dystonia. It is characterized by irregular, jerky, involuntary movements in all extremities, which may become more pronounced during walking [58, 87, 10].

Parkinsonian gait – a late-stage symptom of Parkinson's disease, often regarded as more detrimental to quality of life than other Parkinsonian symptoms. It is marked by small, shuffling steps [70].

Slap gait – a gait abnormality involving the heel, identifiable by the distinctive sound produced during walking. It occurs due to weakness in the foot and ankle dorsiflexors, causing the foot to slap against the floor with each step [44].

Steppage gait – commonly observed in patients with foot drop, caused by weakened dorsiflexion of the foot. This gait is characterized by exaggerated lifting of the leg to prevent the foot from dragging on the floor. Foot drop assistive devices are frequently used to address this condition [58, 102].

Trendelenburg (lurch) gait – caused by unilateral weakness of the hip abductors, primarily the gluteal muscles. This weakness may result from superior gluteal nerve damage or a lesion in the fifth lumbar spine, making it difficult to support body weight on the affected side [69, 73].

2.2.2 Age and Health Related Gait Changes

As individuals age, their gait parameters change over time, which can lead to a reduced quality of life. Common changes in gait include decreased limb mobility, shorter step lengths, and slower walking speeds. Gait features and events can be extracted in a physiotherapist's laboratory. To accelerate the gait evaluation process, a CNN-LSTM algorithm can be used to extract gait features and events from IMU data in real-time [5]. This approach can provide insights into how gait parameters evolve over time and why walking becomes more difficult, as well as how limb movements may become less healthy with age.

Tracking changes in gait is essential for addressing them with interventions such as specialized footwear and exercises, which can reduce joint stress and prevent potential minor injuries. Additionally, environment-dependent differences in gait can be monitored, allowing for context-aware decisions that enhance gait assistance [82].

Neurological disorders have a significant impact on gait quality, often transforming the normal locomotion cycle into an abnormal one. For instance, diseases like Parkinson's Disease (PD) can trigger sudden gait changes, such as freezing episodes [108], while others, like MS, may involve prolonged relapse episodes with gradual progression and varying individual impacts [85]. Identifying gait deviations early and understanding their causes can facilitate rapid decision-making and initiate treatment while the disease is still in its early stages. This can expedite disease screening and alleviate the workload on physiotherapists. For example, by recording a short walk using an IMU [4], it is possible to classify a person's walking pattern and detect potential risks or the presence of disease [66]. These recordings can then be used to classify whether a person exhibits healthy or abnormal gait patterns in real-time using CNNs [76]. Tracking disease progression over time is crucial for adjusting treatment strategies. A gait normalcy index, derived from gait parameters of impaired gait, can be used for this purpose [101].

Such an approach can also be applied to estimate the severity of Parkinson's disease and identify the most suitable machine learning (ML) algorithm for this task by comparing the differentiating capabilities of various ML algorithms [108, 14].

2.2.3 Fall Detection

Elderly people have higher chances of falling due to limited movement in joints and muscle weakness. Such falls have higher chances of severe injuries as well, due to brittle bones. This means that in case of fall detection it is crucial to get timely help and hospitalization. Individuals with gait impairments caused by neurological conditions, particularly neuromuscular diseases, face a significant fall risk due to the high variability and deviations from typical gait patterns [1] [46]. Simple mechanical devices such as ankle-foot orthoses can reduce the risk of falling [97]. However, it is needed to develop fall detection techniques. To do so, fall detection algorithms require fall data to be collected. Most often, simulated falls data is collected by healthy individuals. One of the most popular approaches is to use IMU as the data collection device, which is used to detect activities of daily life, fall events and their directions [77, 17]. Information about daily activities can help to understand what can be leading to the falls.

2.2.4 Abnormal Gait Correction Assistive Devices

During the rehabilitation process and post rehabilitation, physiotherapists use gait assistive devices for patients treatment. Gait assistive devices are either passive or active devices. Most of the time, persons needing assistive device rely on passive devices like crotches and passive knee orthoses. Some devices like ankle foot orthoses can help to correct the foot drop, which can happen after a stroke, by fixing the ankle in the desired position. Neurological diseases are significantly affecting the quality of life, and even simple devices can improve quality of life significantly. However, to achieve higher comfort levels more sophisticated approaches are desired. For example, most active devices are designed to assist individuals during walking, with exoskeletons being some of the most popular. These devices rely on accurate phase detection to reduce stress on joints. Correct phase detection is essential to understand the correlation between actual movement and how sensors perceive it.

Research has shown that FES is an effective gait assistive technique, supporting walking, fall prevention [1, 51], and overall improvement in gait quality [38].

In recent years, wearable motion sensors equipped with multidimensional IMUs have been increasingly integrated into gait assistive devices [57, 63, 67]. These wearable devices can significantly aid patients with neurological diseases, assisting them in performing common daily activities [72].

2.2.5 Available Datasets for Anomaly or Deviation Detection

To estimate the classification performance of different methods, as was shown in Section 2.2.2, in detection of gait deviations it is necessary to collect data. In the early stages of the research it is common to collect simulated gait deviation data [61, 33], as seen in Table 2. This helps to develop methods and algorithms to detect gait deviations in advance before trials with patients, minimizing their stress.

In [61], each gait recording represents a single gait deviation. One session involved normal walking, while others involved adding insoles of varying thickness under either the left or right foot. Another session included adding weight to one leg at a time. In [33], the first session recorded normal walking, and the second session involved using knee and ankle braces to simulate limited joint flexibility.

On the other hand, it is beneficial to collect data from real patients with neurological disorders to assess classification and feature extraction performance. In [96], data was recorded for walking, standing, turning, and stopping from both healthy subjects and subjects with neurological or orthopedic disorders. This data can be utilized for gait mode detection and classification. In [30], data was collected from healthy young and old adults, as well as older adults with Parkinson's disease. In the second session, data was collected from patients in age range of 36–70 yr with Parkinson's disease, Huntington's disease, and amyotrophic lateral sclerosis. Such datasets are valuable for classification purposes.

Various data collection systems were used starting from Kinect2 camera system with time of flight estimation and two mirrors while walking on the treadmill [61], moving to the 6 infrared cameras motion analysis systems [33] and ending with familiar IMUs [96] and force-sensitive resistors [30].

Table 2: Available datasets for anomaly or deviation detection

Authors	Number of Participants	Data Collection System	Number of Recordings	Disability Type
Nguyen T. N. et. al. [61]	9	Camera system with time of flight estimation and two mirrors	81	Insole of different thickness or attached weight to one leg
Shorter K. A., Helwig N.E. et al. [33]	10	6 camera infrared motion analysis system	1800	Unbraced, knee braced, ankle braced
Truong C. et al. [96]	230	Two IMUs	1020	Healthy, neurological, and orthopedic disorders
Goldberger, A., et al. [30]	64	Force-sensitive resistors	64	Parkinson, Huntington diseases, amyotrophic lateral sclerosis, and healthy controls

2.3 Summary of the State of the art

As could be seen in the state of the art, the most popular data collection devices are IMUs. The benefits of IMUs are possibility to use them outside of the controlled environment, small size, to fit into portable device, high accuracy and high relative comfort.

A review of the state of the art revealed that available datasets encompass a wide range of gait recordings. It is common for these datasets to include a control group of healthy individuals performing normal walking, which can then be compared to gait recordings from individuals with disabilities. Other datasets consist of recordings of normal walking as well as simulated gait abnormalities. Gait abnormalities can be simulated by mimicking abnormal movements or by adding insoles under one foot, adding weight, or using braces to restrict leg movement. Some datasets focus exclusively on recordings of healthy individuals walking normally.

In terms of the gait assistive devices, the most popular devices are exoskeletons and devices with FES. Benefits of the FES gait correction devices are small size, ease of use and ability to train muscles. However, existing gait correction devices use uncomfortable periodic stimulation, irrespective of any gait deviation detection. To enhance the effectiveness of FES after rehabilitation, an intermittent stimulation approach is preferred to minimize fatigue. Electrical stimulation at the correct time can be controlled fast and reliably. However, real-time anomaly detection during gait, especially in the swing phase, remains unexplored. Devices capable of detecting gait deviations in real-time are ideal for post-treatment support, enabling softer, more patient-friendly interventions.

Long-term analysis of gait deviations and the effective real-time control of FES devices rely on automated recognition of gait anomalies. In older adults, the average swing phase of a step lasts between 300 and 400 ms [35]. During this brief window, the incoming signal must be processed, an appropriate decision made, and the corrective action executed. Since full muscle contraction via electrical stimulation requires 100 to 200 ms of continuous stimulation [16], gait deviations must be identified within 100 ms. In cases where the swing phase is shorter than average, detection must occur within 50 ms to meet the timing constraints.

According to [83], SVM-based methods are the most commonly used in automated gait analysis, followed by CNNs and heuristic algorithms. SVM offers notable advantages, including the ability to perform well with relatively small datasets (ranging from tens to hundreds of samples) and high computational efficiency [39, 32]. In contrast, CNNs typically require larger datasets—often with thousands of samples—to achieve strong classification performance [76, 59]. While the above works have addressed gait phase detection, gait type classification and fall detection problems, the focus of this thesis is on gait abnormality detection in real-time during the ongoing step. However, limited research exists on evaluating the effectiveness of machine learning methods, particularly SVM, in detecting real-time gait deviations associated with neurodegenerative diseases.

Available datasets can not be used for in-step anomaly detection as they are, due to lack of combination of normal and abnormal steps in them. Thus, to develop real-time in-step anomaly detection algorithms additional dataset should be collected in which there are combinations of normal walking patterns with abnormal walking patterns in one gait recording.

In the next chapter, the summary of **Publications I- VI** is presented, which answers to research questions, stated in chapter 1.4.

3 Summary of the Publications

This section provides an overview of the publications and their contributions to the research questions outlined in Section 1.4.

The primary goal of this thesis is to develop methods for real-time in-step gait anomaly detection. Human gait is inherently complex, requiring advanced methods for effective analysis. Real-time analysis further intensifies the challenges due to the constraints of processing speed and the need for high-quality anomaly detection. These challenges are addressed in this thesis and are reported in different publications. Below, we summarize the central contributions of different publications, additional research which is performed to test the resistance of the algorithms to the changes in gait speed (time-stretching) and preliminary efforts on developing the device, details of this are provided as an appendix to this thesis.

Publication I. The literature review in the preceding chapter identified that while gait anomaly detection is a well-researched area, the specific problem of in-step anomaly detection remains underexplored. A significant gap exists in publicly available datasets that combine normal and abnormal walking patterns for step-wise classification. To address **RQ1** (data availability), this study initiated the collection of a novel dataset.

Data collection, as detailed in Publication I, adhered to a clinical trial protocol approved by the Estonian National Institute for Health Development (Permission No. 818). Using guidance from a professional physiotherapist, abnormal gait patterns (see Section 2.2.1) were simulated based on real patient video recordings. Two IMU sensors were tested, placed on the forefoot and below the knee, with forefoot placement selected for further analysis. Steps were labeled as normal or abnormal using a semi-automated tool validated with video recordings.

The collected dataset serves as a proof-of-concept for step-wise classification using classical machine learning algorithms, such as time-series Support Vector Machines (tsSVM). Results demonstrated high F1 scores (over 90%), validating the dataset's utility and its potential for real-time algorithm development.

Publication II. Building on the promising results from Publication I, this study addressed **RQ2** and partially **RQ3** by developing the RTtsSVM-AD algorithm for real-time in-step anomaly detection. The dataset from Publication I was used for proof-of-concept validation. The algorithm uses tsSVM as its classification "core", with optimized hyperparameters and classification step to enable real-time operation.

Results show that the RTtsSVM-AD algorithm could classify gait deviations during the ongoing step, partially answering **RQ2**. However, its performance in terms of expensive computations and anomaly detection quality (average F1 scores of more than 50%) revealed limitations. The study concluded that a more tailored approach and advanced algorithms are required to achieve optimal real-time detection, providing valuable insights for answering **RQ3**.

Publication III. Publication III aimed to enhance the real-time performance and classification quality of the RTtsSVM-AD algorithm by introducing neural network-based methods, specifically 1D-CNN and LSTM. To validate these algorithms, additional data from 20 subjects were collected, expanding the dataset to 155 recordings, thereby extending the answer to **RQ1**.

The 1D-CNN and LSTM algorithms use a sliding-window approach, independent of gait phases, allowing for rapid and lightweight real-time anomaly detection. Results show that the 1D-CNN algorithm achieved an average F1 score of 88% and consistent earliness (<0.5 seconds), outperforming the LSTM algorithm, which had a moderate F1 score of 70%. While these methods advance real-time detection (**RQ2**) and demonstrate potential for embedded applications (**RQ4**), they lack phase awareness, leading to occasional multiple detections within a single step. Further refinement is necessary to address this limitation.

Publication V. This study introduced the SST-AD algorithm, a heuristic method tailored for real-time in-step anomaly detection. The SST-AD algorithm prioritized simplicity and computational efficiency, addressing the performance limitations of the RTtsSVM-AD and LSTM algorithms. A unified evaluation framework was developed to compare algorithms under identical conditions, enabling fair assessment and answering **RQ3**.

The SST-AD algorithm achieves high average F1 scores (80.7%) and earliness (<0.5 seconds), comparable to 1D-CNN, while outperforming neural network-based approaches in computational efficiency. These results solidify its suitability for real-time applications, contributing to the answers for **RQ2** and **RQ3**.

Patent application VI and Publication IV. As a co-author, I contributed to Publication IV by consulting on the dataset. Evaluation of the MP algorithm for real-time anomaly detection, partly addresses the **RQ2**. The algorithm achieves average F1 scores of 75% and earliness of 1 second on the dataset from Publications I and II.

The patent application VI leverages selected results from Publications II and V. It outlined the working principles of the RTtsSVM-AD and SST-AD algorithms and extends the potential use-cases of the algorithms. It forms a basis for in-step anomaly detection methods and similar signal processing technologies. It also outlines the implementation plan on the single board computer, i.e. Raspberry Pi 2W which extends the answer to the **RQ4**.

Appendix 6. Unpublished results indicate that the 1D-CNN and SST-AD algorithms maintain robust detection under gait speed variations, with F1 scores decreasing to 83% and 71%, respectively. This resilience addresses practical challenges in real-world applications and contributes to **RQ4**.

Preliminary efforts towards personalized gait-assistive devices explore requirements such as optimal electrode placement, integration of sensors with wearable devices, and hardware selection. These findings provide a foundation for developing efficient FES systems, further answering **RQ4** by bridging research outcomes with practical deployment.

4 Conclusion

The research in this PhD thesis revolves around the formulation and investigation of the personalized, comfortable gait assistive devices in terms of hardware and the real-time in-step gait anomaly detection algorithms. This chapter concludes the thesis by taking into account the novel methodologies to advance the real-time anomaly detection in gait analysis. The key findings and contributions in the field of the real-time gait deviation detection are presented through five research papers and a patent application presented within the scope of this thesis. The PhD thesis has contributed to the research project PRG424 by data collection, development of new methods, introduction of earliness metric and achievement of results. In addition to the above main project, the work presented in this PhD thesis also provided additional knowledge to the EXCITE project (topics of Sensing and Sensor Signal Processing in Distributed Data Acquisition Systems and Human Biosignal Analysis for Novel Healthcare Technologies).

Firstly, this chapter presents an overview of the conducted research. Secondly, it addresses the research questions, providing answers and highlighting achievements gained through the research. Lastly, it outlines the future perspectives and potential avenues for further advancement in the field of the real-time in-step gait anomaly detection algorithms and gait assistive devices. Overall, this chapter consolidates the contributions made towards the real-time in-step gait anomaly detection algorithms and personalized, comfortable gait assistive devices.

4.1 Summary

This section provides an overview of this PhD thesis focused on the development of the real-time in-step anomaly detection algorithms and personalized, comfortable gait assistive devices. The thesis explores the algorithms used in gait analysis, adapts the most popular ML algorithms used in gait analysis as well as develops new algorithms for gait anomaly detection. The research consists of five papers and a patent application, that evaluate and collect gait data, develop the algorithms and benchmark framework for real-time gait anomaly detection algorithms evaluation.

The first research paper presents the data collection procedure and evaluates the collected dataset. An evaluation is performed by classifying the data with the time-series SVM algorithm. The second research paper consists of the real-time adaptation of the tsSVM algorithm in a form of the RTtsSVM-AD algorithm for real-time anomaly detection, which is proving the concept, that anomaly can be detected during the ongoing step. The third paper provides additional data collection and research on the second most popular algorithms in the gait analysis, the neural networks, and presents the results for the LSTM and 1D-CNN algorithms. The fourth paper investigates the MP algorithm for gait anomaly detection and presents the results of the real-time in-step anomaly detection. The fifth and final research paper consists of the framework description for the benchmark of the real-time gait anomaly detection algorithms and novel SST-AD algorithm, which is compared to more lightweight SVM based algorithm, the OCSVM algorithm, as well as to the previously presented 1D-CNN and LSTM algorithms. The SST-AD algorithm achieves similar performance to the 1D-CNN algorithm, while requiring significantly less computational power.

The significance of the in-step anomaly detection is providing the information about possible gait deviation to the gait assistive devices. The results from the research papers show that developed algorithms, particularly SST-AD algorithm, provide timely information about the anomaly occurring in the step. This will lead to the more user-friendly gait assistive devices, which would be more comfortable and could be used for prolonged time.

4.2 Answers to the Research Questions

The research questions from section 1.4 of this PhD thesis are answered below.

RQ1. How to develop a methodology for dataset collection that would be suitable for the development of the real-time in-step anomaly detection algorithms? Existing state-of-the-art gait datasets are not adequately designed for in-step gait anomaly detection in real-time scenarios. Therefore, a dataset integrating both normal and abnormal walking patterns within a single gait recording is necessary. To evaluate algorithm performance, simulated gait deviation data was collected following a clinical trial protocol approved by the Estonian National Institute for Health Development, permission No.818. A total of 155 gait recordings were acquired across 27 sessions involving 22 subjects. This dataset uniquely incorporates both normal and abnormal step patterns within individual recordings, addressing a gap in current state-of-the-art resources. To the authors' knowledge, it is the first dataset to comprehensively include eight common gait deviation types in a unified format, enabling more extensive research on gait anomaly detection algorithms.

RQ2. How to adapt benchmark methods and develop new algorithms which are capable of in-step abnormality detection in real-time? The most popular algorithms from gait analysis are ML algorithms, such as SVM and NN. Second most popular algorithms are heuristic algorithms, which are tailored for the specific task. These algorithms were adopted to the real-time application, resulting in the RTtsSVM-AD, OCSVM, LSTM, 1D-CNN and MP algorithms. The heuristic SST-AD algorithm has similar classification performance to the 1D-CNN algorithm, while being computationally more effective. Thus, the NN and heuristic SST-AD algorithm performed the best in this application, while being tested on the PC. Tests on the embedded devices are necessary to confirm these findings.

RQ3. How to compare the benchmark methods and the proposed real-time in-step anomaly detection algorithms performance? The evaluation framework was designed to facilitate a systematic and controlled comparison of algorithms. To achieve this, data collection was conducted under controlled conditions. The collected data undergoes preprocessing and is presented to the algorithms in the same manner as during training, enabling an assessment of real-time anomaly detection performance. The training process and dataset are specific to each algorithm. The trained models are evaluated in a simulated real-time setting, where data is processed sequentially in chunks. This approach allows for the assessment of widely used gait analysis algorithms, establishing a benchmark for in-step anomaly detection during an ongoing step.

RQ4. What are the key elements of personalized and comfortable gait assistive device with efficient FES? As it was described in the SOTA, current assistive devices with FES, are using uncomfortable stimulation during every step. To improve the gait assistive devices, they should provide the intervention only, when the gait deviation is detected. The patients after the rehabilitation are able to walk on their own for a certain period of time, and only occasionally need gait correction. The robustness of the 1D-CNN and SST-AD algorithms was evaluated against the changes of speed (time-stretching). Presented algorithms and preliminary device development are providing insights to the key elements, which are needed for personalized and comfortable gait assistive device with efficient FES. The key elements of the next generation of gait assistive devices are real-time anomaly detection algorithms, easy-to-use electrodes for FES and lightweight and affordable design of the device packaging.

4.3 Perspectives

The collected dataset and the algorithms can be used as candidates for the next generation of gait assistive devices with gait deviation detection for effective FES. Gait deviation detection algorithms can be used in the visualization tools for the physicians, to monitor the patients in real-time and provide valuable feedback. Improvements and optimization of the algorithms can be expected with additional data collection and evaluation of the algorithms with the real patients gait data. Inclusion of emerging AI tools can help to generalize findings and accelerate their use as one of the physiotherapist tools. The hardware development and deployment of gait deviation detection algorithms on the embedded device and real life experiments would provide valuable insights on how the next generation of the gait assistive devices would benefit the patients. The achievements of the thesis would be used in the ongoing Estonian IT Academy project "Sustainable Artificial Internet of Things (SAIoT)" to further develop the gait assistive device by cooperation with the clinicians.

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Abstract

Development of Methods for Real-time In-step Anomaly Detection in Gait Analysis

The increasing number of people suffering from neurological diseases has drawn significant attention to the consequences of neurological diseases and, in particular, to the topic of gait analysis. Neurological diseases can affect gait quality and movement freedom. Con-sequently, the topics of gait assistance, rehabilitation techniques, assistive devices, and anomaly detection are emerging. Some of the most common techniques used after re-habilitation include passive devices or active devices, such as exoskeletons or Functional Electrical Stimulation (FES) devices. These devices rely heavily on gait phase detection for correct actuation or stimulation.

The exoskeletons are mostly bulky heavy weight as a result less applicable for the daily life activities. For most abnormal gait types, the FES approach is more desirable, providing a more lightweight device that maintains the muscles' ability to operate and maintain their health. However, the stimulation patterns in modern devices lack personalization in terms of gait deviation detection. The gait quality of the patient after rehabilitation can be close to normal, meaning that gait correction is required only occasionally. Thus, a gait assistive device with gait deviation detection should be used, which can detect gait deviation in real-time and stimulate only when required. This will improve user experience and allow prolonged usage of the device, compared to current devices that stimulate every step, which can lead to fatigue and skin irritation. A crucial part of such a device is real-time anomaly detection algorithms, which can detect gait deviation from normal gait patterns and provide a signal that stimulation is required during the ongoing step.

Real-time gait anomaly detection in gait analysis, particularly within the mid-swing phase of a step, remains a challenge due to lack of research of 'in-step' gait anomaly detection in existing methods.

This Ph.D. thesis focuses on this gap and presents solutions by evaluating the most popular algorithms and providing a framework and dataset for fair comparison of their performance.

The first contribution of this thesis is the establishment of an evaluation framework accompanied by a novel dataset. To evaluate the performance of gait anomaly detection algorithms, simulated gait deviation data was collected under a clinical trial protocol approved by the Estonian National Institute for Health Development, permission No. 818. A total of 155 gait recordings obtained during 27 sessions involving 22 subjects. This dataset uniquely incorporates both normal and abnormal step patterns within a single recording, a feature previously unavailable in existing resources. To the best of the author's knowl-edge, it is the first dataset to systematically integrate eight common types of gait devi-ations, facilitating more robust and comprehensive research on gait anomaly detection algorithms.

The second contribution of this thesis is the adaptation of popular gait analysis algorithms for real-time operation. The first algorithm, the real-time tslearn support vector machine anomaly detection (RTtsSVM-AD), demonstrated the feasibility of real-time in-step anomaly detection, achieving average accuracy and F1 scores of 64.5% and 49.2%, re-spectively. An improved version of the SVM-based algorithm, the one class support vector machine (OCSVM), yielded enhanced performance with average accuracy and F1 scores of 74% and 54.9%. The MP algorithm achieved average F1 scores of 75% and earliness of 1 second on the dataset presented in the **Publication I**. Neural network-based algorithms specifically tailored for time-series data were also evaluated. The long short-term mem-

ory (LSTM) achieved average accuracy and F1 scores of 86.5% and 70.1%, while the one dimensional-convolutonal neural network (1D-CNN) attained superior performance with 95% accuracy and an F1 score of 88.2%. However, to address the computational demands of neural networks, a heuristic algorithm, the signal shape tracking anomaly detection (SST-AD), was developed. This algorithm achieved average accuracy and F1 scores of 91% and 81%, respectively, offering a performance level comparable to the 1D-CNN algorithm but with significantly lower computational complexity. Furthermore, the SST-AD algorithm demonstrated the best average earliness in anomaly detection, achieving results 0.4 seconds after the initial-swing phase start. Based on these findings, the SST-AD algorithm emerges as the most suitable candidate for real-time gait anomaly detection and is recommended for deployment in future embedded assistive devices.

This thesis introduces a framework for real-time gait deviation detection for future gait assistive device development. It present algorithms which can detect the gait deviations in real-time with high F1 scores. It also outlines initial steps and challenges encountered during the device development. This includes evaluation of the socks with embedded electrodes, FES parameters optimization, assessment of potential hardware and corresponding software for gait deviation detection in-real time. The on-device anomaly detection performance remains to be explored in the future.

Kokkuvõte
Reaalajaliste meetodite arendus sammusiseste kõrvalkallete tuvastamiseks kõnnianalüüsis

Neuroloogiliste haiguste all kannatavate inimeste arvu suurenemine on toonud olulist tähelepanu neuroloogiliste haiguste tagajärgedele ja eelkõige kõnnaku analüüsi teemale. Neuroloogilised haigused võivad mõjutada kõnnaku kvaliteeti ja liikumisvabadust. Seetõttu on esile kerkinud kõnnaku abistamise, rehabilitatsioonitehnikate, abivahendite ja anomaaliate tuvastamise teemad. Levinumad rehabilitatsioonijärgsed tehnikad hõlmavad passiivseid abivahendeid või aktiivseid seadmeid, nagu eksoskeletid või funktsionaalse elektrilise stimulatsiooni (FES) seadmed. Need seadmed tuginevad tugevalt kõnnakufaasi tuvastamisele, et tagada korrektne aktiveerimine või stimulatsioon.

Eksoskeletid on enamasti suured ja rasked, mistõttu on nende kasutamine igapäevaelus piiratud. Enamiku ebanormaalsete kõnnakutüüpide puhul on FES-lähenemine eelistatum, pakkudes kerge kaaluga seadet, mis säilitab lihaste töövõime ja tervise. Kuid kaasaegsete seadmete stimulatsioonimustrid ei ole isikupärastatud ega võta arvesse kõnnaku kõrvalekaldeid. Pärast rehabilitatsiooni võib patsiendi kõnnaku kvaliteet olla peaaegu normaalne, mistõttu on korrektsioon vajalik vaid aeg-ajalt. Seega on vaja kõnnaku abiseadet, mis suudaks reaalajas tuvastada kõnnaku kõrvalekaldeid ja rakendada stimulatsiooni ainult siis, kui see on vajalik. See parandaks kasutajakogemust ja võimaldaks seadet pikemaajaliselt kasutada, võrreldes praeguste seadmetega, mis stimuleerivad iga sammu, põhjustades väsimust ja nahaärritust. Sellise seadme oluline osa on reaalajas anomaaliate tuvastamise algoritmid, mis suudavad tuvastada kõrvalekaldeid normaalsest kõnnakumustrist ja anda signaali, kui stimulatsioon on käimasoleva sammu ajal vajalik.

Reaalajas kõnnaku anomaaliate tuvastamine, eriti sammu keskkiige faasis, on endiselt väljakutse, kuna olemasolevad meetodid ei ole keskendunud "sammu-siseselt"esinevate kõnnaku anomaaliate tuvastamisele.

Käesolev doktoritöö keskendub sellele probleemile ja pakub lahendusi, hinnates populaarsemaid algoritme ning esitades raamistikku ja andmestikku nende jõudluse võrdlemiseks.

Töö esimene panus on hindamisraamistiku ja uudse andmestiku loomine. Kõnnaku anomaaliate tuvastamise algoritmide jõudluse hindamiseks koguti simuleeritud kõnnaku kõrvalekallete andmeid kliinilise uuringu protokolli alusel, mis oli heaks kiidetud Eesti Tervise Arengu Instituudi poolt (luba nr 818). Kokku koguti 155 kõnnaku salvestust 27 sessiooni jooksul, milles osales 22 katseisikut. See andmestik sisaldab ainulaadselt nii normaalseid kui ka ebanormaalseid sammumustreid ühes salvestuses, mis ei ole varem eksisteerinud andmekogudes olnud kättesaadav. Autori parima teadmise kohaselt on see esimene andmestik, mis süstemaatiliselt integreerib kaheksa levinumat kõnnaku kõrvalekallet, võimaldades põhjalikumat ja täpsemat uuringut kõnnaku anomaaliate tuvastamise algoritmide osas.

Töö teine panus on populaarsete kõnnaku analüüsi algoritmide kohandamine reaalajas toimimiseks. Esimene algoritm, real-time tslearn support vector machine anomaly detection (RTtsSVM-AD), demonstreeris reaalajas sammu-sisese anomaaliate tuvastamise teostatavust, saavutades keskmise täpsuse 64,5% ja F1-skoori 49,2%. Parendatud versioon SVM-põhisest algoritmist, one class support vector machine (OCSVM), pakkus paremat tulemust, saavutades keskmise täpsuse 74% ja F1-skoori 54,9%. MP-algoritm saavutas keskmise F1-skoori 75% ja kõrvalekallete tuvastamise kiirusega 1 sekund andmestiku puhul, mis on esitatud **Publikatsioonis I**. Ajasarjadele kohandatud tehisnärvivõrgu algoritmid said samuti hinnatud. long short-term memory (LSTM) saavutas keskmise täpsuse 86,5%

ja F1-skoori 70,1%, samas kui one dimensional-convolutonal neural network (1D-CNN) pakkus parimat tulemust 95% täpsuse ja F1-skooriga 88,2%.

Kuid arvestades närvivõrkude arvutuslikku keerukust, töötati välja heuristiline algoritm signal shape tracking anomaly detection (SST-AD). See algoritm saavutas keskmise täpsuse 91% ja F1-skoori 81%, pakkudes 1D-CNN algoritmiga võrreldavat jõudlust, kuid oluliselt madalama arvutusliku keerukusega. Lisaks demonstreeris SST-AD algoritm parimat keskmist varasemat anomaaliate tuvastust, tuvastades kõrvalekalded 0,4 sekundit pärast algkiige faasi algust.

Nende tulemuste põhjal on SST-AD algoritm kõige sobivam kandidaat reaalajas kõnnaku anomaaliate tuvastamiseks ning seda soovitatakse kasutada tulevastes manustatud abiseadmetes.

Käesolev doktoritöö tutvustab reaalajas kõnnaku kõrvalekallete tuvastamise raamistikku, mis on suunatud tulevaste kõnnaku abiseadmete arendamiseks. Töö esitleb algoritme, mis suudavad reaalajas tuvastada kõnnaku kõrvalekaldeid kõrgete F1-skooridega. Samuti kirjeldatakse seadme arendamise esimesi samme ja väljakutseid, sealhulgas sisseehitatud elektroodidega sokkide hindamist, FES-parameetrite optimeerimist, potentsiaalse riistvara ja vastava tarkvara hindamist reaalajas kõnnaku kõrvalekallete tuvastamiseks. Seadmesisese anomaaliate tuvastamise jõudlus vajab edasist uurimist tulevikus.

Appendix 1

I

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SVM Time Series Classification of Selected Gait Abnormalities

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Abstract. Gait analysis is widely used for human disability level assessment, physiotherapeutic and medical treatment efficiency analysis. Wearable motion sensors are most widely used gait observation devices today. Automated detection of gait abnormalities, namely incorrect step patterns, would simplify the long term gait assessment and enable usage of corrective measures as passive and active physiotherapeutic assistive devices. Automatic detection of gait abnormalities with wearable devices is a complex task. Support Vector Machines (SVM) driven machine learning methods are quite widely used for motion signals classification. However, it is unknown how well actual implementations work for specific gait deviations of partially disabled people. In this work we evaluate how well SVM method works for detecting specific incorrect step patterns characteristics for the most frequent neuromuscular impairments. F1 score from 66% to 100% were achieved, depending on the gait type. Gait pattern deviations were simulated by the healthy volunteers. Angular speed motion data as an input to SVM was collected with a single Shimmer S3 wearable sensor.

Keywords: Gait analysis, Machine learning, SVM, Wearable sensors, Medical applications

1 Introduction

According to World Health Organisation (WHO) report about one billion persons are affected by neurological disorders worldwide [2]. Neurological diseases ranging from migraine to stroke and Alzheimer are the leading cause of Disability Adjusted Life Years (DALY) loss [8]. For example, there is a high risk of falling down for patients with gait impairments from neurological disease [24], [20]. Therefore it is important to assess neurological disease patient gait deviations and, if possible, correct step patterns using certain assistive devices. It is shown that even simple mechanical devices like ankle-foot orthoses certainly can reduce the risk of falling [27]. However, it is shown that Functional Electrical Stimulation (FES) devices that activate in proper moments corresponding muscles, are more effective for fall prevention [14] and generic gate improvements [16]. Essentially, long term gate deviation analysis and efficient run-time control of FES devices requires automated recognition of "incorrect" steps or other gate deviations. According to our previous research [22] we have concluded that Support Vector Machines (SVM) based methods are most widely used ones for automated gait analysis, followed by Convolutional Neural Networks (CNN). The benefits of SVM include capability to operate with relatively small data sets and high computational efficiency [10, 11]. For human activity recognition has been reported by Almaslukh et al. [1] quite impressive accuracy, close to 97 percent. There are several other results indicating 90 percent accuracy, listed in [22]. However, there is a very limited research conducted of analysing how well machine learning methods, particularly SVM, performs in detecting realistic gait deviations, caused by actual neural diseases. Current work focuses on describing test results collected by us in this domain, that are still relying on simulated gait deviations.

Gait of each person is virtually unique. It can be described by a set of parameters such as: step length, length of individual step phases, muscle force and etc. [18]. Especially high variability and deviations from the "normal" gait pattern can be seen in persons gait, who are suffering from neuromuscular diseases [15]. Therefore it is extremely difficult to analyze patients' gate patterns. Certain diseases cause jumpy gait changes - like freezing episodes of Parkinson Disease (PD) [4], other diseases, like Multiple Sclerosis (MS) may contain long duration relapse episodes with individual impact and have slow progression [23]. From the perspectives of physiotherapists, each person has own "normal" (or target) gate that has to be used as a reference in gate assessment procedure.

Various stationary (3D camera systems), portable (pressure mats) and wearable (motion sensors) instrumental solutions are used for gait analysis. However, wearable motion sensors, containing multidimensional Inertial Motion Units (IMUs), are the most widely used gait assessment devices in the recent years [25]. IMUs are also used for gait assessment of neurological disease patients [12,19,21].

Main goal of this research work is to detect abnormality in the gait, caused by some kind of disease, as fast as possible, to prevent person from falling. Current paper proposes analysis of gait using SVM, to classify the normal and abnormal steps. Even if such a full step classification does not solve the main goal, abnormality estimation in the real-time, it will be used as pre-processing stage to produce reference set of good steps for the real-time abnormality detection algorithm. Therefore the current paper proposes time series based "good" and "bad" steps SVM classifier implementation, which is built on the *tslearn* Python library [26] and applied to the time-series gyroscope gait data, which is different from feature based SVM classification, used in other works. Thus, it is possible to compare achieved results to the feature based approach, found in other works.

This paper consist of 5 sections: after the introductory state-of-art overview in section 2 the motion data collection methodology is described; in section 3 proposed application of the SVM based algorithm implementation, applied to the time-series gait data, is presented; the results are presented in the subsection 4 and discussion and conclusion are in the section 5.

2 Gait Data Collection

The fundamental part of each instrumented gait analysis is collection of human walking patterns, which provide relevant information about the gait changes of the subjects. The human gate contains of seven phases [3] (Fig. 1). The ultimate long term goal is to detect deviations of each phase separately for fastest gate corrections. However, current study focuses on classification of whole steps only.

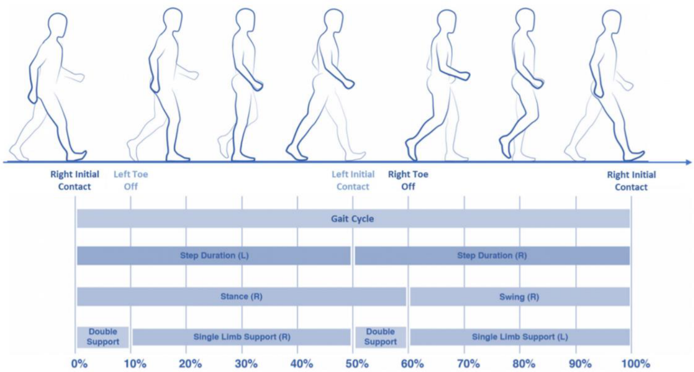


Fig. 1: The seven phases of human gait cycle [3]

During the current study, Shimmer S3 (Dublin, Ireland) wearable sensors were used for lower limb motion data capture. Sensors were configured to work with 256Hz sampling rate, measurement data was recorded on device's memory, later modulus was calculated from three-dimensional 16-bit gyroscope signal to reduce the amount of data feed to machine learning algorithm. Two different sensor placements were initially tested (Fig. 2): right below of the knee that is the location of foot drop FES devices directly stimulating the most important lower limb muscles, namely tibialis anterior and fibularis longus, and on forefoot, which is the most widely used placement of inertial sensors for gate cycle monitoring [9]. According to initial visual analysis of recorded signals, forefoot data was selected for the further analysis.

During the data collection, correct ("good") and incorrect ("bad") steps were mixed according to following procedure:

1. $Normal\ gait + one\ abnormal\ step$
2. $Normal\ gait + one\ abnormal\ step + normal\ gait$
3. $Normal\ gait + N \cdot abnormal\ step + normal\ gait + N \cdot abnormal\ step$, where $N = 0, 1, 2, 3, 4 \ldots$

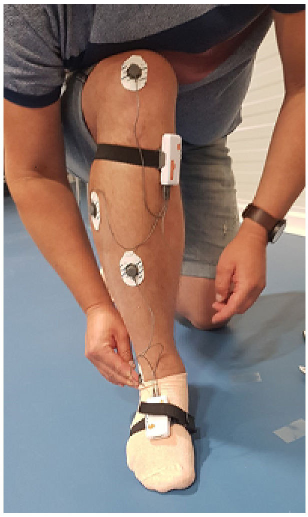


Fig. 2: Sensor placement for data collection

To add more variability to the test data, recording was performed on two types of surfaces: hard and soft (sand) surface. Each recording contains deviations of one specific disability type that is described below. Recordings were annotated using a semiautomatic tool: all correct and incorrect steps were labeled in the data file.

2.1 Data Collection of Simulated Gait Abnormalities

The ultimate goal of present study is to evaluate how well an actual SVM implementation can detect gait deviation caused by neurological impairments. Abnormalities were simulated by 2 healthy persons of different gender, both 23 years old. Simulations were replicating actual patients' videos and instructions of a professional physiotherapist. The chosen, most frequent, gait abnormalities were following:

Steppage gait - seen in patients gait with foot drop (weakness of foot dorsiflexion). This is caused due to an attempt to lift the leg high enough during walking, so that the foot does not drag on the floor [3]. This disability is most widely targeted with foot drop assistive devices.

Hemiplegic gait - includes impaired natural swing at the hip and knee with leg circumduction. The pelvis is often tilted upward on the involved side to permit adequate circumduction.

Diplegic gait - a specific subcategory of the wide spectrum of motion disorders gathered under the name of cerebral palsy.

Ataxic gait - commonly defined as a lack of coordination in body movements or a loss of balance, which is not due to muscle weakness.

Parkinsonian gait - is a feature of Parkinsons disease in later stages. Its often considered to negatively impact the quality of life more than other Parkinsons symptoms. Parkinsonian gait is usually small, shuffling steps.

Hyperkinetic gait - is seen with certain basal ganglia disorders, including Sydenham's chorea, Huntington's Disease, and other forms of chorea, athetosis, or dystonia. The patient will display irregular, jerky, involuntary movements in all extremities. Walking may accentuate their baseline movement disorder [3]

Comparative analysis of applying SVM algorithm to data is in the next section.

3 SVM Performance Assessment

Considering that the SVM is well known in classification applications and, particularly, in gait analysis [1, 5, 13, 17, 28], this method, however, can not be used directly with time series (output of IMU motion sensor), where the input vectors can be of different lengths (feature dimensions). Therefore, time series oriented implementation (*tslearn* [26]) of the SVM classifier (call it as tsSVM) was selected for the current research work and applied to the human gait steps ensemble extracted from the time series data to classify correct and anomaly (incorrect) steps.

TsSVM implementation uses Global Alignment Kernel (GAK) [6], which allows to apply the SVM classifier to time-series data with different duration of samples.

The GAK is related to the soft-Dynamic Time Warping (soft-DTW) [7] through eq. (1), which is used to align time series samples in time. In kernel equation, $\mathbf{x} = (\mathbf{x_0}, \ldots, \mathbf{x_{n-1}})$ and $\mathbf{y} = (\mathbf{y_0}, \ldots, \mathbf{y_{m-1}})$ are two time series of respective lengths $\mathbf{n}$ and $\mathbf{m}$. Hyper-parameter γ is related to the bandwidth parameter σ of GAK through $\gamma = 2\sigma^2$.

$$k(x, y) = exp(\frac{softDTW_\gamma(x, y)}{\gamma}) \tag{1}$$

In eq. (2) soft-DTW could be observed with hyper-parameter γ, that controls smoothing of the resulting metric (squared DTW corresponds to the limit case $\gamma \to 0$), where $(\mathbf{a_1}, \ldots, \mathbf{a_n})$ is time series.

$$soft - min_\gamma(a_1, \ldots, a_n) = -\gamma log \sum_i e^{-a_i/\gamma} \tag{2}$$

The GAK's smoothing hyper-parameter γ was experimentally chosen depending on the data set to get the best actual performance. Usually it was between 20 and 150. Tslearn toolbox was used to convert one-dimensional magnitude, calculated from gyroscope data from data set into time series with same length. Then data set was divided into training and test sets with proportion of 70% to 30% respectively. After that, training was performed and the following results were achieved.

First some preprocessing was required to be able to use the algorithm. Data was divided into individual steps, using timestamps in labels. After that they were combined into required form and normalized in duration by adding Nan's to the shorter steps. Then proper hyperparameter γ was chosen by iteration over potential numbers.

4 Results

In proposed approach 3D gyroscope angular velocity data was used as the initial input, which then was transformed into the magnitude time series format. Assuming that gyroscope axes are called gX, gY and gZ, the magnitude is calculated as in eq. 3, where t_i is given moment of time, and normalized by Min-max feature scaling 4 for every time series instance:

$$gM(t_i) = \sqrt{gX(t_i)^2 + gY(t_i)^2 + gZ(t_i)^2} \tag{3}$$

$$gM(t)_{norm} = \frac{gM(t) - gM(t)_{min}}{gM(t)_{max} - gM(t)_{min}} \tag{4}$$

Calculated gyroscope magnitude time series (eq. 3) is used as an input for the tsSVM algorithm.

To understand the results lets observe support vectors on Fig. 3 for two classes, they represent common step forms, corresponding to a particular class. For each class support vectors looks similar, only for class 2 excess vectors could be observed, what affects results. Ataxic gait test data set had 14 samples: 6 abnormal steps (positive) and 8 normal steps (negative). After training the SVM on 32 samples, two false positives were detected using test data set (Table 1).

This could have happened due to residual "abnormality" in normal steps following abnormal steps. On the Fig. 8c noisier step could be seen than the step on the Fig. 8a. Similar situation could be observed for steppage gait test 1, where there is to much deviation for normal steps (Fig. 5a and Fig. 5c), what could be considered as data collection error. This leads to misclassificaion of abnormal steps which result in 0% f1 score. On the other hand, if normal steps are consistent, as for steppage gait test 2 (Fig. 7), classification of abnormal steps is preformed correctly and f1 score of 100% is achieved.

Lets have closer look at step shapes. For example on Fig. 8a first peak represents a moment, when toe is starting to move in the end of stance phase (40%-60% of phase on Fig. 1), then it is start of a swing phase, till the second

Table 1: Classification quality for data. Where, TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative

Gait type, test number	TP	TN	FP	FN	F1 score
Ataxic, test 2	4	8	2	0	80%
Diplegic, test 1	3	7	0	0	100%
Diplegic, test 3	2	9	0	0	100%
Hemiplegic, test 2	1	9	0	1	67%
Hyperkinetic, test 2	4	8	0	2	80%
Parkinsonian, test 1	7	8	0	1	93%
Parkinsonian, test 2	6	7	1	0	92%
Steppage, test 1	0	10	0	2	*0%
Steppage, test 2	2	10	0	0	100%

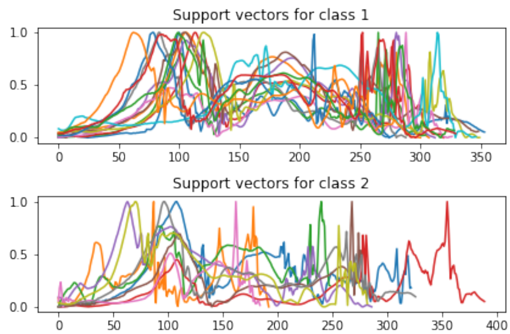


Fig. 3: Support vectors for ataxic gait. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

peak (60%-100%), which represents toe movement, to prepare for initial contact and third peak is, when toe lands on the ground flat (0%-20%), after that it is a stance phase between the toe movement (20%-40%). For abnormal step (Fig. 8b) clear separation between peaks is lost. According to description of ataxic gait type, clear swing phase is lost, what could be observed.

As it was mentioned above, on Fig. 8 and Fig. 10 peaks for normal and abnormal gait steps are located differently and have different amplitudes. F1 score for ataxic gait was 80% and for diplegic gait it was 100%, that shows SVM capability of classifying steps. Good results could be observed also for parkinsonian and hyperkinetic gaits, 93% and 80% respectively, because normal and abnormal steps have very different magnitude and shape. For diplegic gait

* This test has bad data samples, reasons are described in results section.

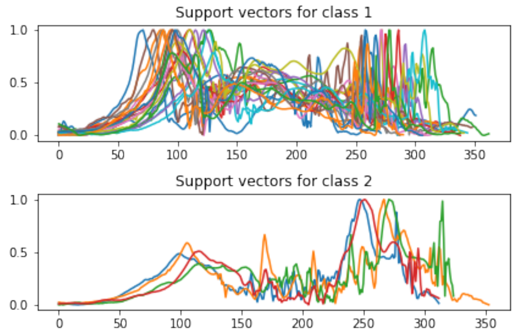
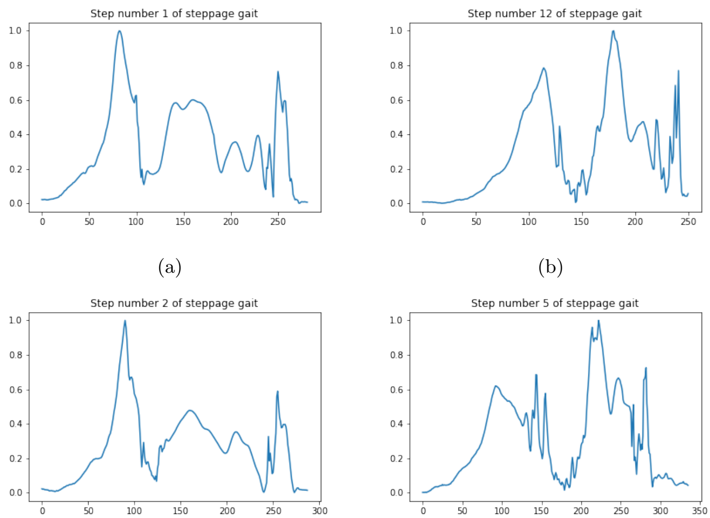


Fig. 4: Support vectors for steppage gait. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).



(a) (b)

(c) (d)

Fig. 5: Normal (left) and abnormal (right) steps. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

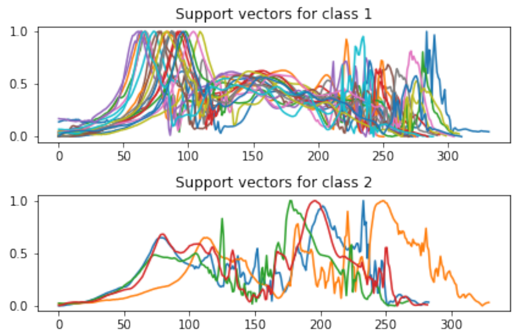


Fig. 6: Support vectors for steppage gait. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

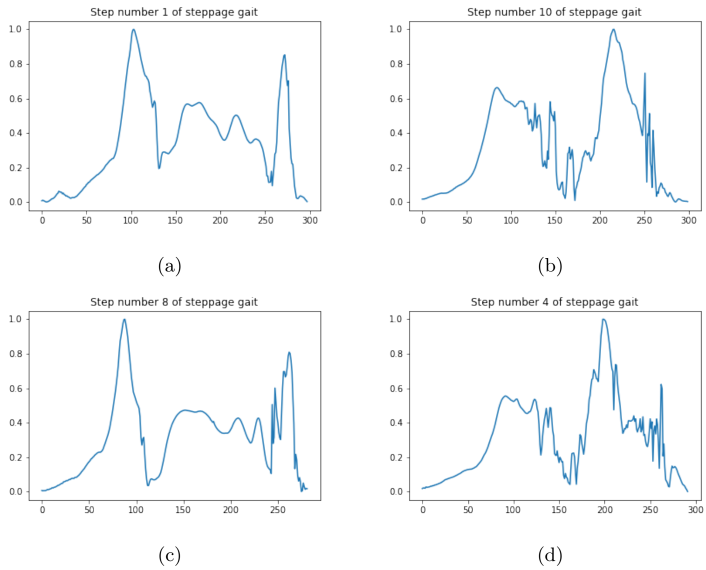
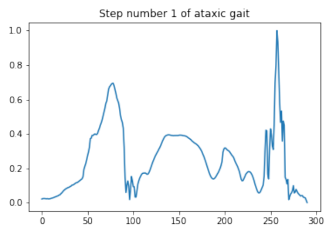
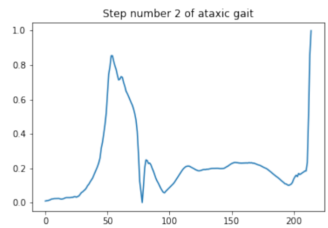


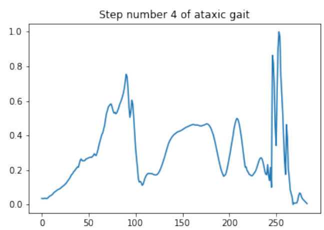
Fig. 7: Normal (left) and abnormal (right) steps. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).



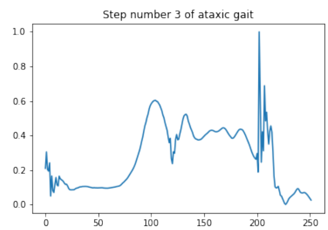
(a)



(b)



(c)



(d)

Fig. 8: Normal (left) and abnormal (right) steps. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

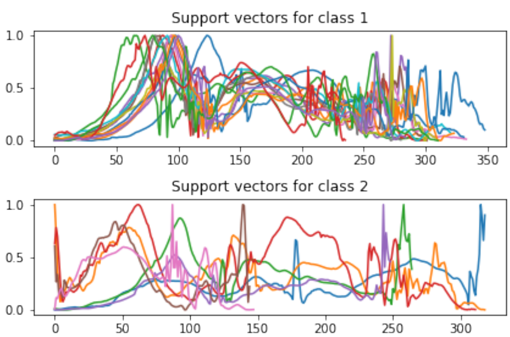


Fig. 9: Support vectors for diplegic gait. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

abnormal step (Fig. 10b) it could be seen, that third peak is unclear, that shows that there is no full contact of toe with ground on that gait type.

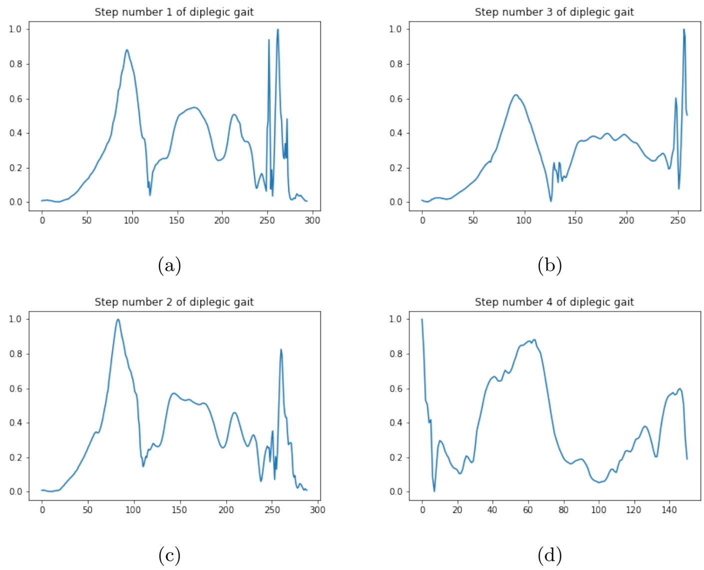


Fig. 10: Normal (left) and abnormal (right) steps. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

Also for diplegic gait type it could be observed, that normal steps have more common features and abnormal steps have different number of peaks and magnitude. That helps tsSVM to differentiate them better and gives higher score. Because of the nature of this anomalous gait, several abnormal steps were performed in the row, that means that number of abnormal steps was more than in some other data sets.

Normal and abnormal steps for hemiplegic gait can be observed in the Fig. 12. They have similarly placed local maximums but with different amplitudes. This is due to abnormal movement, mainly affecting upper body, thus sensor have little impact by that movement. Normal steps have some variation, especially after abnormal step. This leads to misclassification and f1 score of 67%.

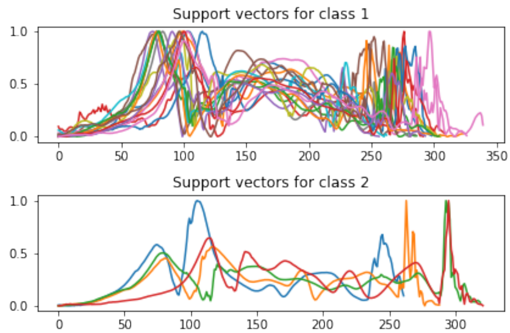
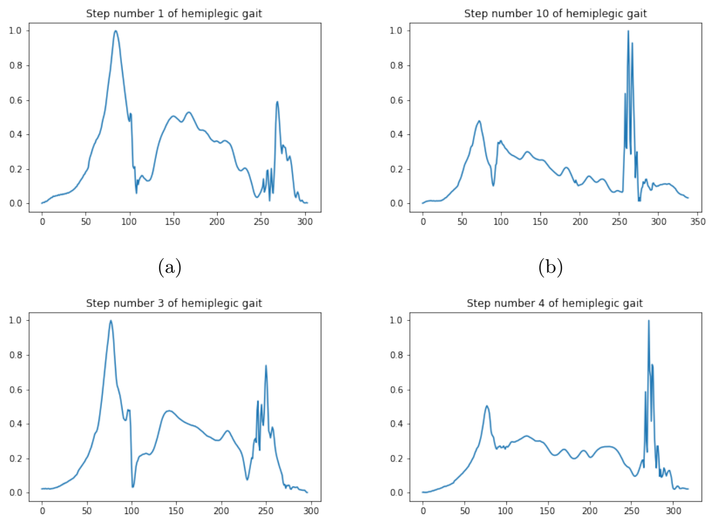


Fig. 11: Support vectors for hemiplegic gait. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).



(a) (b)

(c) (d)

Fig. 12: Normal (left) and abnormal (right) steps. X-axis is the time [ms], Y-axis is normalized gyroscope magnitude values (see eq. 4).

5 Discussion and Conclusion

Ready made tsSVM could be well used for step classification, even using rather small amount of training data (tens of steps), as can be seen in results. The issues still occur, when the dataset is too small, and/or major variability in normal steps is present. As mentioned before, this situation is quite likely to appear with actual patient data. Some issues may arise, if gait deviation is happening in the upper part of the body. That would only lead to small deviations in forefoot placed sensor data, and could easily lead to misclassification of steps. A straightforward solution would be to add more body sensors, but that would increase systems cost and significantly reduce comfort of usage of this system. Obtained results could be useful in determining how different gait types abnormalities affect quality of classification of machine learning algorithms. It is clear, that good reference data presence (correct steps) is crucial for SVM, and, most likely for the other ML based classification methods as well.

Type of gait deviation has significant affect on quality of chosen algorithm results. Achieved average step classification accuracy was near to 80 percent, what is below the numbers published in literature. We assume, that classification performance of real patient data would be even worse. However, besides of performance improvements, with better training data selection and usage, we would develop an algorithm, that can detect anomalies during the gait phases instead of the whole steps. That is crucial to be able to correct gait on basis of needs. In the future we estimate, that applying certain ML techniques, possibly SVM, during the real-time operation of the next generation of FES devices, would make them less intervening and increase patients' comfort.

In real life human gait steps can not be modelled by using two class classifiers, thus multi-class classifier is crucial to distinguish the abnormal steps, related to some kind of disease, from normal steps. Normal steps could be divided into several classes as well, e.g. normal walking steps, turning steps and etc.

Thus, the further work will be focused on the construction of the multi-class classification algorithm for reference step obtaining. That would be used to develop real-time abnormality detection algorithm, that is able to detect abnormal gait in different contexts.

Acknowledgements

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Appendix 2

II J. Rostovski, A. Krivošei, A. Kuusik, M. M. Alam, and U. Ahmadov. Real-time gait anomaly detection using SVM time series classification. In *2023 International Wireless Communications and Mobile Computing (IWCMC)*, pages 1389–1394, 2023

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Real-Time Gait Anomaly Detection Using SVM Time Series Classification

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***Abstract*—In this paper, a real-time implementation of Support Vector Machines (SVM) — Real-Time tsSVM Anomaly Detection (RTtsSVM-AD) algorithm is proposed.**

Here, *real-time abnormality detection* is referencing to the ability of the algorithm to detect true gait anomaly occurrence during the swing phase of ongoing step. Anomaly detection is presented with "earliness" measure. For comparative research, eight different human gait deviations were simulated by two healthy volunteers. Corresponding gyroscope angular velocities, from the sensor placed on the forefoot, were recorded. F1 score, true positive rate (TPR), false positive rate (FPR) and "earliness" values were estimated and analyzed.

Real-time classification results, where classification is performed during the ongoing step, are different from regular classification results, where classification is performed after the full step. Thus, they can not be compared directly.

Achieved results prove the concept, that it is possible to detect anomalies in real-time during the swing phase of a step with RTtsSVM-AD algorithm. Best F1 scores for first person's gait recordings were 57%, 53% and 52% for Steppage, Parkinsonian and Ataxic gait types respectively. For the second person's gait recordings, best F1 scores were 65%, 58% and 50% for Slap, Steppage and Hemiplegic gait types respectively.

RTtsSVM-AD algorithm would be developed further and could be used as a base method for comparison with other algorithms.

***Index Terms*—Real-time, Gait analysis, Anomaly detection, Machine learning, Wearable sensors.**

I. Introduction

According to World Health Organisation (WHO) report about one billion persons are affected by neurological disorders worldwide [1]. Neurological diseases ranging from migraine to stroke, and Alzheimer are the leading causes of Disability Adjusted Life Years (DALY) loss [2]. For instance, there is a substantial risk of falling for patients with gait impairments from neurological diseases [3]. It is especially true for patients suffering from neuromuscular diseases, because high variability and deviations from the optimal gait pattern can be seen in their gait [4]. Therefore, it is difficult to analyze patients' gait patterns in real-time. Certain diseases cause abrupt gait changes, such as freezing episodes of Parkinson Disease (PD) [5]. Other diseases, like Multiple Sclerosis (MS) may contain long duration of relapse episodes, with individual impact and slow progression [6]. This means, that neurodegenerative diseases can affect gait quality and change its locomotion cycle to abnormal. The gait of a person can be described by a set of parameters such as: step length, duration of individual step phases, muscle force, etc. [7]. Wearable motion sensors, containing multidimensional Inertial Measurement Units (IMUs), are the most widely used gait assessment devices in recent years for supporting daily activities [8]. IMUs are also used for gait assessment of patients with neurological diseases. For example, data collected from IMUs is used to detect initial and final contact events of the gait cycle of different persons - healthy, stroke and with other neurological disorders, and select best algorithms and sensor placements for correct classification between them [9]. Also, IMUs can be used to detect activities of daily life, fall events and their directions [10], to determine gait parameters and for identification of persons [11], [12], [13]. Finally, IMUs can be used to discover environment dependent differences in gait, which will help with context-aware decisions [14].

It is shown that Functional Electrical Stimulation (FES) can be used to assist walking and help with fall prevention [15] as well as for generic gait improvements [16]. Long term gait deviation analysis and efficient run-time control of FES devices requires automated real-time recognition of abnormal steps or other gait deviations.

Existing real-time algorithms are used for following: identification by gait [17]; for detecting of gait events like heel-strike and toe-off for elderly healthy subjects; stroke patients and patients with Parkinson disease [18], as well as with other impairments [19], [20]; haptic biofeedback devices are implemented using inertial measurement units (IMUs), to correct toe-in or toe-out during walking in real-time [21].

Notably, none of the previous studies explored real-time anomaly detection in ongoing step, nor base methods are proposed for real-time in step anomaly detection.

According to the previous paper [22], it has been concluded that Support Vector Machines (SVM) based methods are most widely used ones for automated gait analysis, followed by Convolutional Neural Networks (CNN). The benefits of SVM include capability to operate with relatively small datasets and high computational efficiency [10], [23]. However, there is limited research conducted of analysing how well machine learning methods, particularly SVM, performs in detecting realistic gait deviations in real-time during the ongoing step, caused by actual neurological diseases. In our previous paper it was shown, that *tslearn SVM* algorithm implementation [24] can classify normal steps from abnormal and achieve high F1 scores [25] for regular offline full dataset classification. However it can not be used directly for real-time abnormality detection. Thus additional framework should be developed to be able to use *tslearn SVM* in real-time application.

In the view of above discussion, in this paper we provide following contributions:

- Collecting volunteers' walking motion data, with simulated gait deviations, using an industry-standard wearable motion sensor (Shimmer3 IMUs) according to the clinical trial protocol approved by Estonian National Institute for Health Development, permission No.818.
- Proposing novel real-time anomaly detection algorithm, Real-Time tsSVM Anomaly Detection (RTtsSVM-AD) algorithm, which can detect gait abnormalities in real-time during the swing phase of an ongoing step.

This paper consist of five sections: after the introductory state-of-the-art overview, in section II data acquisition and gait types are described, as well as metrics used for analysis; in section III novel RTtsSVM-AD algorithm is described, including data preparation; parameters of the algorithm, results and discussion are presented in the section IV and paper is concluded in section V.

II. METHODS

A. Data Acquisition

Eight types of the human gait abnormalities were selected, which were simulated by 2 healthy persons of different gender, both 23 years old, while walking in straight line (Table I).

Collected data was labeled step wise, thus all steps were annotated as *normal* or *abnormal*.

TABLE I: *Labeled gait recordings, collected for this study.*

Person №	Ataxic	Diplegic	Hemiplegic	Hyperkinetic	Parkinsonian	Slap	Steppage	Trendelenburg	Total
p1	1	5	2	2	2	3	5	2	21
p2	4	6	5	4	4	5	9	4	41
Total	5	11	7	6	6	8	14	6	62

Simulations were recreating actual patients' gait recordings on videos and instructions from a professional physiotherapist. Detailed data collection process was described in previous paper [25]. Most frequent gait abnormalities were chosen: Ataxic, Diplegic, Hemiplegic, Hyperkinetic, Parkinonian, Slap, Steppage and Trendelenburg (lurch) gait types [26].

B. Evaluation metrics

For evaluation, several calculated parameters were used, which include F1 score, true positive rate (TPR), false positive rate (FPR) and *earliness*. *Earliness* in this paper is defined as – time between the beginning of a step and moment in time when step was correctly classified as abnormal. The minimal achievable earliness naturally depends on the gait deviation type. Such measure has been introduced, because concrete moment when anomaly is starting to occur can fluctuate, depending on a gait type.

III. PROPOSED ALGORITHM

In this paper new algorithm is presented, which is able to detect anomalies during the ongoing step of human gait. Such, in-step SVM based anomaly detector was named Real-Time tsSVM Anomaly Detection Algorithm (RTtsSVM-AD). Differences from regular *tslearn SVM* [24] is added framework, to be able to classify incoming signal of ongoing step, which includes automatic hyperparameter optimization and real-time classification.

Hypothesis of RTtsSVM-AD algorithm is following: if by cumulatively replacing the model step chunks with new chunks from ongoing step, collected from IMU placed on a forefoot, the algorithm can classify ongoing step as normal or abnormal, then it is possible to detect abnormality during the swing phase of this step in real-time.

A. Data preparation

Each person datasets are assessed separately. Data is prepared by taking all accessible recordings for current gait type, except for one gait recording, which would be used as validation dataset for real-time step anomaly detection estimation. All other recordings are combined into one dataset and divided into training and test datasets with ratio of 70%:30% correspondingly. Then each step from these datasets is resampled to constant length and normalized.

B. Algorithm description

Algorithm has two phases: training and real-time classification phases. In the proposed implementation synchronous time series data is used to train classifier. For every recording gyroscope vector magnitude is calculated, using the L_2 norm (1) from gyroscope angular velocities around sensor axes.

$$\mathbf{Mag} = \sqrt{\mathbf{X}^2 + \mathbf{Y}^2 + \mathbf{Z}^2} \quad (1)$$

where $\mathbf{X}, \mathbf{Y}$ and $\mathbf{Z}$ are vectors of gyroscope angular velocities around sensor axes, $\mathbf{X} = [x_0, x_1, \ldots, x_i, \ldots, x_n]^T$, $\mathbf{Y} = [y_0, y_1, \ldots, y_i, \ldots, y_n]^T$ and $\mathbf{Z} = [z_0, z_1, \ldots, z_i, \ldots, z_n]^T$, sample index $n \in \mathbb{N}$. The $\mathbf{Mag}(X, Y, Z)$ is the gyroscope vector magnitude.

RTtsSVM-AD algorithm training phase is following:

- First is training of the classifiers with particular value for hyper-parameter *gamma* (γ) on training dataset;
- Second step is to estimate classification quality of these classifiers on test dataset using F1 score;
- Best classifiers and corresponding model steps for these classifiers are used in real-time classification of validation dataset.

Hyper-parameter γ is the main parameter of the proposed algorithm, which is responsible for smoothing of the resulting metric for soft-DTW [24]. Quality of classification for this particular γ value is estimated with test dataset. For this hyper-parameter optimization from predetermined options is performed and it stops:

- If F1 score on test dataset for given γ value is 100%;
- If for three different γ values F1 score is the same;
- If all given γ values have been tested.

After training phase, real-time classification performance is estimated, which is described in more details in next subsection. For this best classifiers and model steps are used from the training phase. Several classifiers could be chosen, if they have similar performance, which should increase robustness of the algorithm. Model step is calculated as normal step ensemble average from test dataset, where normal steps that have been classified correctly were chosen. For correct operation of algorithm in real-time phase, data used for model step calculation is not resampled and not normalized.

C. Anomaly prediction

Real-time classification is performed in online-fashion. Validation dataset is fed to the algorithm as streaming data, which arrives as a series of packages or chunks. Step start and step end events are detected when incoming streaming gyroscope vector magnitude is exceeding certain value. The size of each chunk is selected small enough for real-time operation (for reasonable latency of anomaly alarming) and large enough for more efficient processing and data transferring through communication channels. In the current implementation the amount of collected data in one chunk is M samples for each gyroscope vector. Classification is performed on whole classification step. For this incoming chunks are replacing corresponding chunks in model step (Fig. 1). Then this classification step is resampled and normalized. After that probability score is obtained, by classification of classification step by classifier or classifiers. This scores are collected to score buffer. Resulting anomaly detection $Score$ is value (2), which will be compared with the selected *threshold*. If *threshold* has been exceeded, alarm is triggered (3), which is finalizing anomaly detection.

$$Score = \frac{\sum Scores}{N_{cl}}, \tag{2}$$

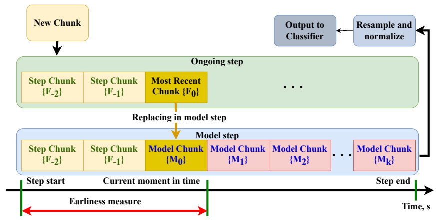

Fig. 1: Replacing chunks from incoming data to model step and resulting step for classification. If anomaly is detected in the current moment of time, earliness is time, shown on figure.

where N_{cl} is the number of classifiers.

$$Alarm = \begin{cases} 1, & \text{if } S > threshold \\ 0, & \text{if } S \leq threshold \end{cases} \tag{3}$$

If alarm is triggered, then earliness is time duration from step start to current moment in time (Fig. 1).

After the end of the current step, model step is restored to original state and real-time classification is repeated for the next step.

IV. Results and Discussion

Results for the RTtsSVM-AD algorithm are presented in current section.

Parameters used in this work are following: sample rate is set to 256 $Samples/s$, one chunk is $M = 12$ samples long which is approximately 43 ms. Predefined γ values are in the range from 100 to 1000 with increase of 100 and in the range from 5 to 100 with increase of 10. Gyroscope angular value for step detection is 200 °/s.

TABLE II: Best thresholds across gait types

Gait type	p1	p2	avg.
Ataxic	0,7	-	0,7
Diplegic	0,6	0,6	0,6
Hemiplegic	0,9	0,8	0,85
Hyperkinetic	0,8	0,8	0,8
Parkinsonian	0,9	0,5	0,7
Slap	0,8	0,4	0,6
Steppage	0,8	0,7	0,75
Trendelenburg	0,9	0,1	0,5

Aforementioned threshold is chosen after real-time phase, where all scores are obtained, because in real world use case best threshold would be adjusted individually for each person (Table. II). Lets observe F1 scores for different gait types. In terms of F1 score (Fig 2) it could be observed, that algorithm is able to detect abnormalities in real-time for most of the gait types. Best results for first person was for Steppage, Parkinsonian and Ataxic gait types, with F1 scores of 57%, 53% and 52% respectively.

For second person best results were for Slap, Steppage and Hemiplegic gait types with F1 scores of 65%, 58% and 50% respectively. Acceptable results were seen as well for

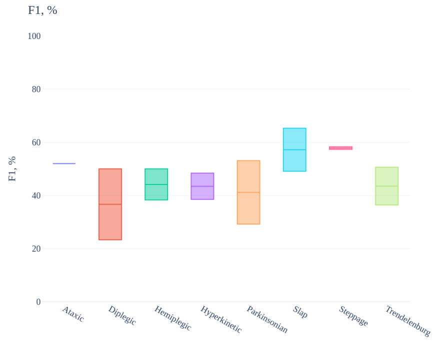

Fig. 2: Distribution of F1 scores for all persons for different gait types. On y-axis is F1 score in percents, on x-axis is different anomalies. Most frequent results are in the boxes, and outliers are shown by whiskers and dots.

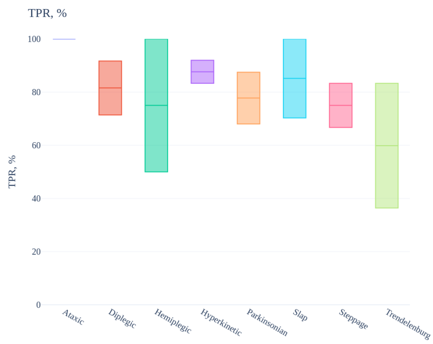

Fig. 3: Distribution of True Positive Rate for all persons for different gait types. On y-axis is True Positive Rate in percents, on x-axis is different anomalies. Most frequent results are in the boxes, and outliers are shown by whiskers and dots.

Trendelenburg and Diplegic gait types with F1 scores of 51% and 50% respectively for first person. Steppage gait type have noticeable difference from the normal step, which makes it easier to classify for two class classifier. Worst performing gait types were Hyperkinetic, Hemiplegic and Slap gait types for first person with F1 scores of 48%, 38% and 49% respectively. For second person it was Diplegic, Hyperkinetic, Parkinsonian and Trendelenburg gait types with F1 score of 23%, 38%, 29% and 36% respectively. Hemiplegic gait type is different from normal gait by swing of a leg to the side, which on magnitude graph does not have major differences from normal step. Average F1 scores shows, that algorithm is able to detect abnormalities in real-time for most gait types, presented in this paper.

For Slap and Parkinsonian gait recordings of first person and Trendelenburg, Hemiplegic, Steppage and Diplegic gait

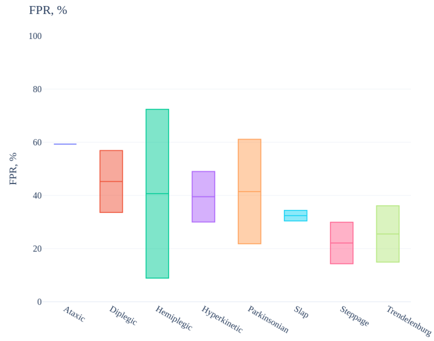

Fig. 4: Distribution of False Positive Rate for all persons for different gait types. On y-axis is False Positive Rate in percents, on x-axis is different anomalies. Most frequent results are in the boxes, and outliers are shown by whiskers and dots.

recordings of second person low true positive rate (Fig. 3) could be observed: 70%, 68%, 36%, 50%, 67% and 71% respectively. For other gait types true positive rate was above 83%, where best results were for Ataxic and Hemiplegic gait types for first person and Slap gait type for second person with F1 score of 100%. Average true positive rate remains high.

On the other hand false positive rate (Fig. 4) was high for most of the gait types, excluding Parkinsonian gait type for first person and Hemiplegic, Steppage and Trendelenburg gait types for second person with 22%, 9%, 14% and 15% respectively, which were the lowest false positive rates in current results. Highest false positive rates was for Diplegic and Parkinsonian gait recordings for second person with 57% and 61% respectively. For first person it was high for Hemiplegic, Hyperkinetic and Ataxic gait types with 72%, 49% and 59% respectively. For all other gait types false positive rate stayed between 30-40%. High average false positive rate is main reason for low F1 scores, which shows that two class classification algorithm can struggle with such task. This is because abnormal steps can vary in shape, which can confuse such algorithm and lead to misclassification.

For earliness measure (Fig. 5) it could be observed, that for most gait types earliness is less than one second. Typical step duration is usually around 1.2-1.4 seconds for persons in this paper. For Steppage gait type most common earliness measure is around 1-1.2 seconds, which is end of a step. However for Steppage gait faster detection is needed, because anomaly is happening at the beginning of a step, during swing phase. For other gait types it could be observed, that detection was mainly in the middle of a step, which shows, that algorithm can detect anomaly early, during the swing phase of a step.

As can be seen, RTtsSVM-AD algorithm is capable to detect abnormalities in a human gait in real-time as achieved earliness results showed. These detection results are corresponding to the moments of anomaly occurrence in chosen gait types. For

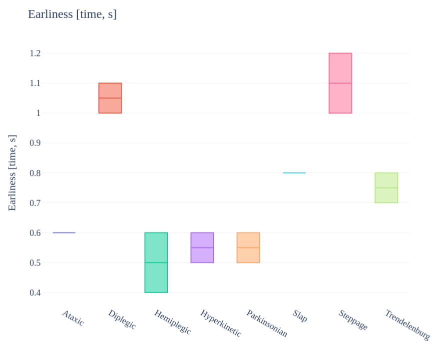

Fig. 5: Distribution of Earliness for all persons for different gait types. On y-axis is earliness in seconds, on x-axis is different anomalies. Most frequent results are in the boxes, and outliers are shown by whiskers and dots.

most of the mentioned gait types main anomaly is happening in forefoot motion, which is captured by IMU placed on forefoot. Gyroscope angular velocities from this sensor were used in this work. Even with small training dataset, this algorithm was able to detect abnormalities in real-time.

This research have following limitations: simulated gait could have differences from actual patients gait. However it should not be an issue for the performance of the proposed algorithm. Data collected from two persons is enough to prove the concept, that real-time anomaly detection is possible, however for conclusion more data should be collected.

V. Conclusion

Simulated gait deviations data was collected by two healthy volunteers. RTtsSVM-AD algorithm was developed, by introducing preprocessing and post-processing of streaming data, to be able to use it with classical machine learning algorithm like *tslearn SVM*.

Real-time classification results, where classification is performed during the ongoing step, are different from regular classification results, where classification is performed after the full step. Thus, they can not be compared directly. This is why proposed algorithm could be used as a base method, due to lack of such algorithms for real-time in-step gait abnormality detection.

Best results were observed for Steppage, Parkinsonian and Ataxic gait types with F1 scores of 57%, 53% and 52% for first person respectively and for Slap, Steppage and Hemiplegic gait types with F1 scores of 65%, 58% and 50% for second person respectively.

In future works it is planned to test presented and other algorithms, as well as to collect additional data from more persons, with different age, weight and height.

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Appendix 3

III J. Rostovski, M. H. Ahmadilivani, A. Krivošei, A. Kuusik, and M. M. Alam. Real-time gait anomaly detection using 1D-CNN and LSTM. In M. Särestöniemi, P. Keikhosrokiani, D. Singh, E. Harjula, A. Tiulpin, M. Jansson, M. Isomursu, M. van Gils, S. Saarakkala, and J. Reponen, editors, *Digital Health and Wireless Solutions*, pages 260–278, Cham, 2024. Springer Nature Switzerland

Real-time Gait Anomaly Detection using 1D-CNN and LSTM*

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Abstract. Anomaly detection and fall prevention represent one of the key research areas within gait analysis for patients suffering from neurological disorders. Deep Learning has penetrated into healthcare applications, encompassing disease diagnosis and anomaly prediction. Connected wearable medical sensors are emerging due to computationally expensive machine learning tasks, which traditionally require use of remote PC or cloud computing. However, to reduce needs for wireless communication channel throughput, for data processing latency, and increase service reliability and safety, on device machine learning is gaining attention. This paper presents an innovative approach that leverages one dimensional convolutional neural network (1D-CNN) and long-short term memory (LSTM) neural network for the real-time detection of abnormal gait patterns during the step. Real-time anomaly detection pertains to the algorithm's ability to promptly detect true gait abnormality occurrence during the swing phase of an ongoing step.

For the experiments, we have collected eight different common gait anomalies, simulated by 22 persons, using motion sensors containing multidimensional inertial measurement units (IMUs).

Results have demonstrated that the proposed 1D-CNN-AD algorithm achieves an average accuracy of 95% and an average F1-score of 88% for all gait types and can run in true real-time. Average earliness for 1D-CNN-AD algorithm was 0.6 seconds, which is mid-swing phase of the step. Proposed LSTM-AD algorithm achieved average accuracy of 87% and average F1-score of 70% for all gait types.

Keywords: Human gait · Anomaly detection · Gait analysis · Machine learning · Real-time · 1D-CNN · LSTM · Wearable sensors

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1 Introduction

According to the World Health Organisation (WHO) report about one billion persons are affected by neurological disorders worldwide [3]. Neurological diseases ranging from migraine to stroke, and Alzheimer are the leading causes of Disability Adjusted Life Years (DALY) loss [7]. For instance, there is a substantial risk of falling for patients with gait impairments from neurological diseases [23]. It is especially true for patients suffering from neuromuscular diseases, because high variability and deviations from the optimal gait pattern can be seen in their gait [13]. Therefore, it is challenging to analyze patients' gait patterns in real-time. The gait of a person can be described by a set of parameters such as: step length, duration of individual step phases, muscle force, etc. [19]. Wearable motion sensors, containing multidimensional Inertial Measurement Units (IMUs), are the most widely used gait assessment devices in recent years for supporting daily activities [25]. For example, motion sensors are used to detect initial and final contact events of the gait cycle for different persons - healthy, with stroke, and with other neurological disorders, and select the best algorithms and sensor placements for correct classification between them [10]. Motion sensors can be employed to detect activities of daily life, fall events and their directions [9], to determine rehabilitation progress and analyze gait normalcy index [36, 2]. Also such devices can be used to discover environment dependent differences in gait, which will help with context-aware decisions [29]. Finally, in combination with Neural Networks (NNs), identify if person has balance disorder [20], to track rehabilitation progress for broken limbs [4] etc.

It is shown that Functional Electrical Stimulation (FES) can be used to assist walking and help with fall prevention [12] as well as for generic gait improvements [17]. Long-term gait deviation analysis and efficient run-time control of FES devices require automated real-time recognition of gait deviations. Average swing phase of a step is 300-400 ms long [8], and the time of full contraction of the muscle using electrical stimulation is 100-200 ms long [5], thus the detection time of step pattern deviations should be under 100 ms. Considering that the incoming signal must be processed, a correct decision made, and stimulation actuation started, a detection time of 50 ms is required since the gait abnormality has started.

Connected wearable medical sensors are emerging due to computationally expensive machine learning tasks, which traditionally require use of remote PC or cloud computing [14]. Nowadays, it is common to offload such data analysis from wearable sensors to wirelessly connected smartphones [11]. For example, data processing unit, sensors and muscle stimulator shall be wireless for gait correction system, i.e. based on Bluetooth or SmartBAN standard. However, to reduce needs for wireless communication channel throughput, for data processing latency, and increase service reliability and safety, on device machine learning is gaining attention [31]. Existing real-time algorithms are used in gait analysis for identification by gait [15]; detecting of gait events like heel-strike and toe-off for elderly healthy subjects; stroke patients and patients with Parkinson disease [35], as well as with other impairments [37, 24]; haptic biofeedback devices are implemented using inertial measurement units (IMUs), to correct toe-in or toe-out during walking in real-time [32].

Notably, there are not found state-of-the-art solutions in gait analysis for real-time anomaly detection of realistic gait deviations during the ongoing step, caused by neurological diseases.

In our prior research work [27, 28] we proposed a base method for real-time anomaly detection in gait during the ongoing step, with an algorithm based on Support Vector Machines (SVM), which is one of the most popular algorithms used in gait analysis. On the other hand, NNs are widely adopted in gait analysis [30]. They are capable of solving complex tasks in time-series data. Nonetheless, to the best of our knowledge, there is no research exploiting NNs for real-time anomaly detection during the ongoing step in gait analysis. In this paper, for the first time, we leverage Convolutional Neural Network (CNN) and Long Short-Term Memory NNs for real-time anomaly detection during the ongoing step in human gait.

The contributions of this work are:

– Estimation of the performance of One Dimensional-Convolutonal Neural Network-Anomaly Detection algorithm (1D-CNN-AD) and Long Short-Term Memory Neural Network-Anomaly Detection algorithm (LSTM-AD) on the collected simulated gait deviation dataset in comparison to the Real-time tsSVM Anomaly Detection algorithm (RTtsSVM-AD).
– Exploiting hyperparameters for the neural networks to optimize performance on simulated gait dataset for real-time in-step anomaly detection.

This paper consists of six sections: after the introduction, in section 2 data acquisition and gait types are described, as well as metrics used for analysis in addition to presenting the proposed 1D-CNN-AD and LSTM-AD algorithms, then in section 3 we briefly describe evaluation metrics and the SVM-based algorithm – RTtsSVM-AD, which is continued with experimental setup in section 4; this is followed by the results and discussion in the section 5 and the paper is concluded in section 6.

2 Methodology

2.1 Dataset

Data Acquisition The dataset in our experiments is collected from twenty-two healthy persons of different genders, ages, heights and weights (Table 1), while walking in a straight line and simulating abnormalities. Simulations are recreating actual patients' video recordings of gait deviations in collaboration and guidance from a professional physiotherapist of Tallinn East Central Hospital. We have included the most frequent human gait abnormalities, regarding reference [1]: Ataxic, Diplegic, Hemiplegic, Hyperkinetic, Parkinonian, Slap, Steppage, and Trendelenburg (lurch). Table 2 shows eight under-study gait types and the number of collected gait recordings per gait type. Collected data is labeled step-wise, thus all steps are annotated as *normal* or *abnormal*. Fig. 1 illustrates the patterns of each gait type in comparison with a normal step.

Table 1: *Persons' Information Used in This Study (Mean ± Standard Deviation)*

No. of subjects	Age (years)	Height (cm)	Mass (kg)
15 (Male)	32.1±11.1	177.7±5.5	76.8±15.1
7 (Female)	26.3±5.5	169.5±6.2	62.7±8.9

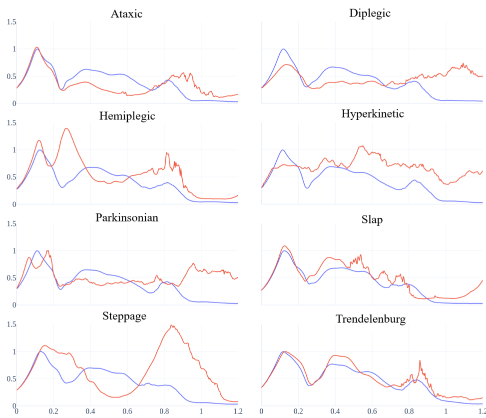

Fig. 1: Example of the typical shape of simulated step of studied gait types in comparison to normal step shape, from the data used in this study. Blue line is normal step shape and red line is corresponding typical shape for this gait type. On X-axis is time in seconds and on Y-axis is normalized magnitude of angular velocities of gyroscope.

Such dataset to the best of authors knowledge is first to have combination of normal and abnormal steps in one dataset. Other datasets are focusing on normal gait patterns; have only abnormal steps in the dataset; compare separate normal gait datasets and abnormal gait datasets, etc. [26, 18, 33, 6].

Data Preprocessing The collected data is in a form of time-series including a three-axis gyroscope and their calculated magnitude (1).

Table 2: *Labeled data collected for this study.*

Gait type	Total number of recordings for all persons
Ataxic	32
Diplegic	25
Hemiplegic	17
Hyperkinetic	6
Parkinsonian	29
Slap	8
Steppage	32
Trendelenburg	6

$$\mathbf{Mag}(X, Y, Z) = \sqrt{\mathbf{X}^2 + \mathbf{Y}^2 + \mathbf{Z}^2}, \tag{1}$$

where $\mathbf{X}, \mathbf{Y}$ and $\mathbf{Z}$ are gyroscope axes data vectors, $\mathbf{X} = [x_0, x_1, \ldots, x_i]^T$, $\mathbf{Y} = [y_0, y_1, \ldots, y_i]^T$ and $\mathbf{Z} = [z_0, z_1, \ldots, z_i]^T$, sample index $i \in \mathbb{Z}$. And the $\mathbf{Mag}(X, Y, Z)$ is the magnitude vector of these axes.

To address future works with embedded devices in regard to data transmission and data gathering, data is collected into chunks. One chunk contains M samples for each gyroscope axis. The collected data sample rate is $256 Samples/s$ in the current study. Collected data is labeled stepwise as *"normal"* step or *"abnormal"* step.

Data preparation for Real-Time Anomaly Detection For 1D-CNN-AD and LSTM-AD algorithms each person's data is assessed separately. Data for one gait type is prepared by separating training and validation datasets. One gait recording is used as a validation dataset in real-time step anomaly detection estimation, and all other recordings are combined into one training dataset. The ratio between the training and validation datasets can change depending on the person, gait type and available gait recordings for particular gait type.

To enable real-time abnormality detection in the swing phase of the ongoing step, training dataset is divided into overlapping sliding windows. Fig. 2 depicts how the windowing of the dataset is designed. As it is shown, each window contains P chunks (i.e., window factor), and each chunk includes M samples and the overlap is N chunks.

Labeling of the windows is conducted according to the labels of the steps. In edge cases, where one step is ending and new step is begging, label is assigned by the proportion of samples of abnormal steps in the window. If this proportion is less than *abnormality proportion threshold* then the window is labeled as *normal*, if more, then it is labeled as *abnormal*.

One of the key advantages of the sliding windows for this study is independence of the anomaly detection algorithms from gait phases.

As a part of hyperparameters optimization, hyperparameters, which affect sizes, overlaps and labels of the sliding windows are investigated. These hyperparameters are a) chunk duration – time in milliseconds, where number of samples M in one chunk is calculated from chunk duration as $M = round(Chunk\ duration * Sample\ rate)$; b) window factor P – determines window size and is proportional to P chunks; c) Abnormality proportion threshold – fraction of the window, which should contain abnormal samples, to consider the label of the window to be abnormal.

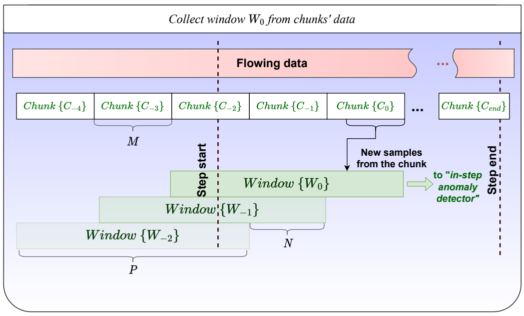

Fig. 2: Windowing of the data for training and for real-time anomaly detection performance estimation. Ongoing gait data is incoming as flowing data, which is split into chunks. From these chunks sliding windows are collected and used in real-time in-step anomaly detector. Step start can be misaligned with sliding window. Chunks are aligned with the sliding windows If abnormality is detected during the chunk C_0, then earliness is time between step start and end of the chunk C_0.

2.2 Proposed Neural Networks

One Dimensional-Convolutonal Neural Network-Anomaly Detection Algorithm The hypothesis of the 1D-CNN-AD algorithm is following: if real-time gait data could be collected in the form of sliding windows, and neural network could be trained on the dataset using same form of sliding windows with known labels, then it is possible to detect abnormalities in gait during the ongoing step.

The CNN in this study consists of two 1D convolutional layers, max pooling layer, and two fully-connected (dense) layers to provide a binary classification. The 1D-CNN-AD algorithm has the following hyperparameters: i) number of filters; ii) kernel size; iii) batch size; iv) and number of epochs. These hyperparameters would be optimized in this study to achieve the best performance for 1D-CNN-AD algorithm.

In the explorations, the CNN is initialized with a fixed seed of parameters (i.e., weights and bias). The neural network is trained on training dataset with Adam optimizer and cross-entropy loss function. Moreover, a 20% dropout is also considered between the convolutional layer and dense layers.

Long Short-Term Memory Neural Network-Anomaly Detection Algorithm Hypothesis of the LSTM-AD algorithm is identical to the hypothesis of the 1D-CNN-AD algorithm.

The LSTM-AD algorithm in this work consists of one layer of LSTM followed by two fully-connected (dense) layers to provide a classification probability. The number of cells in the LSTM layer is equal to the number of neurons in the first dense layer. The LSTM-AD algorithm has the following hyperparameters: i) number of LSTM cells; ii) batch size; iii) and number of epochs. These hyperparameters would be optimized in this study to achieve the best performance for LSTM-AD algorithm.

In the explorations, the LSTM is initialized with a fixed seed of parameters (i.e., weights and bias). The LSTM-AD algorithm is trained on training dataset with Adam optimizer and cross-entropy loss function.

2.3 Anomaly Detection

To estimate performance of the real-time anomaly detection of the algorithms, validation dataset is processed in online-fashion. It means, that data is arriving sample by sample. Each sample is collected into chunks. Chunks are collected into windows, as was described in the section 2.1. Algorithms return anomalous class probability for each window, which is collected to the buffer. After the real-time estimation, collected probabilities are analyzed. Different thresholds for anomalous class probability are estimated to achieve best results. This results in the binary classification. These classification results are compared to the labels of the validation dataset, resulting in confusion matrix. Accuracy and F1 score are calculated from confusion matrix.

3 Baseline and Evaluation

3.1 Real-time tsSVM Anomaly Detection Algorithm

RTtsSVM-AD algorithm is based on a *tslearn* [34] Python library. Optimization of hyperparameters is done by dividing training data into two datasets: training and testing with ratio of 70%:30%. Trained classifier with best results for test dataset is used in real-time performance estimation. Model step is calculated as normal step ensemble average from test dataset, which consist of normal steps that have been classified correctly.

The hypothesis of the algorithm is following: if full time-series step pattern could be collected in real-time by combining the average normal step from training phase with the ongoing step data, then anomaly could be detected during the swing phase of the ongoing step by the RTtsSVM-AD algorithm.

We have adopted the RTtsSVM-AD algorithm in our prior work [28] as a baseline for comparing the results of the proposed 1D-CNN-AD and LSTM-AD algorithms in this paper.

Brief overview of the algorithm. Data is collected chunk wise, when step start is detected. Step start and end events are detected if the step detection threshold crosses 20% of the gyroscope magnitude range. Hyperparameter γ is optimized on training and testing datasets. This hyperparameter is used by the global alignment kernel (GAK), where γ is the hyperparameter controlling soft dynamic time warping (softDTW) smoothness [34]. Multiple classifiers with different values of γ could have same performance. Average normal step is created from correctly classified normal steps from training dataset. In real-time in-step gait anomaly detection performance estimation, if step start is detected, data is collected into a chunk. This chunk is replacing corresponding chunk in the model step. Such chunkwise replacement converts regular time-series SVM into the real-time anomaly detection algorithm.

3.2 Evaluation Metrics

For evaluation, several metrics are exploited: Accuracy, F1-score, *earliness*, and real-time factor (RTF). *Earliness* in this paper is defined as – time between the beginning of a step and the moment in time when anomaly is detected in this step. The minimal achievable earliness naturally depends on the gait deviation type. Such a measure has been introduced, because the concrete moment when anomaly starts to occur can fluctuate, depending on a gait type.

3.3 Score and Alarm.

For estimation of the performance of the algorithms, anomalous class probability is collected from the classifier. Binary decision is performed later in post-processing of the results. *Score* is the resulting anomalous class probability. For RTtsSVM-AD algorithm *Score* is avarage score from used classifiers in estimation, because multiple classifiers could be used simultaneously. *Score* is compared with the selected *threshold*, giving alarm signal in (2), finalizing the anomaly detection.

$$Alarm = \begin{cases} 1, & \text{if } S > threshold \\ 0, & \text{if } S \leq threshold \end{cases} \tag{2}$$

If *Alarm* is triggered, then earliness is the time duration from the beginning of the step to the current moment in time.

4 Experimental Setup

For 1D-CNN-AD and LSTM-AD algorithms, the considered hyperparameters are presented in the Table 3 and Table 4.

Table 3: Global hyperparameters for 1D-CNN-AD and LSTM-AD algorithms

Hyperparameter	**Values**
Window factor (P)	6 to 10. Default 8
Chunk size	25ms to 100ms. Default 50ms
Samples in a chunk (M)	6 to 25. Default 12
Sliding window overlap (N)	1
Abnormality proportion threshold	50% to 90%. Default 70%
Batch size	2^n where n is from 3 to 8. Default n is 5
Number of epochs in training	1 to 30. Default 20

Table 4: Algorithm-Specific Hyperparameters

Algorithm	**Specific Hyperparameters**
LSTM-AD	Number of LSTM cells: 20, 25, 30. Default: 25
1D-CNN-AD	Number of filters in convolutional layer: 2^n where n is from 3 to 8. Default n is 6 Kernel size in convolutional layer: 2, 3, 5, 7, 9, 11. Default 5 Dense layer with 100 neurons

For the RTtsSVM-AD algorithm parameters used in this work are as follows: a) one chunk is $M = 12$ samples; b) predefined γ values are in the range from 100 to 1000 with an increase of 100 and in the range from 5 to 100 with an increase of 10; c) the step detection threshold is $200°/s$.

All training and validation experiments are implemented in Python 3.10.13, tslearn 0.6.2, and TensorFlow 2.9.1 and performed on a prebuilt HP computer with Intel Core i7 and 16Gb of DDR4 memory. We conducted CPU experiments to model the execution on the embedded devices in future works.

5 Experimental Results and Discussion

Results for the 1D-CNN-AD , LSTM-AD and RTtsSVM-AD algorithms are presented in this section.

5.1 Optimization of 1D-CNN-AD and LSTM-AD Algorithms Hyperparameters

In this paper, optimization is performed by one parameter at a time, while the other parameters are set to their default values.

Chunk Length The first hyperparameter to consider is the length of the chunk. Table 5 shows the best mean F1 scores with corresponding chunk sizes. It is observed that the best results are achieved with chunk sizes of 75 and 100 ms for all gait types for LSTM-AD and most of the gait types for 1D-CNN-AD. Chunk size of 40 and 50 ms performed better for Steppage, and Trendelenburg gait types for 1D-CNN-AD algorithm. Despite the better performance with longer chunks for some gait types, chunk size is set to 50 ms, with consideration of fast anomaly detection. Larger chunk sizes would lead to slow anomaly detection.

Table 5: *Best mean F1 scores for different chunk sizes (CS)*

Gait type	LSTM-AD		1D-CNN-AD	
	F1	CS, ms	F1	CS, ms
Ataxic	62.63%	100	79.28%	75
Diplegic	72.36%	100	87.49%	100
Hemiplegic	81.03%	100	83.52%	75
Hyperkinetic	75.95%	100	96.3%	75
Parkinsonian	75.24%	100	84.65%	100
Slap	57.45%	75	78.7%	75
Steppage	75.09%	100	84.17%	40
Trendelenburg	59.65%	75	81.3%	50

Window Factor and Abnormality Proportion These hyperparameters should be considered in correlation with each other because both of them change the number of samples in the window, which can change the final label of the window. Table 6 presents the best mean F1 scores for combination of window factor and abnormality proportion. It could be seen, that 1D-CNN-AD algorithm is performing best with shorter windows for most of the gait types, whereas LSTM-AD algorithm is performing best with longer windows for most of the gait types. In terms of abnormality proportion threshold, for most of the gait types for both 1D-CNN-AD and LSTM-AD algorithms higher threshold is needed. Only for Hyperkinetic and Steppage gait types it was 70% for LSTM-AD and 60% for 1D-CNN-AD algorithms respectively. It means, that for Hyperkinetic and Steppage gait types edge cases are important for correct anomaly detection. Thus, in general, most of the windows should contain mostly abnormal samples to be labeled abnormal for best performance. With the default settings for other parameters, 1D-CNN-AD algorithm achieves mean F1 scores of 96.3% for Hyperkinetic gait type. On the other hand, LSTM-AD algorithm achieves best mean F1 score of 73.78% for Hemiplegic gait type.

Diplegic and Hyperkinetic gait types have anomalies in the middle and end of the step, thus short windows should be best suited for them to detect abnormality early, as can be seen in 1D-CNN-AD algorithm results. Both Ataxic and Parkinsonian gait types have multiple abnormal steps in a row, which can be similar to normal steps, thus requiring well defined long abnormal windows during the training phase. Slap gait is usually characterized by the sharp short peak at the end of the step, whereas the rest of the step can be similar to normal, thus making it more critical to have a correct classification in edge cases. Steppage gait type have different amplitudes from the normal step for its peaks when the knee is raised up to compensate for lack of movement in the forefoot. Hemiplegic gait type can be similar to a normal gait, which makes it more difficult to differentiate from normal steps which require well-defined shorter windows.

Table 6: *Best mean F1 scores for different window factor (WF) and abnormality proportion threshold (AP)*

Gait	LSTM-AD			1D-CNN-AD		
type	F1	WF	AP	F1	WF	AP
Ataxic	58.16%	9	90%	78%	10	90%
Diplegic	58.31%	8	90%	82.81%	7	80%
Hemiplegic	73.78%	10	90%	84.03%	6	90%
Hyperkinetic	69.05%	10	70%	95.15%	7	90%
Parkinsonian	63.25%	9	90%	84.38%	10	80%
Slap	62.55%	8	80%	86.9%	6	80%
Steppage	64.83%	10	80%	88.39%	6	60%
Trendelenburg	64.75%	10	80%	83.75%	6	90%

Number of filters and kernel size in the Convolutional Layer for 1D-CNN-AD algorithm and number of LSTM cells for LSTM-AD algorithm As presented in Table 7, the best scores for 1D-CNN-AD algorithm are generally achieved with a higher number of filters of 128 and 256, except for Diplegic gait type with 32 filters. This means that extracting more features from the data improves the performance of the 1D-CNN-AD algorithm demonstrating the complexity of the human gait. For Diplegic gait type a smaller network is best suited, meaning that extracting too many features can confuse the 1D-CNN-AD algorithm, because the shapes of the abnormal steps for them are more defined than the ones in other gait types.

Best performance is achieved for 1D-CNN-AD algorithm with medium kernel size of 7 except for Hyperkinetic and Steppage gait types with a kernel size of 11 and for Parkinsonian and Trendelenburg gait types with kernel size of 9. For Hyperkinetic, Steppage, Parkinsonian and Trendelenburg gait types bigger kernel size is needed to neglect the variance between individual abnormal steps in the data.

For LSTM-AD algorithm larger number of LSTM cells results in a better performance, due to the complexity of the gait signal. For Ataxic, Diplegic and Slap gait types algorithm performs best with 25 cells showing, that they have simpler shapes, compared to other gait types. For Parkinsonian gait type the best performance was with 20 cells, meaning, that this gait type, has more pronoun shape, compared to other gait types.

Batch Size and Number of Epochs in Training As presented in Table 8, the best scores are generally achieved with a bigger batch size of 128 and 256,

Table 7: Best mean F1 scores for different numbers of LSTM cells (#C) and 1D-CNN kernel size (KS) and number of filters (#F)

Gait	LSTM-AD		1D-CNN-AD			
type	F1	#C	F1	KS	F1	#F
Ataxic	52.4%	25	75.31%	7	75.04%	128
Diplegic	56%	25	81.67%	7	80.3%	32
Hemiplegic	61.37%	30	82.3%	7	87.87%	256
Hyperkinetic	69.5%	30	92.45%	11	86.7%	128
Parkinsonian	57.49%	20	85.45%	9	87.74%	128
Slap	56.95%	25	87.1%	7	81.8%	256
Steppage	60.17%	30	85.23%	11	87.43%	256
Trendelenburg	59.85%	30	83.05%	9	81.75%	128

except for Trendelenburg gait type with a size of 32 for 1D-CNN-AD algorithm, and Slap and Trendelenburg gait types with size of 16 and 64 respectively for LSTM-AD algorithm. This means, that a more accurate training gradient of the neural network is needed for these gait types.

Table 8: Best mean F1 scores for different batch size (B) and number of epochs (#E)

Gait	LSTM-AD				1D-CNN-AD			
type	F1	B	F1	#E	F1	B	F1	#E
Ataxic	56.11%	128	55.95%	5	77.52%	256	78.95%	3
Diplegic	68.77%	256	71.06%	5	85.92%	256	89.33%	5
Hemiplegic	77.08%	256	81.32%	2	85.08%	256	85.45%	4
Hyperkinetic	60.7%	256	73.2%	2	92.45%	256	98.1%	5
Parkinsonian	68.43%	256	66.38%	4	86.81%	256	88.36%	2
Slap	59.8%	16	55.8%	10	83.9%	256	90.8%	4
Steppage	64.89%	128	67.8%	5	87.7%	256	88.1%	2
Trendelenburg	55.4%	64	57.05%	10	81.3%	32	81.3%	20

In terms of the amount of training required by the algorithms, it is clear, that more than 5 epochs could lead to overfitting, thus reducing classification quality in this study. Only LSTM-AD algorithm performed better with 10 epochs for Slap and Trendelenburg gait types, and 1D-CNN-AD algorithm performed better with 20 epochs for Trendelenburg gait type. This could be due to similarities between normal step and typical step shape for Trendelenburg gait type, thus needing more time to properly fit the network. Considering the overall performance of 55.8% for Slap gait type for LSTM-AD algorithm in epoch optimization, algorithm struggled with this gait type. Training dataset usually contains around 5000 windows, thus every epoch has around 39 iterations with batch size of 128. Normal and abnormal steps have mostly consistent shapes in one gait type. Thus, smaller number of epochs can fit such data better. Larger number of epochs could lead to lower performance due to overfitting of the training data and would trigger anomaly detection while classifying unknown data. Therefore, better results are generally achieved with 2 to 5 epochs.

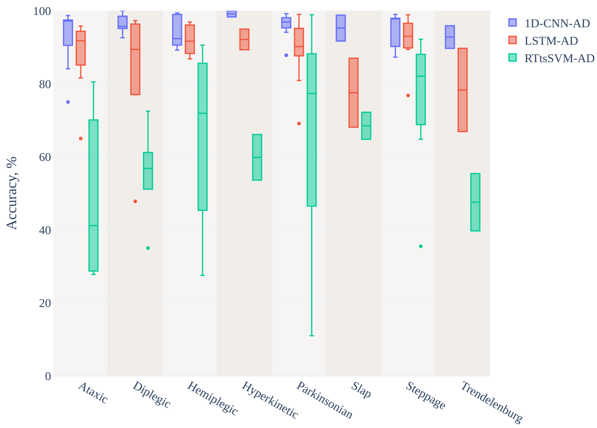

Fig. 3: Distribution of accuracy across different chunk sizes for all persons for different gait types. On y-axis is accuracy in percents or time in seconds, on x-axis are different gait types.

Comparison of algorithms In Fig. 3 and Fig. 4 could be seen, that both 1D-CNN-AD and LSTM-AD algorithms are outperforming the RTtsSVM-AD base comparison algorithm. The best scores for all gait types are achieved by 1D-CNN-AD algorithm with an average accuracy of 95% and average F1-score of 88%. LSTM-AD algorithm achieved an average accuracy of 87% and average F1-score of 70%. Best results for 1D-CNN-AD algorithm are for Hyperkinetic and Slap gait types with F1 scores of 98.1±2.7% and 90.8±9.3% respectively. It could be observed that for Ataxic, Hemiplegic, Slap, Steppage, and Trendelenburg gait types there are some deviations in results from person to person, that could be improved with additional optimization. Best result for LSTM-AD algorithm is achieved for Hemiplegic gait type with average F1 score of 81.32±9.96%. 1D-CNN-AD algorithm is achieving accuracies over 92.6% for all gait types and F1 scores of over 83% for all gait types, except for Ataxic gait type with F1 score of 78.95±15.43%. LSTM-AD algorithm achieved accuracies over 78.3% for all gait types with F1 scores of 71.06±12.47%, 73.2±22.77% and 79.61±14.92% for

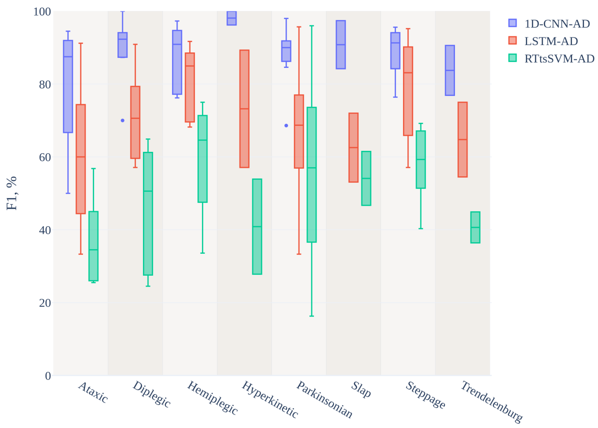

Fig. 4: Distribution of F1 scores across different chunk sizes for all persons for different gait types. On y-axis is F1 score in percents, on x-axis are different gait types.

Diplegic, Hyperkinetic and Steppage gait types respectively. Lowest F1 score of 60.24±18.65% is achieved for Ataxic gait type.

Time of detection is relevant, when classification accuracy is high. Typical normal step length in this study is ranging from 1 to 1.2 seconds depending on the person, whereas abnormal step duration ranges from 1 to 1.7 seconds, depending on the person and gait type. Mid-swing phase of the step is starting at around 0.2-0.4 seconds from the step beginning. Therefore, for the earliness metric depicted in Fig. 5, it could be observed that for most gait types the earliness is less than one second. For Steppage gait type the most common earliness measure is around 0.6 seconds for RTtsSVM-AD and LSTM-AD algorithms and 0.2 seconds for 1D-CNN-AD algorithm which is in the middle or at the beginning of a step. For other gait types it could be observed that detection was mainly in the middle of a step, which shows, that algorithms can detect anomalies early, during the mid-swing phase of a step. For some gait types RTtsSVM-AD and LSTM-AD are detecting abnormality earlier than 1D-CNN-AD, but in combination with quality of prediction, 1D-CNN-AD is outperforming other presented algorithms.

In Table 9, it can be observed that the main issue of RTtsSVM-AD algorithm is *computational real-time factor*. It means that for every second of incoming data, it takes 9.13±6.54 seconds to classify it, which is 3 to 15 times longer than the amount of collected data in real-time. The main reason for this is the usage of prediction probability in *tslearn* classifier, which uses an expensive 5-fold cross-

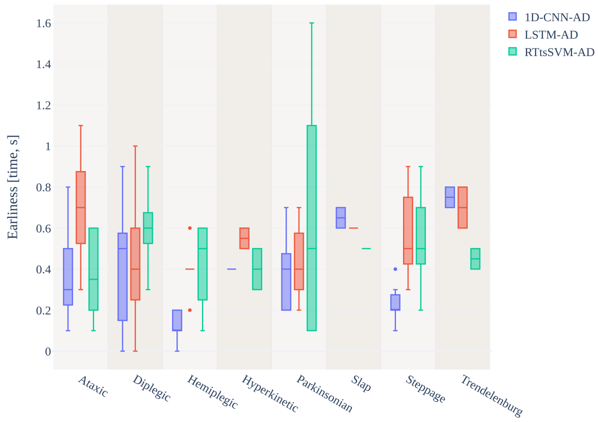

Fig. 5: Distribution of Earliness across different chunk sizes for all persons for different gait types. On y-axis is time in seconds, on x-axis are different gait types.

Table 9: *Average real-time factor for all algorithms*

Algorithm	RTF
1D-CNN-AD	0.09±0.03
LSTM-AD	1±0.07
RTtsSVM-AD	9.13±6.54

validation method to calculate probability. Using regular class prediction is not possible due to inaccurate results from the classifier, as it outputs only zero or one as class identification, drastically reducing classification quality. LSTM-AD algorithm is performing classification in near real-time but not faster than it, because recurrent operations of the algorithm are computationally expensive. Thus, 1D-CNN-AD algorithm is most suitable for real-time applications, for example, to operate in real-time on a real gait assistive device.

This work have several limitations: a) Simulated gait deviation could differ from the real patient's gait with neurological disorders. However, the main goal in this study is to classify the step as normal or abnormal during the mid-swing phase of the step. If patient's normal step pattern after the rehabilitation is sufficiently different from the patient's abnormal step pattern (i.e. because of fatigue or other reasons), then algorithms will be able to detect gait abnormalities during the mid-swing phase of the step as they are able to detect them in this study with simulated gait. Also, as it was stated in the section 2.1: simulations are recreating actual patients' video recordings of gait deviations in collaboration and guidance from a professional physiotherapist of Tallinn East Central Hospital. Thus, such simulated gait types are representing real gait types as close as possible. b) Neural networks in this study are not aware of the gait phase, thus multiple alarms could be triggered during one abnormal step, thus they would be optimized further. Cross-correlation of different hyperparameters could improve classification performance and would be studied in future work.

6 Conclusion

Proposed in this study real-time in-step anomaly detection algorithms are at the very beginning of the research towards context aware assistive devices, which will help to improve gait quality and reduce falling risk for patients suffering from neurological disorders.

Results of this study shows that 1D-CNN-AD algorithm is suitable for real-time anomaly detection in realistic gait deviations during the ongoing step with average earliness of 0.4 seconds. An average accuracy of 95% and average F1 score of 88% across different studied gait types is achieved for 1D-CNN-AD algorithm, with best F1 score of 98.1±2.7% for Hyperkinetic gait type. Benefits of this algorithm are, that it is not dependent on gait phases, resistant to the non-optimal hyperparameters and can run in real-time. Second proposed LSTM-AD algorithm achieved average accuracy of 87% and average F1-score of 70% across different studied gait types and best result is achieved for Hemiplegic gait type with F1 score of 81.3±9.96%.

Future gait correction systems and assistive devices will benefit from context awareness in a form of real-time anomaly detection algorithms, leading to more tailored approach for patients suffering from neurological disorders. This will help them to maintain better gait quality, which they obtained after rehabilitation, giving higher chance to continue daily living activities without major restrictions. Main benefit of context aware assistive devices compared to regular assistive devices would be less muscle fatigue from using it. Considering, that FES is used in current assistive devices [21, 22, 16], where electrical stimulation is given every step, context aware FES would be used only, when step deviation is detected and stimulation is necessary.

Future work will be focusing on further optimization of the presented algorithms, in-step abnormality estimation with more persons and real-time in-step abnormality detection tests with embedded devices running proposed in this study algorithms.

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Appendix 4

IV

B. Gerazov, E. Hadzieva, A. Krivošei, F. I. Soto Sanchez, J. Rostovski, A. Kuusik, and M. Alam. Matrix profile based anomaly detection in streaming gait data for fall prevention. In *2023 30th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pages 1–5, 2023

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Matrix Profile based Anomaly Detection in Streaming Gait Data for Fall Prevention

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***Abstract*—The automatic detection of gait anomalies can lead to systems that can be used for fall detection and prevention. In this paper, we present a gait anomaly detection system based on the Matrix Profile (MP) algorithm. The MP algorithm is exact, parameter free, simple and efficient, making it a perfect candidate for on the edge deployment. We propose a gait anomaly detection system that is able to adapt to an individual's gait pattern and successfully detect anomalous steps with short latency. To evaluate the system we record a small database of enacted anomalous steps. The results show the system outperforms a more complex Neural Network baseline.**

***Index Terms*—gait, anomaly, matrix profile, fall detection, edge**

I. Introduction

Certain neurological disorders reflect on an individual's ability to maintain stable gait. This can lead to falls and cause significant physical, emotional and financial setbacks for the individual and their family, as well as a burden to health-care providers [1], [2]. Even though 46% of neurological patients fall at least once a year, potential predictors of falls are poorly investigated and understood [3].

There are two general approaches to analyzing the causes of falls: fall risk assessment through clinical investigations [3]–[6], and computerized gait analysis [1], [2], [7]–[9]. In [3], the authors distinguish fallers from non-fallers among neurological patients, based on spatio-temporal, variability and asymmetry gait parameters. Similarly, [7] make a retrospective classification between fallers and non-fallers among patients with Multiple Sclerosis based on accelerometer and gyroscope data, applying deep learning models. The desire is to develop early, automatic prediction of missteps that might cause falling and a way to intervene and prevent it.

The wrong step in one's gait is an anomaly, or outlier, in the sequence of normal steps [10]–[12]. Detecting anomalies in streaming data is a challenging task: (i) the stream is infinite, which makes storing the entire stream impossible; (ii) the stream contains mostly normal instances and much less anomalies; and (iii) streaming data evolves over time, imposing the need for adaptation [11], [13]. When dealing with anomalies in gait, there's an additional challenge in that there is both interpersonal variability, i.e. each person's gait is unique, as well as intrapersonal variability as one's gait is not set in stone.

Solving the problem requires a robust algorithm that will work on streaming data, in an unsupervised and automated fashion, and that will be able to detect the anomaly with the highest possible accuracy as early as possible, a problem termed early classification of time series [14]. Many anomaly detection algorithms exists, supervised and unsupervised, yet the vast majority of them are unsuitable for real-time streaming applications [15]. Moreover, algorithms operating on small data, e.g. shapelets [16], are still in its nascence.

In this paper, we present a gait anomaly detection system based on the Matrix Profile (MP) algorithm [17]. The MP algorithm is exact, simple and parameter free, with low complexity. Additionally, it is shaplet-based and thus interpretable [18]. We first explore the plausibility of using the MP as a basis for a gait anomaly detection system and then develop it's design. To evaluate the system's performance we record a small database of enacted anomalous steps. Finally, we compare the proposed system to a more complex Neural Network baseline.

II. Matrix Profile

The following definitions of the MP are slightly modified from [17], [19] and [20], in favor of mathematical correctness and conciseness. A **time series** $\mathbf{T} = \{t_k\}_{k=1}^{n}$ is a sequence of n real values. The sub-sequence of m consecutive terms of $\mathbf{T}$, starting from the position i, where $1 \leq i \leq n - m + 1$, will be denoted by $\mathbf{T}_{i,m}$. Thus, $\mathbf{T}_{i,m} = \{t_k\}_{k=i}^{i+m}$. The sub-sequences will be compared using the *z-normalized Eucledian distance*. An **all-subsequences set** $\mathbf{A_T}$ of a time series $\mathbf{T}$ is an ordered set of all possible sub-sequences of $\mathbf{T}$ obtained by sliding a window of length m across $\mathbf{T}$: $\mathbf{A_T} = \{\mathbf{T}_{1,m}, \mathbf{T}_{2,m}, \ldots, \mathbf{T}_{n-m+1,m}\}$. The **matrix profile** (MP) is a vector of length $n-m+1$ corresponding to all-sub-sequences set, whose i-th location is the distance of the sub-sequence $\mathbf{T}_{i,m}$, to its nearest neighbor, under z-normalized Euclidean Distance.

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TABLE I
DATASET OF ANOMALOUS STEPS RECORDED FOR THE ANALYSIS.

Pathology	recordings	ok	ab	duration [min]
Antalgic	7	156	42	6.61
Ataxic	4	82	27	3.90
Diplegic	6	139	36	6.05
Hemiplegic	5	100	28	6.61
Hyperkinetic	4	95	30	4.04
Parkinsonian	4	100	30	4.07
Slap	5	105	37	4.59
Steppage	9	185	58	7.05
Trendelenburg	4	85	30	4.13
Total	48	1047	318	44.60

Note that trivial matches are avoided, that is the sub-sequences that overlap at least in the half length with $\mathbf{T}_{i,m}$ are not taken into account in computing the i-th component of the matrix profile of $\mathbf{T}$ ([17]). Given a time series $\mathbf{T}$, the sub-sequence $\mathbf{T}_{i,m}$ is said to be the **discord** of $\mathbf{T}$ if $\mathbf{T}_{i,m}$ has the largest distance to its nearest (non-trivial) match.

In the whole algorithm there is only one parameter to set – the length of the sub-sequence. In our application scenario, this would correspond to the length of a single step. Extracting the motif, i.e. reoccurring pattern, and discord from our generated gait data set means extracting the normal and anomalous step, correspondingly. We used the STAMP (Scalable Time series Anytime Matrix Profile) [17] and STOMP (Scalable Time series Ordered-search Matrix Profile) [17], [21] algorithms for generating the matrix profile and detecting both motif and discord of particular time series.

III. Dataset

We recorded a small dataset that includes anomalous steps dispersed amidst normal walking patterns by a single male subject on a hard surface. The anomalous steps were meant to mimic pathological step patterns from different disorders. In total 9 pathological step patterns were included in the dataset as shown in Table I. The recording protocol comprised of walking a straight line of around 10 steps and acting out a pathological step pattern in the middle. Each recording contains around 4 stretches of 10 steps.

We recorded the data using a Shimmer Inertial Measurement Unit (IMU) sensor placed on the foot of the subject that records accelerometer and gyroscope signals in the 3 axes [23]. All the data was annotated in a two-step process: (i) steps were automatically segmented, q.v. Sec V-A, and (ii) the segments were manually corrected and labeled with three labels: “ok” for a normal step, “ab” for an anomalous step.

IV. Plausibility

We first explore the plausibility of using the MP for anomalous gait detection by implementing a naïve algorithm shown in Fig. 1. In it, signal samples are accumulated in a Frame buffer, which is updated at a specified hop length analogous to a sliding window. As new samples are added to the Frame buffer, the oldest ones are transferred to a larger History buffer.

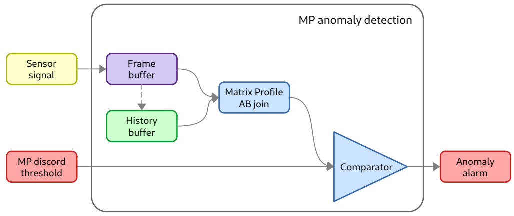

Fig. 1. Architecture of the naïve implementation of a MP-based anomaly detection algorithm.

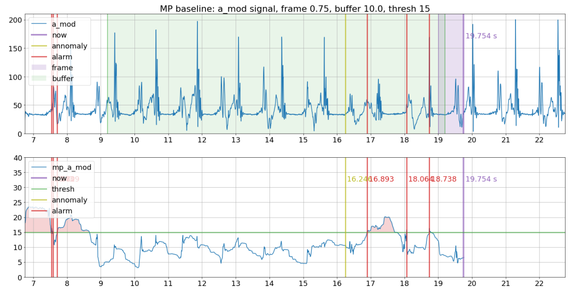

Fig. 2. Visualization of the functioning of the naïve algorithm for a sample acceleration signal from the database (top plot) in which there are 7 normal steps followed by 2 anomalous steps and then 3 more normal steps. The contents of the Frame and History buffers are highlighted in violet and green. The MP discord is calculated for each update of the Frame Buffer (bottom plot) and is compared to a threshold (green) raising an alarm if it goes above (red lines).

The contents of these two buffers overlap up to the specified exclusion zone for the MP algorithm (25%).

For each update of the Frame and History buffers, the MP is calculated by using the Frame buffer to query the History buffer. The value for the MP is then compared to a discord threshold and if larger the system activates an Anomaly alarm. The Frame buffer size, i.e. the subsequence length m, and the discord threshold are the two critical system parameters.

Fig. 2 shows a qualitative inspection of the naïve algorithm for a sample acceleration signal. We can see that the algorithm does indeed successfully detect the onset of anomalous steps raising an alarm, thus validating the approach.

V. MP-based gait anomaly detection system

In the results from the naïve implementation, we can see that there is a problem at the start of the signal, where it generates false alarms. This is because at this point in time the History Buffer does not contain any step signatures. Based on our inspection, we designed an improved MP system architecture in which we integrate step detection, shown in Fig. 3. The input sensor signals are now forwarded from the Frame buffer and accumulated in a Current step buffer. The step detection module analyses the contents of the Current step buffer on each update, and upon detecting the start of a new step it moves the contents of the Current step buffer to the History buffer.

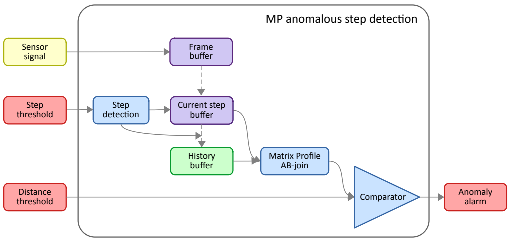

Fig. 3. Architecture of the MP step based anomaly detection algorithm.

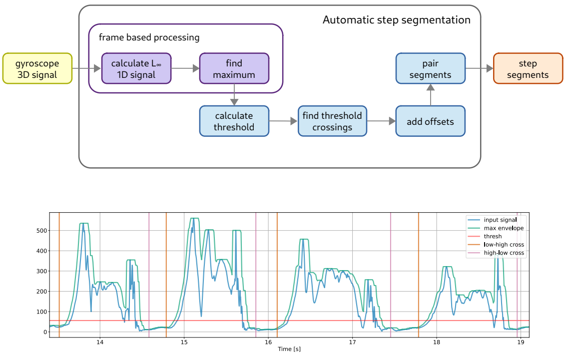

Fig. 4. Block schematic of the step detection algorithm (top), and step detection results for a sample signal (bottom).

The MP is calculated for each update of the Current step buffer, but only if the Step detection module has detected a step has started. In this case, the subsequence length m changes and is equal to the length of the signal stored in the Current step buffer.

A. Step detection algorithm

The block schematic of our step detection algorithm is shown in the top plot of Fig. 4. It is based on an adaptive threshold that's used to detect crossings of the maximum amplitude envelope of the input signal. Offsets are applied to the crossings to account for the step onset and release below the threshold. The amplitude envelope is calculated with a wide 100 ms window that also acts as a low-pass filter. The threshold is adaptive and is recalculated with each update of the History buffer from the maximum value of the envelope signal stored in the History buffer. In fact, setting the step segmentation threshold high initially, let's the algorithm adapt only when actual steps are buffered in the History buffer. The results from using it on the sample signal are shown in the bottom plot. In a subset of experiments we determined that the L_∞ 1D projection of the gyroscope signal gives the best step segmentation results.

VI. Experiments

We conducted a set of experiments to optimize and evaluate the proposed system.

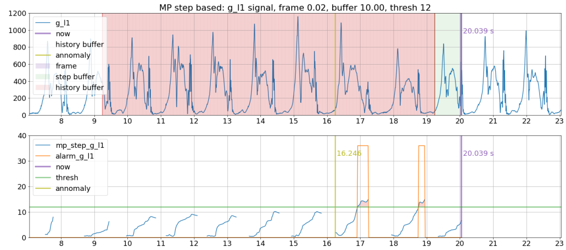

Fig. 5. Visualization of the functioning of the MP-based baseline system for gait anomaly detection.

Plausibility. As with the naïve implementation, we qualitatively evaluated our MP-based gait anomaly detection system with sample signals from our database.

Sensor signal. We analyzed the performance of the MP algorithm when the three different axes of the gyroscope and accelerometer signals are used, and their L_1, L_2 and L_∞ norms.

External signals as reference. We evaluate the possibility of using preset normal steps from external sources as reference in the History buffer. This has the potential to ease deployment, but comes at the cost of curbing adaptation. Here, we make two subexperiments: 1) extracting the reference from the diplegic/hemiplegic signals, and 2) using a mix of segments from all anomalies, 10 s each. For a fair comparison we also use increased lengths of the History buffer.

Neural Network baseline. To evaluate the comparative performance of our proposed algorithm we design, train and optimize a Neural Network baseline system based on recurrent LSTM (long short-term memory) layers. The optimized architecture of the model comprises two layers of bidirectional LSTMs with a size of 256, followed by a 3-hidden layer feedforward network, sizes 256, 128, and 64, and a final output neuron with a linear activation function. All layers in the network were followed by batch normalization and a dropout of 0.2. The network was fed 2 s of the Sensor signal.

While for the other experiments we use a smaller subset of the data for efficiency, here we use a larger proportion to get a better estimate for in-the-wild performance.

Evaluation metrics. To evaluate the performance of our proposed system we employed metrics commonly used in binary classification tasks including the F1 score, ROC (Receiver Operating Characteristic) and earliness, i.e. the average latency in seconds needed for the system to raise an alarm upon the onset of an anomalous step.

VII. Results

Plausibility. Fig. 5 shows the contents of the Current step and History buffers as well as the calculated MP and detected alarms for the L_1 norm of a sample gyroscope signal. We can see that indeed the MP algorithm is capable of detecting anomalous steps, and also and deals efficiently with the start of the signal.

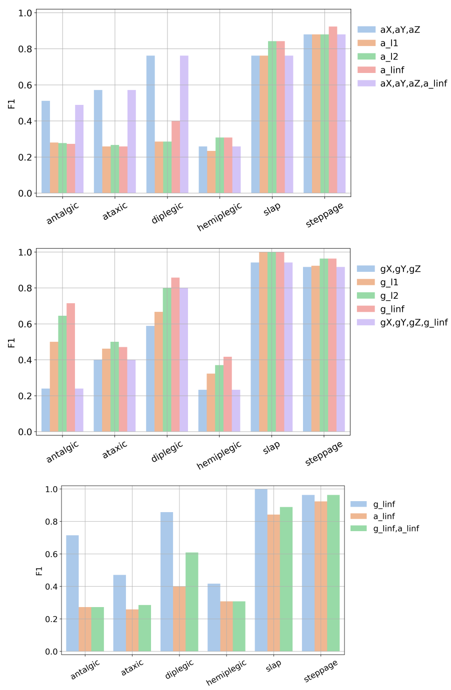

Fig. 6. Best case $F1$ - score for different axes and norms from the accelerometer (top), gyroscope (middle), and both (bottom) signals.

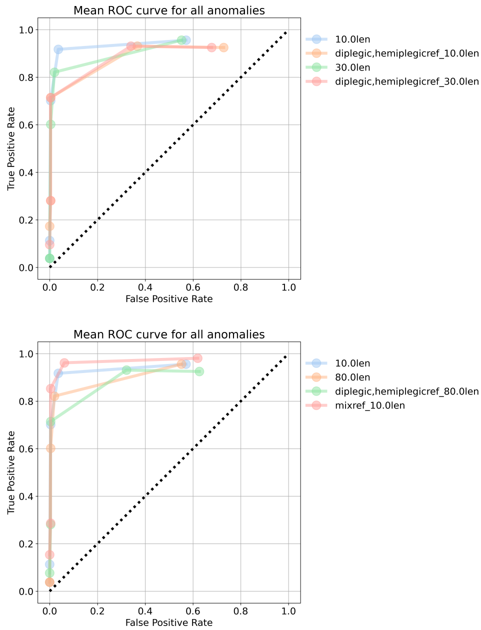

Fig. 7. Mean ROC for the MP-based system for different lengths of the History buffer and different signals used as reference.

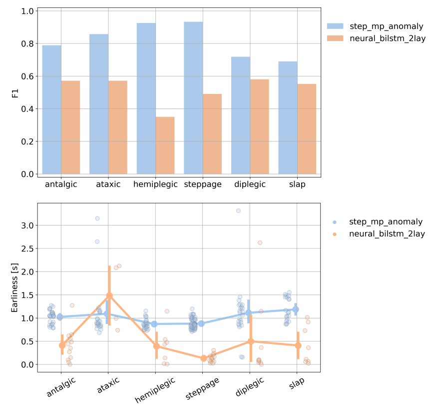

Fig. 8. Mean F1 (top) and earliness (bottom) for the MP-based system compared to the Neural Network baseline.

Sensor signal. The F1 results for the accelerometer and gyroscope signals, across all anomalies, are shown in Fig. 6. The relative F1 really varies across the anomalies for the accelerometer signal. For the gyroscope signal they are more consistent, with the L_∞ norm performing better, while using or adding multiple axes, degrades performance. In the bottom, we can see that the gyroscope L_∞ norm outperforms the accelerometer L_∞ norm, as well as when both signals are used.

External signal reference. The results from using different lengths of the History buffer and different signals used as reference are shown in Fig. 7. Comparing the mean ROC curves, we can see that on average, there is benefit of using a mixed signal reference. Closer inspection however, omitted here for brevity, shows that the results vary by anomaly.

Neural Network baseline. The F1 results comparing the Neural Network baseline to the proposed model are shown in the top of Fig. 8. It can be seen that the MP-based algorithm outperforms the Neural Network baseline by a wide margin. The Neural Network does provide faster reaction times than the MP-based system as can be seen in the bottom plot. We also measured the real-time factor of the two algorithms and found that it is 10× higher for the Neural Network baseline. This might point towards possible deployment issues on edge devices.

VIII. Conclusion

We propose a gait anomaly detection system based on the Matrix Profile algorithm. The system relies on lean digital signal processing to adapt to an individual's gait pattern and to successfully detect outliers with low latency. The system obtains high F1 scores across anomalies, outperforming a more complex Neural Network baseline. Its low complexity makes the MP based gait anomaly detection system a good candidate for edge deployment.

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Appendix 5

V

J. Rostovski, A. Krivošei, A. Kuusik, Y. Le Moullec, I. K. Niazi, and M. M. Alam. Signal shape tracking algorithm for real-time in-step gait anomaly detection. *IEEE Access*, 12 2024

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Signal Shape Tracking Algorithm for Real-time In-step Gait Anomaly Detection

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ABSTRACT Real-time gait anomaly detection in gait analysis is an active area of research. However, anomaly detection within the swing phase of a step is not being well addressed in existing research. To address this, we propose a real-time gait deviation detection algorithm called signal shape tracking anomaly detection (SST-AD) and a framework to estimate the performance of anomaly detection in the proposed and other state-of-the-art algorithms. The SST-AD algorithm is compared to widely used algorithms, namely One-Class Support Vector Machine (OCSVM), Long Short-Term Memory (LSTM) and One Dimensional-Convolutonal Neural Network (1D-CNN). F1 score, recall, precision, real-time factor (RTF), and ”earliness” measures are estimated and analyzed. The ”earliness” is a new metric which defines the time between the beginning of a step and the moment in time when the step is classified as abnormal. The results demonstrate that the SST-AD algorithm can detect gait abnormalities during the mid-swing phase of an ongoing step. In terms of accuracy and F1 score, the SST-AD algorithm achieves similar performance to that of 1D-CNN algorithm but with significantly lower computational complexity. SST-AD can process 1 second of data in 90ms while 1D-CNN requires 550ms. Importantly, the best average earliness is achieved by the SST-AD algorithm at 0.4s from the initial-swing phase start. Based on the results, SST-AD is found to be the best suited algorithm for real-time gait anomaly detection and should be considered to be used in future embedded assistive devices.

INDEX TERMS Anomaly detection, Earliness, Gait assessment, Machine Learning, Real-time system, Signal Shape Tracking Anomaly Detection algorithm

I. INTRODUCTION

Neurological diseases, ranging from migraine to stroke and Alzheimer, are the leading causes of Disability Adjusted Life Years (DALY) loss [1]. Gait quality is one of the primary aspects of daily life that can be detrimentally affected. To help address problems with gait quality, different assistive gait correction devices are used. Simple mechanical devices such as ankle-foot orthoses can reduce the risk of falling [2], but do not completely eliminate it. Patients with gait impairments stemming from neurological diseases, especially those suffering from neuromuscular diseases, are at substantial risk of falling due to high variability and deviations from the optimal gait pattern [3] [4]. For example, certain diseases cause abrupt gait changes, such as freezing episodes of Parkinson’s Disease (PD) [5]. Other diseases, such as Multiple Sclerosis (MS), may contain long durations of relapse episodes with individual impact and slow progression [6]. Consequently, neurodegenerative diseases can affect gait quality and change its locomotion cycle to abnormal [7].

In recent years, wearable motion sensors containing multidimensional Inertial Measurement Units (IMUs) have been widely used in gait assistive devices [8]–[10]. Such devices are used to support patients with neurological diseases and in performing regular daily activities [11]. IMUs are also used as data input devices to detect initial and final contact events of the gait cycle and select the best algorithms and sensor placements for correct classification between persons who are healthy, had a stroke have Alzheiemr or Parkinson's disease or with other neurological disorders [12], [13]. Such data is also used to detect activities of daily life, fall events and their directions [14], determine gait parameters, identification of persons [15]–[17], and discover environment-dependent differences in gait, which can help to make context-aware decisions [18].

Studies have shown that one of the effective gait assistive techniques is based on Functional Electrical Stimulation (FES), which is used to assist walking and help prevent falls [19], as well as to improve gait quality in general [20]. Long-term gait deviation analysis and efficient run-time control of FES devices require automated real-time recognition of gait deviations. During the normal walking of older adults the average swing phase of a step lasts 300-400 ms [21]. Within this time, it is required that the step's incoming signal is processed, the correct decision made, and gait correction executed. Considering that the full contraction of the muscle using electrical stimulation requires 100-200 ms of continuous muscle stimulation [22], gait deviation should be detected in less than 100 ms. However, the swing phase duration can be shorter than the average swing phase duration, and thus the target detection time should be under 50 ms to meet the time constraint.

Existing real-time algorithms are used to detect gait events such as heel-strike and toe-off in healthy young and elderly persons, stroke patients, and patients with Parkinson's disease [23]–[25], children with cerebral palsy [26], as well as patients with other impairments [27], [28], by means of e.g. recurrent neural networks (RNN), heuristics, thresholds, support vector machine (SVM), reduced support vector machine (RSVM), and finite state machine (FSM) algorithms. Real-time haptic biofeedback devices are implemented to correct toe-in or toe-out during walking, using foot progression angle gait algorithm [29]. Real-time algorithms, such as convolutional long short-term memory neural network (CLSTM-NN), heuristic and fast complementary filter (FCF) algorithms are widely studied for classification of gait terrain and walking modes such as overground walking, stair ascend or descend, and others [30]–[32]. Lastly, real-time gait trajectory prediction [33] and gait pattern classification for full steps are implemented using a convolutional neural network (CNN) [34].

According to the [35], SVM-based methods are the most widely used for automated gait analysis, followed by CNN. SVM's advantages include the capability to operate with relatively small datasets (10's to 100's of samples), and high computational efficiency [14], [36], whereas CNN tends to require larger datasets for good classification performance, for which the datasets have close to or more than 1000's of samples [30], [34]. However, there is a lack of research for analyzing how well machine learning methods, particularly SVM, perform in detecting real-time typical gait deviations caused by neurodegenerative diseases.

In the [37], real-time performance of the thereal-time tslearn support vector machines anomaly detection (RTtsSVM-AD) algorithm was explored, which was able to detect abnormalities in the step. The downside of this algorithm is its computationally expensive five-fold correlation used to calculate probabilities of the abnormal class, which means it does not process the real-time signal fast enough. Real-time operation is crucial for the possibility of the algorithms to be deployed on low-power embedded devices. Thus, to truly estimate the performance of the SVM based algorithm, in this paper we propose the one-class support vector machine (OCSVM) algorithm which does not have the same limitation as the RTtsSVM-AD algorithm. The aim of the OCSVM algorithm is to estimate the most popular machine learning method in gait analysis, i.e. SVM, in real-time in-step gait deviation detection. The second most popular algorithms in gait analysis are based on neural networks and in [38] we investigated the performance of the 1D-CNN and LSTM based real-time in-step gait deviation detection algorithms. Neural network based algorithms are promising and achieve high accuracy, but require time-consuming hyperparameter adaptation and can be prone to underfit or overfit the data with sub-optimal parameters. To overcome this, a heuristic algorithm is proposed in this paper, which mitigates the need for time-consuming hyperparameter optimization and high computational power need for the model training and is able to achieve or surpass the performance of the presented neural-network based algorithms.

In view of the above, in this paper we provide the following novel contributions:

- In this work, a benchmark framework is presented to estimate the real-time anomaly detection performance of different algorithms. This framework provides data preprocessing tools and allows estimating the data in a way that allows to perform real-time in-step gait deviation detection. To estimate the performance of the algorithms, simulated gait deviation data was collected according to the clinical trial protocol approved by Estonian National Institute for Health Development, permission No.818. In total, approximately, 11625 steps collected in 155 gait recordings during 27 recording sessions by 22 subjects. The resulting dataset combines both normal and abnormal step patterns within a single gait recording, which was not available in the state of the art until now. To the best of the authors' knowledge, it is the first dataset that incorporates eight common types of different gait deviations in a unified manner, thereby providing an opportunity for more comprehensive research on gait anomaly detection algorithms.
- We propose and implement novel real-time in-step gait deviation detection algorithm - the signal shape tracking

anomaly detection (SST-AD), which can be used for in-step anomaly detection. The SST-AD algorithm is compared to state-of-the-art algorithms, namely One-Class Support Vector Machine, Long Short-Term Memory and One Dimensional-Convolutonal Neural Network. The presented algorithms achieve an average accuracy and F1 scores of 91% and 81% for SST-AD; 86.5% and 70.1% for LSTM; 95% and 88.2% for 1D-CNN; 74% and 54.9% for OCSVM, respectively. Results for in-step anomaly detection earliness are on average from 0.4s to 0.5s, which is during mid-swing phase of the step. The SST-AD algorithm is the best performing over the tested algorithms, which includes simple hyperparameter optimization and lightweight algorithm structure. The SST-AD algorithm achieves fast gait deviation detection time and low latency and is suitable for implementation in embedded devices.

The rest of the paper is organized as follows: In Section II we outline the data collection protocol, data preparation, and classification measures. Section III provides an overview of the proposed benchmark and framework for evaluating the real-time in-step anomaly detection algorithms. Sections IV to VI offer detailed insights into the proposed algorithms. Section VII begins with the evaluation setup and proceeds to comprehensively describe results achieved for real-time in-step classification. These findings are discussed in section VIII and concluded in section IX.

II. DATA COLLECTION PROTOCOL, GAIT TYPES AND PERFORMANCE METRICS

To evaluate the performance of the algorithms, we collected simulated gait deviation data from 22 healthy subjects of different genders, ages, heights and weights (Table 1). The healthy subjects simulated gait deviations by recreating video recordings of gait deviations from actual patients, with the collaboration and guidance of a professional physiotherapist of Tallinn East Central Hospital, Estonia.

A. GAIT TYPES

The most frequent eight gait abnormalities which can be treated or corrected with FES are selected as follows: Ataxic [39], Diplegic [40], Hemiplegic [41], [42], Hyperkinetic [43], [44], Parkinsonian [45], Slap [46], Steppage [47] and Trendelenburg (lurch) [48] gait types [49]. In the rest of this study we use the wording "gait type" in terms of a human gait with an abnormal step pattern.

B. DATA ACQUISITION

During the 27 sessions of the data collection process, normal and simulated abnormal steps were combined according to the following procedure depending on the gait type:

1. $Normal\ gait\ steps\ +\ one\ abnormal\ step$
2. $Normal\ gait\ steps\ +\ one\ abnormal\ step\ +\ normal\ gait\ steps$
3. $Normal\ gait\ steps\ +\ f\cdot abnormal\ steps\ +\ normal\ gait\ steps\ +\ f\cdot abnormal\ steps,$

where $f \in \mathbb{N}$.

Each motion data recording contains deviations of one specific gait type. Such procedures were chosen as per the recommendations of the physiotherapist. In actual patient gait video recordings, it can be seen that the number of abnormal steps, which is present in their gait type, is dependent on the gait type itself, fatigue levels and can change over time. Therefore, imbalanced datasets have been collected to reflect this. Most of the chosen gait types affect either both sides of the body or whole body, excluding Hemiplegic, Slap and Steppage gait types. Thus, procedure 3 was commonly used for them to mimic real patients gait patterns. Hemiplegic and Steppage gait types usually affect one side of the body or one leg, whereas Slap gait can affect either one or both sides. Thus, the first two procedures were possible for Hemiplegic, Slap and Steppage gait types. The amount of abnormal steps in one data recording corresponds to between 20% to 35% of all steps, depending on the type of gait, reflecting the proportion of abnormal to normal steps of the actual patients. Such an imbalance is considered as minor imbalance and should not have significant effect on the training quality.

TABLE 1: *Subjects' Information Used in This Study (Mean ± Standard Deviation)*

No. of subjects and gender	Age (years)	Height (cm)	Mass (kg)
15 Males	32.1±11.1	177.7±5.5	76.8±15.1
7 Females	26.3±5.5	169.5±6.2	62.7±8.9

During the study, one wearable IMU sensor (Shimmer3 IMU (Dublin, Ireland) [50]) was used to capture motion data from the lower limbs. Accelerometer and gyroscope data were collected, with accelerometer range set to $\pm 8g$ and gyroscope range set to ± 1000 °/s. Given the recommendation of the physiotherapist and neurologist, we use a small number of devices, which should be more comfortable and easy to use for the end user. The wearable sensor is placed on the forefoot, i.e. the most widely used placement of inertial sensors for gait cycle monitoring [51]. The benefits of the sensor placement on the forefoot are, that IMU can detect the small movements in the forefoot and have bigger range of motion. This can be used to detect the gait events in parallel with the abnormal gait patterns detection. In this work, only overground walking in straight line was performed.

For the proposed algorithms, the initial 3D vector of the angular velocities of the gyroscope is extended with 4^{th} dimension:

$$\mathbf{G_4} = \{\mathbf{X}, \mathbf{Y}, \mathbf{Z}, \mathbf{Mag}\} \quad (1)$$

where $\mathbf{X}, \mathbf{Y}$ and $\mathbf{Z}$ are vectors representing the gyroscope angular velocities around the sensor axes (3) and $\mathbf{Mag}$ is the magnitude of this initial 3D vector:

$$\|\mathbf{Mag}\| = \sqrt{\mathbf{X}^2 + \mathbf{Y}^2 + \mathbf{Z}^2} \quad (2)$$

The vectors $\mathbf{X}, \mathbf{Y}$ and $\mathbf{Z}$, in turn, can be represented as discrete samples:

$$\begin{aligned} \mathbf{X} &= [x_0, x_1, \ldots, x_i, \ldots, x_n]^T \\ \mathbf{Y} &= [y_0, y_1, \ldots, y_i, \ldots, y_n]^T \\ \mathbf{Z} &= [z_0, z_1, \ldots, z_i, \ldots, z_n]^T \end{aligned} \tag{3}$$

where $n \in \mathbb{N}$ is the sample index.

C. DATA ANNOTATION

Data annotation was carried out semi-automatically: each recording was segmented into individual steps algorithmically; then, a label for each step was manually assessed and adjusted if needed. Each step was annotated either as a ***normal*** or ***abnormal*** step. Annotation was performed by means of definitive differences between step shapes and with video recordings of simulated gait data collection process for reference.

TABLE 2: *Total number of collected datasets for different gait types in this study*

Gait type	Total number of recordings across all subjects
Ataxic	32
Diplegic	25
Hemiplegic	17
Hyperkinetic	6
Parkinsonian	29
Slap	8
Steppage	32
Trendelenburg	6

The total number of gait recordings collected for this study is presented in Table 2. Each of the gait types was simulated by different numbers of subjects, resulting in 6 to 32 recordings for each gait type.

D. ANOMALY CLASSIFICATION MEASURE

In this paper, for the algorithms' evaluation, the following evaluation metrics are calculated:

- **Accuracy**;
- **F1 score**;
- **Recall**;
- **Real-time factor (RTF)** – time of processing, which shows how fast the algorithm can process a signal on the selected computing platform:

$$RTF = \frac{processing\ time\ [s]}{duration\ of\ the\ signal\ [s]} \tag{4}$$

- **Earliness** – In contrast to the RTF, which estimates the processing speed of an algorithm, the *earliness* is defined as the time between the beginning of a step and the moment in time when the step is classified as abnormal. The minimal achievable earliness naturally depends on the gait deviation type. Such a measure has been introduced because the actual time instant when an anomaly starts occurring can fluctuate, depending on the gait type. If multiple abnormal steps are performed in a row and each step is detected, then earliness is calculated individually for every step. Earliness can demonstrate how stable is the anomaly detection and in what phase of the step the anomaly is detected.

III. PROPOSED FRAMEWORK FOR REAL-TIME GAIT ANOMALY DETECTION AND REAL-TIME IN-STEP ANOMALY DETECTION ALGORITHMS

In this section, we first describe how the evaluation of the algorithms performance is carried out. For this, algorithms first need to be trained, which we refer to as 'training mode', and second real-time performance of the in-step anomaly detection is evaluated, which we refer to as 'prediction mode'. Then we present the three complementing tools that have been developed as parts of the proposed evaluation framework: *i) Step detector*, *ii) Frames synchronization to step's beginning*, and *iii) Generation of alarm*.

A. REAL-TIME IN-STEP ANOMALY DETECTION EVALUATION

The real-time in-step anomaly detection evaluation has two operation modes: training mode (Fig. 1a) and prediction mode (Fig. 1b,c,d). These two modes relate to the repeated training process and evaluation of in-step anomaly detection in real-time and are described below.

1) Training mode

The flow diagram of the training mode is shown in Fig. 1a. At first, the input time series data is divided into individual labeled steps using the *step detector* (presented in the section III-B). Next, the collection of labeled steps is used in the training method of a given algorithm. The training procedure is algorithm-specific and is described individually for each algorithm in Sections IV-C, V-B, and VI-B.

2) Prediction mode

The flow diagram of the prediction mode is shown in Fig. 1b. Here, input data is arriving continuously in a series of packages or chunks (in the rest of the paper we use the term *chunks* for the sequential pieces of the input data) into the frame collection unit, where the newest frame is collected into a buffer in real-time. This procedure, in more detail, is shown in Fig. 1c and Fig. 1d. The size of each chunk is selected small enough for real-time operation (to achieve an anomaly alarm latency within tens of milliseconds) and large enough for more efficient processing and data transfer through communication channels.

The collected frames are synchronous with the ongoing step, which means that the first frame collection procedure is started only when a step's beginning is detected by the *step detector*. Each freshly collected frame F_0 is applied to the *in-step* anomaly detector (see the yellow box in Fig. 1b). The *n-step* anomaly detector uses algorithm specific *model* and *threshold* value. This *in-step* anomaly detector returns a prediction score which is compared with the optimal threshold.

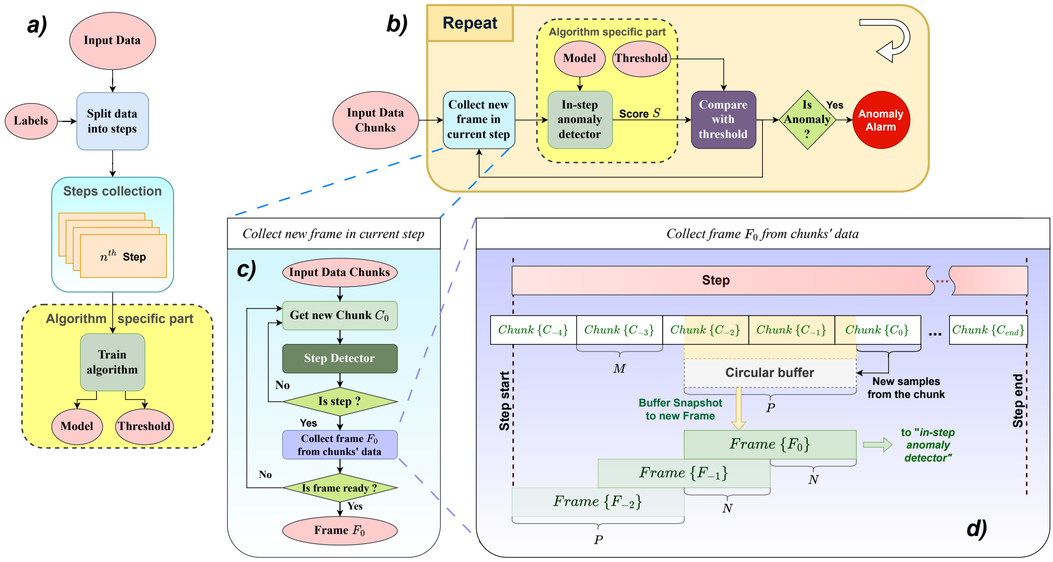

FIGURE 1: Block diagrams of the **Training mode** (*a*) and **Prediction mode** (*b,c,d*) for the proposed algorithms . *a)* The yellow block contents algorithm specific training procedures and is described in the following sections IV-C, VI-B; *b)* Main diagram. The yellow block represents algorithm-specific *in-step* prediction procedures and are described in sections IV-D, VI-C; *c)* Flow diagram describing the collection process of a new *frame*; *d)* Construction of frames synchronous to steps from asynchronous chunks. Frames are periodically created as snapshots of a circular buffer, starting from the detection of a step start event, until the detection of a step end event. Frames, chunks, and intervals between the frames are set individually for each algorithm.

This prediction process is repeated for every collected frame of every step. More details of the *in-step* anomaly detector are presented in sections IV-D, V-C and VI-C.

B. STEP DETECTOR

One of the most important components of all the proposed algorithms is the step detector, which aims to detect step's start and end events. Such a step detector is used in the main part of all the proposed algorithms, presented in Fig. 1c (dark green box). The input data for the step detector is each data sample. To operate, each sample in every input chunk is assessed separately. This is done for better synchronization of the step model with the streaming step data. The input for the step detector is the gyroscope vector magnitude calculated by (2). The complete algorithm of step detection is shown in *Algorithm 1*.

Input samples are collected in the buffer, in the form of a sliding window, and the maximum value of this buffer is compared to a threshold value. The selection of the threshold value for the step detector is based on the settings of the wearable motion sensor used for data collection. The threshold for the step detector and the minimum step duration were determined empirically. The step detector threshold was set to 10% of the gyroscope magnitude range, and the minimum step duration was defined as 90% of the samples within a one-second interval, based on the selected sampling rate.

The function `Detect_Step()` from Algorithm 1 is applied to every sample from the input chunk (Fig. 1b). Output variables `step`, `step_start`, `step_end` are used for the construction of the frames (described in Fig. 1d and section III-C).

C. FRAMES SYNCHRONIZATION TO STEP'S BEGINNING

This subsection introduces a proposed tool designed to construct synchronous frames to the step beginning. Frame is constructed as a snapshot of a circular buffer, which continuously updates with incoming data in the form of chunks. Frames are inline with the step and are proportional in length to several chunks. This tool corresponds to the block *"Collect frame F_0 from chunks' data"* in Fig. 1c.

Thus, if a new step is detected in the *"Step Detector"* block, or if the current step continues, then samples (from the current chunk) are appended to the circular buffer of length P (Fig. 1d). This is done to synchronize frames with the model of a normal step. The step model is also synchronous with the step beginning, to increase the quality of the abnormality detection. In Fig. 1d, the step start event corresponds to the time instant when the step beginning is detected.

The circular buffer receives the newest samples available from the newest chunk C_0 available in the detected step. Snapshots of the circular buffer are named "Frame F_k", where $k \in \mathbb{Z}$ (Fig. 1d). Frames are made from the fully filled circular buffer, by copying its content to the new array, after

Algorithm 1 Step Detector

```
Input parameters:
buffer_length ← 51
threshold ← 100                          ▷ value of gyroscope vector magnitude
step_min_length ← 256
Variables:
counter ← 0
buffer[buffer_length] ← array
Outputs:
step ← false
step_start ← false
step_end ← false

function DETECT_STEP(input)
    append input to buffer
    envelope ← max(buffer)

    if envelope > threshold then
        step ← true
    else
        step ← false
    end if

    if step_end is true then
        if counter < step_min_length then
            step ← true                  ▷ Step continues, if it is short
            step_end ← false
        end if
    end if

    if step is true then
        counter ← counter + 1            ▷ counting samples in the step
    else
        counter ← 0                      ▷ stop counting samples in the step
    end if

    step_start ← true if positive edge of step
    step_end ← true if negative edge of step

    return step, step_start, step_end
end function
```

every N new samples.

In the proposed solution, the N and P are related as per:

$$\begin{aligned} N &= (1-\alpha)P \\ P &= \beta M, \end{aligned} \tag{5}$$

where:

P – length of the circular buffer and frames $[samples]$

N – update interval (shift) of the frames $[samples]$

M – chunk size $[samples]$

α – algorithm specific parameter, $\alpha \in \mathbb{R}$ (frames' overlapping factor)

β – algorithm specific parameter, $\beta \in \mathbb{R}$

All values for these parameters are presented in section VII-A. The shortest possible interval L for anomaly detection, in this case, is

$$L = \max(N, M) \tag{6}$$

D. GENERATING AN ALARM

In the prediction mode, the score value S is the output of each anomaly detection algorithm. It is calculated for every frame of the real-time evaluation dataset and collected to the buffer. If the S value exceeds the $threshold$ value, an alarm signal is generated:

$$Alarm = \begin{cases} 1, & \text{if } S > threshold \\ 0, & \text{if } S \leq threshold \end{cases} \tag{7}$$

The $threshold$ value is configured for the purpose of testing the algorithms. The selection of the optimal threshold value is performed in the prediction mode, after all scores have been obtained. The optimal threshold is selected individually for every subject and gait type.

In the next sections, the proposed algorithms are described. For each algorithm, we present a general overview thereof, then its hypothesis, and then its specific dataset preparation, which is concluded by the description of the training and prediction modes.

IV. One-Class Support Vector Machine algorithm

The first proposed algorithm (OCSVM) is based on the One-Class SVM Python package from the Scikit-learn [52] which is used as the classification core. In this study, we added two key elements to the One-Class SVM, i.e. i) a continuous classification of the streaming data, and ii) a supervised approach for hyperparameter optimization. The proposed OCSVM algorithm is faster than the RTtsSVM-AD algorithm [37], [38] and is able to run in real-time (i.e. the computation time is faster than the real-time data-flow).

The hypothesis behind the OCSVM algorithm is as follows: if a full time-series pattern could be collected in real-time by combining the average normal step from the training phase with the data of the ongoing step, then anomalies could be detected during the swing phase of the ongoing step. This is possible under the assumption that the full combined pattern is classified as abnormal.

A. PREPARATION OF DATASETS FOR THE OCSVM ALGORITHM

Real-time in-step anomaly detection is evaluated using each gait recording individually, which is performed by subject and by gait type. To evaluate one specific gait recording, all the other gait recordings are combined into a classification dataset which is used to train the classifier. The classification dataset is divided into training, testing, and validation datasets, with a ratio of 60:20:20%. The validation dataset is required to convert the regular unsupervised One-Class SVM into the supervised OCSVM algorithm.

B. KERNEL DESCRIPTION AND HYPERPARAMETERS

In this study, a linear kernel is used for the OCSVM algorithm because the time series data already represents a high-dimensional space since each sample is considered as a feature (one step can have several hundred samples). This means that the linear kernel should be capable of separating one class (core) from all the outliers. The main hyperparameter for this kernel is ν (*nu*), which is *"an upper bound* *on the fraction of training errors and a lower bound of the fraction of support vectors"* [52]. The selection of the best ν hyperparameter values is described in what follows.

C. THE TRAINING MODE OF THE OCSVM ALGORITHM

The training mode of the OCSVM algorithm is presented in Fig. 2b. All classifiers $C_1, \ldots, C_n$ with different values of corresponding hyperparameter $\nu_1, \ldots, \nu_n$ are estimated. The main goal of the training mode for the OCSVM algorithm is to. 1) choose the best classifiers $BC_1, \ldots, BC_i$, 2) estimate the waveform of the reference step (or *model step*) $MS_1, \ldots, MS_i$, and 3) find the optimal threshold values for the obtained score values. Multiple classifiers can have similar performance and can be used simultaneously. Every classifier has a unique hyperparameter value ν, which can lead to different classification probabilities. This can result in better classification performance.

The hyperparameter optimization for the OCSVM algorithm has three parts i.e. i) *classifiers optimization* $C_1, \ldots, C_n$, ii) *model steps creation* $MS_1, \ldots, MS_n$, and iii) *scaling value calculation* $d_1, \ldots, d_n$. *Classifiers optimization* is done in three phases (see Fig. 2b), which are described in what follows.

1) Collection of the performance results for all ν hyperparameter values

In this phase, all classifiers $C_1, \ldots, C_n$ with different corresponding hyperparameters $\nu_1, \ldots, \nu_n$ are estimated. Here, the classification is unsupervised, i.e. some steps are classified as core and the others as outliers. Each classifier is trained on the training dataset. The obtained offline classification performance is estimated with the testing dataset. To estimate real-time performance, a model step is created from the testing dataset. *Model steps* $MS_1, \ldots, MS_n$ for corresponding classifiers $C_1, \ldots, C_n$ are created. Each normal step from the test dataset (that is also classified correctly) is used to create the model step $MS_1, \ldots, MS_n$ for each corresponding classifier. To be able to use this model step in real-time prediction mode, we use *raw steps* data before performing resampling and normalization. The model step is calculated as an average waveform from an ensemble of given normal steps' raw data.

Next, the validation dataset is used to estimate real-time classification performance. The estimation is performed in an online fashion, where each step from the validation dataset is classified frame by frame (Frames $F_{-2}, F_{-1}, F_0, \ldots, F_f$ in Fig. 2a). During this phase, the algorithm collects the frame index corresponding to when an anomaly is detected, for example, index "3" if the detection was on the third frame from the step start, and corresponding hyperparameter value ν. If the outlier is not detected (for example for a normal step), then the final frame index f and the corresponding hyperparameter value ν are collected. In summary, the frame index is collected for every hyperparameter ν and for every step in the validation dataset when each classifier detects an anomaly. Thus, the results for every normal step $NR_1, \ldots, NR_z$ and every abnormal step $AR_1, \ldots, AR_k$ are obtained.

2) Selection of the subset with best performing classifiers

In this phase, the best performing classifiers $BC_1, \ldots, BC_i$ are selected. This is done in two stages: a) choosing the best parameters for normal steps classification, and b) choosing overlap of these parameters for abnormal steps classification. $BC_1, \ldots, BC_i$

a) First, the results for all the normal steps from the validation dataset $NR_1, \ldots, NR_z$ are estimated. If the anomaly has been detected during the evaluation for the normal step, then this is not the desired outcome; thus, the parameters and classifiers which achieve the largest frame index for anomaly detection are selected. This results in the best suited hyperparameters $BN\nu_1, \ldots, BN\nu_j$, for which the corresponding classifiers $BNC_1, \ldots, BNC_j$ do not misclassify normal steps.

b) The best hyperparameters for the abnormal step classification results $FAR_1, \ldots, FAR_y$ are chosen from these hyperparameters $BN\nu_1, \ldots, BN\nu_j$, which results in best hyperparameters $B\nu_1, \ldots, B\nu_i$ and $BC_1, \ldots, BC_i$.

Overall, the best hyperparameters and corresponding classifiers are those for which a) normal steps are not misclassified as abnormal, and at the same time b) abnormal steps are detected correctly and as soon as possible.

3) Scaling value calculation

To estimate the performance of the OCSVM algorithm, raw score values $sr_1, \ldots, sr_i$ should be scaled. The obtained raw scores from the classifier using the linear kernel are values larger than 1 (i.e. hundreds-thousands). Thus, they should be scaled into the range from 0 to 1 to meet the criteria of in-step anomaly detector input values (see Section III-D). For this, scaling values $d_1, \ldots, d_k, \ldots, d_i$ are chosen for each classifier as the maximum raw score obtained from the classification of the testing dataset (8).

$$d_k = \max(sr_1^k, \ldots, sr_t^k), \tag{8}$$

where sr_t^k is the classification score for each step in the testing dataset, t is the number of steps in the testing dataset, and k is the k^{th} classifier.

After the training phase is completed, a set of classifiers $BC_1, \ldots, BC_i$, model steps $BMS_1, \ldots, BMS_i$, and scaling values $d_1, \ldots, d_i$, are used in the prediction mode, as presented in what follows.

D. PREDICTION MODE OF THE OCSVM ALGORITHM

In the prediction mode of the OCSVM algorithm, real-time anomaly detection is performed (Fig. 1b). For this, every ongoing step is evaluated frame by frame by the *in-step anomaly detector*, which is described next.

The *in-step anomaly detector* of the OCSVM algorithm uses *classification step* $CS_1, \ldots, CS_i$ to detect anomalies (Fig. 2a). The classification step is created as follows: if the

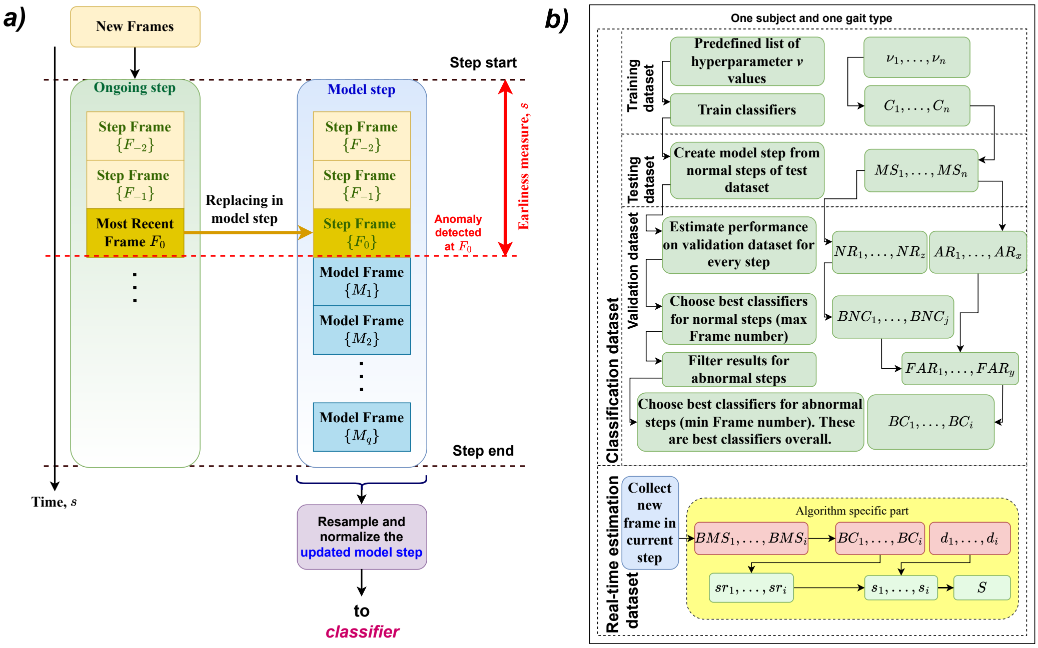

FIGURE 2: OCSVM algorithm classification step construction and supervised training logic . a) Construction of real-time classification steps from the model step snapshot by replacing its frames by the incoming frames of the ongoing step. A copy of the real-time classification step, with such replacements, is resampled, normalized and then classified. Frames are described in section III-C. b) Logic of the supervised part of the OCSVM algorithm. The dotted lines divide the classification dataset into training, testing, and validation datasets, as well as separate real-time in-step anomaly detection estimation dataset. The logic of supervised training of the OCSVM algorithm is presented in classification dataset box. On the left is a brief textual description of the training process, which corresponds to the symbolic description on the right. This symbolic description is used in the main text explaining this figure. In the real-time estimation dataset box, the OCSVM algorithm specific best classifiers, model steps, and scaling values are presented, highlighted by the yellow box. This yellow box corresponds to the yellow box in Fig. 1b; the symbolic names are described in the main text.

step detector has detected a step start, then the incoming frame of the ongoing step (new frame in the figure) is used to replace the corresponding frame in the model step (the most recent frame F_0 replaces the model frame M_0 in the figure). Then a copy of the classification step is resampled and normalized in the same way as done for the training and testing datasets. After that, the classification probability of the classification step corresponding to the abnormal class is obtained and scaled as shown in (9).

$$s_h = \left| 1 - \frac{sr_h}{d_h} \right|, \tag{9}$$

where s_h is the score for the h^{th} classifier, sr_h is the raw score from the h^{th} classifier, and d_h is the corresponding scaling value from (8).

If an anomaly is detected at the time instant when frame F_0 has been collected, then the earliness measure is equal to the one presented in the figure (earliness, shown by the vertical red line representing the time from the step start to the moment of anomaly detection). This continues until the end of a given step. When a new step is detected, the model step is returned to its original state, and the procedure is repeated.

For example, smaller raw scores correspond to outliers, which is classified as anomaly.

The final score, S, is calculated by averaging scores from all k classifiers that are used in the evaluation phase.

The score S is compared with the selected *threshold* value, which results in an alarm signal (7) if the threshold has been crossed, finalizing the anomaly detection.

In the next section, the second most popular gait analysis methods are described. They are aimed at solving the classification accuracy and misclassification problem.

V. 1D-CNN AND LSTM ALGORITHMS

The second and third algorithms are briefly described in this section. The neural networks are the second most popular algorithms in gait analysis. The performance as well as hyperparameters optimization of the 1D-CNN and LSTM based algorithms was estimated in [38]. Neural network-based algorithms solve the classification performance issue.

The hypothesis of the 1D-CNN and LSTM algorithms is following: if real-time gait data could be collected in the form of sliding windows, and neural network could be trained on the dataset using the same form of sliding windows with known labels, then it is possible to detect abnormalities in gait during the ongoing step.

The 1D-CNN algorithm structure is two 1D convolutional layers, max pooling layer, and two fully-connected (dense) layers to provide a binary classification. A 20% dropout is added between the convolutional layer and the dense layers for 1D-CNN algorithm. The LSTM algorithm structure is one LSTM layer, followed by two fully-connected (dense) layers to provide a classification probability. The number of cells in the LSTM layer is equal to the number of neurons in the first dense layer. The 1D-CNN algorithm hyperparameters are: i) number of filters; ii) kernel size; iii) batch size; iv) and number of epochs. The LSTM algorithm hyperparameters are: i) number of LSTM cells; ii) batch size; iii) and number of epochs.

The 1D-CNN and LSTM algorithms are initialized with a fixed seed of parameters (i.e., weights and bias). The neural network is trained on the training dataset with Adam optimizer and cross-entropy loss function.

A. DATA PREPARATION FOR THE NN

Each person's data is estimated separately for 1D-CNN and LSTM algorithms. Datasets for one gait type are prepared by separating training and validation datasets. Validation dataset for real-time step anomaly detection estimation is one gait recording excluded from training dataset. Training dataset combines all the remaining gait recordings for particular person and gait type. The ratio between the training and validation datasets can change depending on the person, gait type and available gait recordings for a particular gait type.

To estimate the performance of the real-time anomaly detection of the algorithms, the validation dataset is processed in an online-fashion. This means that data arrive sample by sample and each sample is collected into chunks. Chunks are collected into windows without synchronization to the step beginning in similar manner as was described is section III-C.

Windows are labeled according to the label of the step, where window was obtained from. In edge cases, where one step is ending and a new step is beginning, the label is assigned by the proportion of samples of abnormal steps in the window. If this proportion is less than *abnormality proportion threshold* then the window is labeled as *normal*, if more, then it is labeled as *abnormal*.

Hyperparameters, which affect sizes, overlaps and labels of the sliding windows are a) chunk duration – time in milliseconds, where the number of samples M in one chunk is calculated from chunk duration as $M = round(Chunk\,duration * Sample\,rate)$; b) window factor P – determines window size and is proportional to P chunks; c) Abnormality proportion threshold – fraction of the window, which should contain abnormal samples, to consider the label of the window to be abnormal.

B. TRAINING MODE OF THE 1D-CNN AND LSTM ALGORITHMS

In contrast to the OCSVM and SST-AD algorithms, the training mode for the 1D-CNN and LSTM algorithms is using training data in a form of the collection of the sliding windows instead of a collection of the individual steps (Fig. 1a). The result of the training mode is optimized neural network, which is used in the prediction mode as a classifier.

C. PREDICTION MODE OF THE 1D-CNN AND LSTM ALGORITHMS

In contrast to the OCSVM and SST-AD algorithms, the prediction mode for the 1D-CNN and LSTM algorithms does not use the step detector during the frame collection (Fig. 1b) and instead collects a new window with every new chunk, independent of the step phases. Fig. 3 depicts how the windowing of the dataset is designed. As shown, each window contains P chunks (i.e., window factor), and each chunk includes M samples and the overlap between windows is N chunks (see Section III-C).

1D-CNN and LSTM algorithms return anomalous class probability for each window, which is collected into the buffer. After the real-time estimation is performed, the collected probabilities are analyzed. Different thresholds for anomalous class probability are estimated to achieve the best results. This results in a binary classification. These classification results are compared to the labels of the validation dataset, resulting in a confusion matrix. Finally, the accuracy and F1 score are calculated from confusion matrix.

In order to enhance precision in anomaly detection performance, robustness against noise and training issues, the lightweight SST-AD algorithm has been developed.

VI. Signal Shape Tracking Anomaly Detection algorithm

The fourth and final proposed algorithm, SST-AD, is based on the calculation of the continuous distance between the current step and the model step.

The hypothesis of the proposed algorithm is that if a single step waveform can be split into sufficiently short frames, such that cross similarities between all the pairs of these frames are negligible, then anomaly can be detected during the mid-swing phase of the ongoing step.

A. PREPARATION OF DATASETS FOR THE SST-AD ALGORITHM

The training dataset for the SST-AD algorithm uses only normal steps from the selected datasets. Selection of the training dataset is conducted as follows: i) one subject data is selected, ii) the gait type for real-time anomaly detection performance estimation is chosen, and iii) the training dataset is created by combining data from all the remaining gait types datasets for this subject.

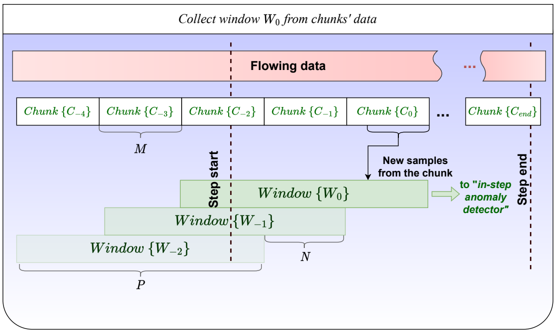

FIGURE 3: Windowed data collection for training and for real-time anomaly detection performance estimation of the NN algorithms. Ongoing gait data is incoming as flowing data, which is split into chunks. Sliding windows are collected from chunks and used in real-time in-step anomaly detector. Step start can be misaligned with sliding window. Chunks are aligned with the sliding windows. If abnormality is detected during the first window W_0 containing the chunk C_0, then earliness is time between step start and end of the chunk C_0.

B. TRAINING MODE OF THE SST-AD ALGORITHM

The goal of the training mode for the SST-AD algorithm is to estimate the model step which is used for the detection of abnormalities (Fig. 1a).

Data used in the SST-AD algorithm is 4-dimensional (1).

The proposed SST-AD algorithm has three routines to estimate the model step. The first routine is the *prefitted routine*, which estimates the model step off-line, before the in-step anomaly detection is performed. The second routine is the *adaptive routine* which estimates the model step during the real-time operation on the streaming data. The third routine consists in using these two routines in combination. First, the model step is prefitted off-line and then continuously updated in real-time from the streaming data, as a combined routine.

1) Prefitted routine for model estimation

Firstly, the training dataset is divided into individual steps, using the step detector algorithm (Section III-B and Fig. 1a). Next, the ensemble of the steps is filtered by an outlier detector, removing abnormal steps from the collection. This is done in an unsupervised manner, using the Principal Component Analysis Based (PCA) outlier detector from the PyOD python library [53].

After filtering out outliers, the average normal step is calculated from the remaining normal steps ensemble (averages are calculated separately for every axis of 4-dimentional dataset (1)).

2) Adaptive routine for model estimation

The model step is constructed similarly to the prefitted routine. The main difference is that the collection of steps is implemented as a circular buffer. First, an initial set of steps is collected (H steps for the current implementation), and an initial model from this set of steps is constructed like in the prefitted routine. Next, all newly detected steps are compared to the steps already collected (history steps collection of size H) for their outlier status. Each incoming step is fully collected from the streaming data and filtered by the outlier detector, as in the prefitted model construction. If the step is classified by the outlier detector as inlier (i.e. not outlier), it is appended to the circular buffer. Steps are detected by the step detector from the incoming data (Section III-B and the block *Step Detector* in Fig. 1c). If a new step is classified as an outlier, then it is discarded.

3) Combined routine for model estimation

Combined routine for the model step construction uses the outlier detector and model step from the prefitted routine and the circular buffer from the adaptive routine. The prefitted model step is used as a history step, and newly collected steps are filtered by the outlier detector and managed the same way, as in adaptive routine. For real-time performance estimation, the combined routine works as the adaptive routine, and the model step and circular buffer are updated every time a normal step is obtained.

C. PREDICTION MODE OF THE SST-AD ALGORITHM

In the prediction mode of the SST-AD algorithm, real-time anomaly detection is performed. For this, every ongoing step is assessed frame-by-frame by the in-step anomaly detector, which is described in what follows (Fig. 1b).

The block diagram corresponding to the in-step anomaly detection algorithm is shown in Fig. 4, where the *current frame* is collected from the input streaming data and synchronized with the detected step (Section III-C). *Model frames* are the frames from the model step. The length of the *current frame* is equal to the length of the *model frame*.

To obtain the *model frames*, the model step (1) is sliced into indexed frames F_j^{model} of length P with shift N (5), where $j = \{0, \ldots, q\}$ and are indexes of model frames $q \in \mathbb{Z}$.

The main in-step anomaly detection procedure starts from the detection of the beginning of a step. Then, if the *first frame* is collected, the current model index is set to zero ($j = 0$) and distances between the *current frame* (first frame in this case) and three *model frames* with indexes $\{j, j+1, j+2\}$ are calculated (10).

For the second frame, the calculation of distances is performed between the *current frame* and four *model frames* with indexes $\{j-1, j, j+1, j+2\}$, and starting from the third frame, distances are calculated for five model frames with indexes $\{j-2, j-1, j, j+1, j+2\}$ (10). A number of model frames for comparison have been chosen so that anomaly detection occurs as soon as possible and is enough for performance estimation.

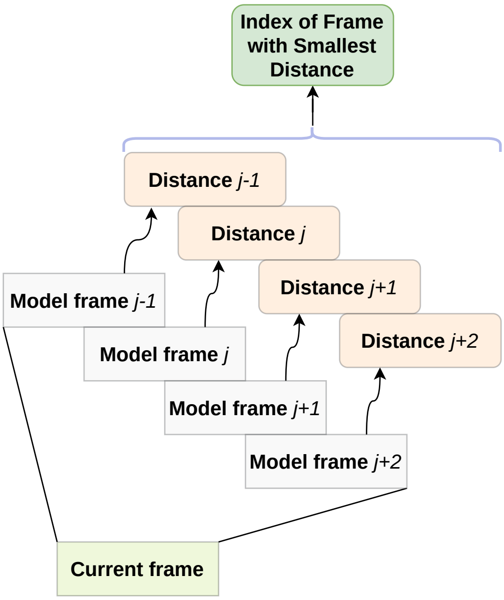

FIGURE 4: In-step distance estimation. Here distances between current frame and several model frames are calculated. The index with the smallest distance is taken as the result of the estimation. If the smallest index is not j, the score would be more than zero (see Eq. 12).

$$j^q_{min} = \begin{cases} \arg\min\limits_{i=j,\ldots,j+1} D_i, & j = 0 \\ \arg\min\limits_{i=j-1,\ldots,j+1} D_i, & j = 1 \\ \arg\min\limits_{i=j-2,\ldots,j+2} D_i, & j > 1 \end{cases} \tag{10}$$

where, the final distance D_i is calculated as average of individual distances to four axes (11). The individual distances $d_{\{X,Y,Z,Mag\}}$ to each axis, of four-dimensional model step (1), are calculated as Euclidean distances between the model frame and the current streaming frame.

$$D_j = (d_X + d_Y + d_Z + d_{Mag})/4 \tag{11}$$

Next, the index j^q_{min} with the smallest distance between the model frame and the current streaming frame (10) is compared to the index j of the current *model frame* F^{model}_j and a score value is calculated as is shown in (12).

$$S = |j - j^q_{min}|/10 \tag{12}$$

This S score is compared with the selected *threshold* value, which results in alarm signal (7) if the threshold has been crossed, finalizing the anomaly detection.

VII. PERFORMANCE EVALUATION AND RESULTS

This section presents the performance evaluation results for the proposed real-time in-step anomaly detection algorithms, i.e.(OCSVM, 1D-CNN, LSTMand SST-AD) in terms of **earliness**, **accuracy**, **F1 score**, **precision** and **recall**. Firstly, this section presents the evaluation setup, including all the parameters used in the performance evaluation, and secondly, the section presents the results. The results are then discussed in Section VIII.

A. PERFORMANCE EVALUATION SETUP

All computations are performed on a pre-built HP computer with an Intel Core i7-9700 CPU and 16 GB of DDR4 memory, running Ubuntu Cinnamon 4.4.8, Python 3.10.13, scikit-learn 1.3.1 and TensorFlow 2.9.1. All the parameters used in the performance evaluation are provided in Table 3.

TABLE 3: *Parameters and quantitative values for all variables and notations*

Sensor configuration:	256 Hz sampling rate, recording on device memory, gyroscope range ± 1000 °/s
Chunk size:	$M = 12$, $T_M \approx 47\ ms$,
Step detector:	`buffer_length` $= 51$ *samples*, `threshold` $= 100$, `step_min_length` $= 256$
OCSVM:	ν = [0.1, 0.2, . . . , 0.9] $\alpha = 0$, $\beta = 1$, $P = N = M$
SST-AD:	PCA ($n\_comp = 3$, $n\_selected = 1$), $\alpha = \frac{2}{3}$, $\beta = 3$, $P = 3N = 3M$, combined mode, $M = 10$
NN Global Hyperparameters:	Window factor (P): 6 to 10. Default 8 Samples in a chunk (M): 6 to 25. Default 12 Sliding window overlap (N): 1 Abnormality proportion threshold: 50% to 90%. Default 70% Batch size: 2^n where n is from 3 to 8. Default n is 5 Number of epochs in training: 1 to 30. Default 20
LSTM:	Number of LSTM cells: 20, 25, 30. Default: 25
1D-CNN:	Number of filters in convolutional layer: 2^n where n is from 3 to 8. Default n is 6 Kernel size in convolutional layer: 2, 3, 5, 7, 9, 11. Default 5 Dense layer with 100 neurons

B. RESULTS

1) Earliness

Firstly, the anomaly detection time of the real-time in-step anomaly detection algorithms should be observed, which is reflected by the earliness metric. In Fig. 5, it can be seen that the 1D-CNN and SST-AD algorithms has the most consistent earliness results for most of the gait types; it can also be seen that all presented real-time in-step anomaly detection algorithms have average earliness less than 1 s. On the other

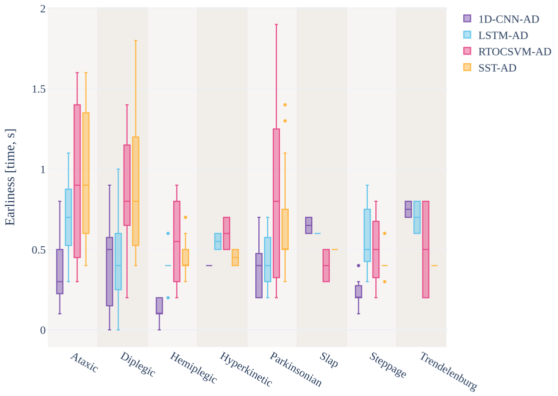

FIGURE 5: Earliness of the proposed real-time in-step anomaly detection algorithms for different gait types. The y-axis represents earliness in seconds, while the x-axis represents the different anomalies. The most frequent values are placed in the boxes and outliers are shown by the whiskers and dots.

hand, high variability in detection time for Ataxic, Diplegic and Parkinsonian gait types can be seen, which is explained by multiple abnormal steps in the row.

Moreover, for Slap, Steppage and Trendelenburg gait types, the SST-AD algorithm has consistent earliness of less than 0.5 s, while the OCSVM algorithm have variable earliness ranging between 0.25 and 0.8 s. For Ataxic, Hemiplegic, Hyperkinetic, Parkinsonian and Steppage gait types the 1D-CNN algorithm is achieving earliness less than 0.5 s, reaching stable earliness of 0.4 s for Hyperkinetic gait type and 0.2 s for the Steppage gait type. For Diplegic gait type the LSTM algorithm achieves average earliness of 0.45 s. For the Slap gait type the OCSVM algorithm achieves average earliness of 0.4 s.

The earliness measure is affected by the gait type for two main reasons. The first reason is that for Ataxic, Diplegic, and Parkinsonian gait types, multiple abnormal steps are performed in a row during the data collection process. This is required to achieve the closest representation of the true abnormal step pattern. Thus, if multiple steps are performed in a row, the detection time is longer. The second reason is the length of the step. The typical normal full swing phase in this study ranges from 1 to 1.2 s depending on the subject, whereas an abnormal full swing phase ranges from 1 to 1.7 s, depending on the subject and gait type. Because abnormal steps usually are longer, or because multiple abnormal steps can be performed in a sequence, the earliness requirement should be around 600 - 700 ms from the pre-swing phase for abnormalities with one abnormal step in sequence and can be longer for the other gait types. This detection time should be short enough to be able to correct the ongoing step in real-time. The achieved earliness results show that all proposed real-time in-step anomaly detection algorithms detect abnormalities during the mid-swing phase of a step.

2) Accuracy

Secondly, the accuracy presented in Fig. 6a, highlights that the 1D-CNN and the SST-AD algorithms are the best performing algorithms for all gait types, with average accuracy calculated across all gait types of 95% and 91% respectively. Moreover, the standard deviation of the accuracy is 4.12% and 4.75% for the 1D-CNN and the SST-AD algorithms respectively, which is smaller compared to that of the OCSVM and LSTM algorithms with standard deviation of 14.54% and 10%, respectively. The OCSVM and LSTM algorithms achieved average accuracies of 74% and 86.5% respectively; however, their standard deviations are higher than for the SST-AD algorithm.

It can be seen that the lowest accuracies overall for all algorithms are achieved for Slap and Trendelenburg gait types.

The SST-AD algorithm achieves higher accuracies for the Ataxic, Diplegic, Hemiplegic, Parkinsonian and Steppage gait types, with lower or comparable standard deviation to the 1D-CNN algorithm. On the other hand, 1D-CNN algorithm achieves higher accuracies for the Hyperkinetic, Slap and Trendelenburg gait types.

However, the OCSVM and LSTM algorithms are suffering from misclassification, which results in lower accuracy. The OCSVM and LSTM algorithms classification quality suffers from a high number of false positives (normal step classified as abnormal) due to either similarities between normal and abnormal steps or some inconsistencies in normal steps. This is amplified by the training errors for the OCSVM algorithm, because training classification performance is gait type dependent. The accuracy of the classification on the testing dataset ranges between 76% and 89% for OCSVM. Low accuracy values are achieved for the Slap and Trendelenburg gait types because the abnormality of the step is at the end of the step, whereas in the main body of the step the shape of abnormal steps are similar to the normal steps. This especially affects the classification abilities of the OCSVM algorithm. Moreover, because in the Slap and Trendelenburg gait types the anomaly occurs at the terminal swing phase, it is affecting the SST-AD algorithm, because of the weak classification performance at the terminal swing phase. The LSTM algorithm presented in this paper is struggling with the training the model on such dataset. This can be due to the limited size of the available data. The hyperparameters optimization yielded in lower accuracies overall compared to the 1D-CNN and SST-AD algorithms. Considering the computational power demand, the current implementation of the LSTM algorithm is not suitable for the embedded devices. Converting to the lighter model would result in better real-time operation performance, but would further sacrifice the classification accuracy. More advanced LSTM neural networks or similar methods should be tested in future works.

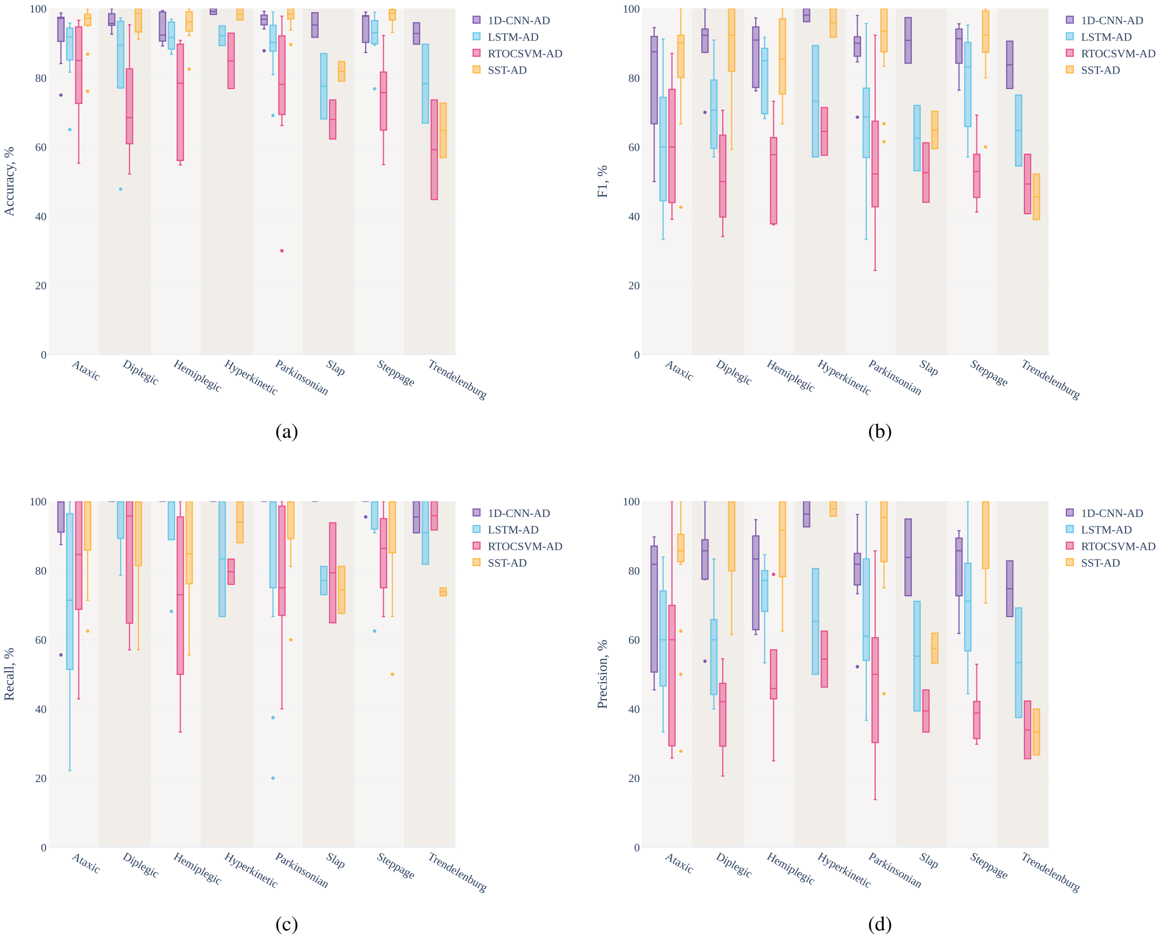

FIGURE 6: Comparison of performance metrics for proposed real-time in-step anomaly detection algorithms for different gait types. The x-axis represents the different anomalies. The y-axis represents the metric in percent. The most frequent values are placed in the boxes, and outliers are shown by the whiskers and dots. a) Accuracy. b) F1 score. c) Recall. d) Precision.

3) F1 score

Thirdly, since the dataset in this study is imbalanced, the F1 score should be calculated. In Fig. 6b, the F1 scores can be observed. Similarly to the observed accuracy, the 1D-CNN and SST-AD algorithms outperform the OCSVM and LSTM algorithms consistently with an average F1 score of 88.2% and 80.7% vs. 54.9% and 70.1%, respectively.

The SST-AD algorithm is outperforming other algorithms in terms of F1 scores for Ataxic, Parkinsonian and Steppage gait types, achieving higher or comparable to the 1D-CNN algorithm stability in results as can be seen in Table 4.

The 1D-CNN algorithm is clearly outperforming other algorithms for Slap and Trendelenburg gait types with F1 scores of 90.8±9.3 and 83.8±9.7 respectively. However, the LSTM, SST-AD and OCSVM algorithms are performing similarly in terms of the F1 scores for the Slap and Trendelenburg gait types. The LSTM algorithm achieves F1 scores of 62.6±13.4 and 64.8±14.5 for Slap and Trendelenburg gait types, respectively, whereas SST-AD algorithm achieves F1 scores of 64.9±7.6% and 45.6±9.3%, respectively, which is closer to the OCSVM algorithm with F1 scores of 52.6±12.2 and 49.3±12.2%, respectively.

4) Recall

The main reason for the achieved F1 scores for the Slap and Trendelenburg gait types can be found by looking at the achieved recall values shown in Fig. 6c. The recall is demonstrating are the anomalous steps classified correctly or not. Correct abnormal steps classification is crucial for gait correction systems. For the SST-AD algorithm, the recall

TABLE 4: Best mean F1 Scores in percent with standard deviation for different algorithms. In bold is best achieved F1 score over all gait types for every algorithm.

Gait Type	SST-AD	1D-CNN	LSTM	OCSVM
Ataxic	84.5±14.9	78.9±15.4	60.2±18.7	59.9±17.7
Diplegic	88.8±13.1	89.3±9.6	71.1±12.5	51.7±13.7
Hemiplegic	85.3±12.5	87.9±9	**81.3±10**	54.4±14.5
Hyperkinetic	**95.8±5.9**	**98.1±2.7**	73.2±22.8	**64.5±9.8**
Parkinsonian	90.7±11.8	88.4±7.5	68.4±18.8	54.2±19.8
Slap	64.9±7.6	90.8±9.3	62.6±13.4	52.6±12.2
Steppage	90.4±11.2	88.4±7	79.6±14.9	52.6±9.6
Trendelenburg	45.6±9.3	83.8±9.7	64.8±14.5	49.3±12.2

is high for most of the gait types, with a mean recall of 86.5±11.1% and with lowest recall of 73.8±1.6% for the Trendelenburg gait type. For the 1D-CNN algorithm, the recall is high for all of the gait types, with mean recall of 98.5±2.7% and with lowest recall of 93.2±13.3% for the Ataxic gait type. For the LSTM and OCSVM algorithms, the recall value is on the higher side, but more unstable, with average recall of 85.5±16.9% and 81.7±16.3% respectively and lowest recall of 68.2±27.8% for Ataxic gait type for the LSTM algorithm and 70.8±25.9% for the Hemiplegic gait type for the OCSVM algorithm.

5) Precision

Moreover, the achieved precision, shown in Fig. 6d is explaining the achieved F1 scores and accuracy. The SST-AD and 1D-CNN algorithms clearly have advantage over the OCSVM and LSTM algorithms for most of the gait types. Reviewing the precision results for the Slap and Trendelenburg gait types it could be seen that the SST-AD algorithm is struggling to correctly classify at the terminal swing phase of a step, leading to a large number of false positives, as well as false negatives, which is seen in the recall results. This results for the SST-AD algorithm in the lowest precision of 33.4% and 57.5% for the Trendelenburg and Slap gait types respectively. On the other hand only 1D-CNN algorithm is able to achieve higher precision values for the Slap and Trendelenburg gait types with precision scores of 83.8±15.7% and 74.8±11.4% respectively, because of the independence of the gait phases and windows taking into account the end phase of a step as well. Overall, the SST-AD algorithm's precision is highest for all other gait types, with mean value over 78% including the Slap and Trendelenburg gait types and 89.7% excluding them, compared to the 1D-CNN algorithm with 80.8% including them and 81.3% excluding them. The LSTM and OCSVM algorithms achieve noticeably lower and less stable precision with average precision of 63±18.5% and 44.4±14.7% respectively.

6) Potential sources of misclassification

The SST-AD algorithm for Slap and Trendelenburg gait types achieve a lower recall than for the other gait types. This means that abnormal steps are misclassified as normal, thus anomaly is not detected for gait types with lower recall. One of the reasons for lower recall results for the OCSVM algorithm is misclassification, which is explained by the test classification F1 scores that range from 38% to 72%. For the SST-AD algorithm for Slap and Trendelenburg gait types, lower precision shows that there is no consistency in the classification results. For Trendelenburg gait type, the main anomaly occurs in the upper body at the terminal swing phase, which influences the classification ability of the algorithms and leads to lower F1 scores. On the other hand, the OCSVM algorithm have closer performance to the SST-AD algorithm.

7) Real-time factor

TABLE 5: *Average real-time factor for all algorithms*

Algorithm	RTF
SST-AD	0.09±0.03
OCSVM	0.17±0.06
1D-CNN	0.55±0.27
LSTM	1.2±0.15

Finally, the value of real-time factor (RTF) represents how much computation time the proposed real-time in-step anomaly detection algorithms need on the personal computer platform (described in Section VII-A) to process 1 s of streaming data. In Table 5 and Figure 7, it can be seen that the average RTF is 1.2±0.15 for the LSTM algorithm, i.e., to process 1 s of streaming data, this algorithm requires more that 1 s of computation time. This is due to the expensive recurrent nature of the algorithm, which involves sequential processing and maintenance of multiple states and gates for each time step. On the other hand, the SST-AD algorithm only requires distance estimation between limited number of parameters and achieves RTF of around 0.09. Different to the LSTM algorithm the 1D-CNN algorithm is using efficient matrix multiplication routines and have less sequential dependencies, which results in the RTF of 0.55±0.27. This is still more computationally expensive compared to the SST-AD algorithm, but the 1D-CNN algorithm can run in real-time on the selected PC. Even further, it could be seen that estimation of the signal for the Hemiplegic gait type took 1.15±0.54 times longer than real-time. Similarly to the SST-AD algorithm, the OCSVM algorithm requires less computations, only requiring transformation of the signal

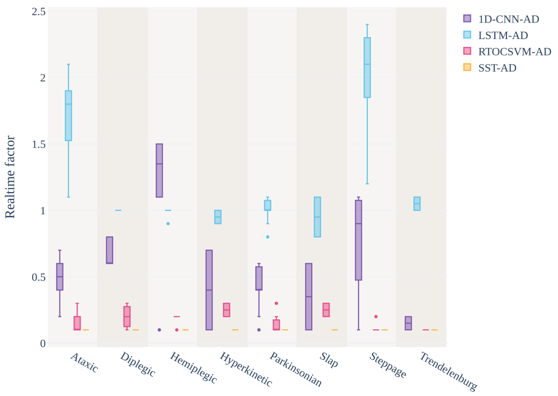

FIGURE 7: Real-time factor of the proposed real-time in-step anomaly detection algorithms for different gait types. Real-time factor is the proportion of how much time it took for the algorithm to evaluate 1 s of the flowing data. The y-axis represents the real-time factor, while the x-axis represents the different anomalies. The most frequent values are placed in the boxes, and outliers are shown by the whiskers and dots.

to high dimensional space and distance estimation to the support vectors, which results in the average RTF of 0.17.

The 1D-CNN algorithm can be optimized further, by reducing the neural network size with minor loss in classification accuracy, whereas the SST-AD algorithm achieves similar F1 scores and accuracies with computationally light model. Thus, the SST-AD, OCSVM and 1D-CNN algorithms can process incoming streaming data in real-time. Further optimization of the LSTM algorithm can lead to better performance and should be researched further.

8) Detailed review of the performance of the algorithms

It should also be noted that for some individual subjects, the OCSVM algorithm is able to achieve a classification accuracy of 98.9% and F1 score of 96%, which means that the algorithm is able to detect abnormalities in real-time operation. The OCSVM algorithm is able to create support vectors, such that the normal steps and abnormal steps have significant enough differences to be divided by hyperplane. However, abnormality detection consistency and how individual datasets influence classification quality, would be investigated in future work. This will show how inconsistencies in the gait speed between the steps can influence the algorithms performance.

Table 4 displays the achieved best F1 scores. Notably, the SST-AD algorithm attains the highest F1 scores for the Hyperkinetic, Parkinsonian, and Steppage gait types, with mean F1 scores of 95.8±5.9%, 90.7±11.8%, and 90.4±11.2%, respectively. Conversely, the lowest F1 scores are observed for the Slap and Trendelenburg gait types, at 64.9±7.6% and 45.6±9.3%, respectively. F1 scores exceeding 84% are achieved for all other gait types. Thus, SST-AD algorithm can detect in-step abnormalities for multiple gait types with high F1 scores and low computational power requirements.

Furthermore, the 1D-CNN algorithm achieves highest F1 scores for the Hyperkinetic, Slap, Steppage and Parkinsonian gait types with the F1 scores of 98.1±2.7%, 90.8±9.3%, 88.4±7%, 88.4±7.5% respectively. On the other hand, the lowest F1 scores is achieved for the Ataxic gait type with 78.9±15.4%. For all other gait types the 1D-CNN algorithm achieves average F1 scores over 83%. Thus, 1D-CNN algorithm can detect in-step abnormalities for all gait types with high F1 scores as well.

However, the LSTM algorithm falls behind, with highest F1 scores for the Hemiplegic, Steppage and Hyperkinetic gait types with scores of 81.3±10%, 79.6±14.9% and 73.2±22.8% respectively. The lowest F1 score of 60.2±18.7% is achieved for the Ataxic gait type. Classification quality issues and average F1 score of 70% shows that current implementation of the LSTM can detect in-step abnormalities for some gait types only.

Moreover, the OCSVM algorithm yields its optimal results for the Hyperkinetic, Ataxic, and Hemiplegic gait types, with mean F1 scores of 64.5±9.8%, 59.9±17.7%, and 54.4±14.5%, respectively. The lowest F1 score, 49.3±12.2%, is observed for the Trendelenburg gait type. Mean F1 scores exceeding 51% are achieved for all other gait types.

9) Summary of results

In summary, the SST-AD and 1D-CNN algorithms attains the highest accuracy of 98.4±2.3% and 99.2±1.2% respectively for the Hyperkinetic gait type, followed by the LSTM and OCSVM algorithms with highest accuracy of 92.2±4% and 84.9±11.3% respectively for the Hyperkinetic gait type as well. Similarly to the observed accuracy, the 1D-CNN and SST-AD algorithms outperform the OCSVM and LSTM algorithms consistently with an average F1 score of 88.2% and 80.7% vs. 54.9% and 70.1% respectively. The 1D-CNN and SST-AD algorithms has the most consistent earliness results for most of the gait types, which is detecting the abnormalities at either the initial-swing or mid-swing phases of the step. Thus, the SST-AD algorithm is capable of timely detecting in-step abnormalities with high accuracy and F1 scores while being computationally efficient and easy to train.

VIII. DISCUSSION

This section discusses the results previously presented in Section VII.

Gait correction devices can benefit from the algorithms presented in this study. Despite the availability of various gait correction devices, obtaining a truly effective device can be challenging because many of them lack a robust scientific research background. Exoskeletons and mechanical devices, though popular, pose questions about efficacy and usability, emphasizing the need for more comprehensive research in the field of gait assistive devices [54]. Existing FES devices have proven to be effective in post-stroke rehabilitation, addressing common issues such as foot drop [8]–[10]. Such device works with a predetermined stimulation algorithm, which stimulates muscles during the swing phase, and stops the stimulation in the stance phase. While FES devices improve gait quality, patients often express concerns about skin irritation and muscle fatigue. To optimize FES use, a more intermittent stimulation approach is desirable post-rehabilitation to reduce fatigue. Smart devices capable of detecting gait deviations and adapt in real-time would be preferable for post-treatment assistance, promoting softer and more patient-friendly interventions.

The main goal of this study is to show that real-time in-step anomaly detection algorithms can provide information about gait deviation to the gait assistive devices. Compared to the SoTA, such algorithms are able to detect gait deviations in real-time during the swing phase of a step. This will enable the further steps to be taken for building the next generation of real-time gait assistive devices.

A. ERROR ANALYSIS

From the results, it could be seen that low classification performance of the real-time implementation of SVM algorithm in form of OCSVM algorithm is not comparable to the high offline classification performance of the regular SVM algorithm. The main problem is the introduction of the changing patterns for the classifier in the form of the classification step, which is used in the real-time classification phase.

The classification step can have irregularities because of the combination of the model step and ongoing step. For example, if the gyroscope values in the incoming frame are noticeably different from the gyroscope values in the model frame, then they might not align. Such classification step would be considered abnormal, even if the incoming step is normal, but is slightly out of synchronization, i.e. it was slower or faster and misalignment occurred. Another reason could be that the abnormal step pattern is not different enough for the SVM classifier to create hard support vectors. This is seen from the test dataset F1's scores of offline classification where the classifier from the beginning was not performing at its best.

The achieved F1 scores mirror the accuracy results; however, the gap in F1 scores between the SST-AD and 1D-CNN algorithms and the OCSVM and the LSTM algorithms is greater, thus showing that abnormal steps are misclassified more often by the latter two algorithms. So, the main challenge for the OCSVM and LSTM algorithms in classifying is a high number of false positives. This is clearly more pronounced for the Slap and Trendelenburg gait types.

The LSTM algorithm is hard to optimize due to time-consuming hyperparameter optimization, and considering the high computational power demand it might be very challenging to improve the performance of this algorithm in the context of porting to the embedded device.

In terms of errors for the gait assistive devices, it is better to stimulate the normal step, than to miss the stimulation of the abnormal step. Thus, high recall is an indication that the proportion of false negatives should be as low as possible. The precision of the algorithms should be also high for timely detection of gait deviations for the gait assistive devices. To exceed the current SoA gait assistive devices in terms of lower fatigue levels due to more user-friendly stimulation intervals by achieving lower proportion of false positives.

B. OCSVM AND SST-AD ALGORITHMS NOVELTY

The novelty in the proposed OCSVM algorithm is the real-time implementation and the supervised hyperparameter adaptation of the most popular gait analysis algorithm - SVM.

Time of abnormality detection, in terms of earliness, shows that all algorithms performed similarly, but the SST-AD and 1D-CNN algorithms are more stable in detection time and in combination with high F1 scores and low computational cost. The 1D-CNN algorithm on one hand is showing exceptional performance and high F1 scores, but on the other hand lacks gait phase awareness in this implementation. Considering that the SST-AD algorithms achieves similar performance with less computational power demand, the 1D-CNN algorithm needs further optimization to be feasible option for the deployment on embedded devices. The SST-AD algorithm is performing clearly the best for potential use in embedded devices. Best performance means that the anomaly is detected correctly and early during the mid-swing phase of a step. The main reason for that is the working logic of the algorithm which compares the ongoing step shape to the target shape. Such an approach has a higher success rate in finding differences. This algorithm is very fast to train, can be improved during the real-time operation by incorporating normal steps into existing model step shape. It is simple and lightweight and is strong candidate to be tested on embedded device in real world tests.

C. COLLECTED DATASET NOVELTY

The collected dataset could be used for anomaly detection algorithms development. Such a dataset, to the best of authors' knowledge, is the first to feature a combination of normal and abnormal steps in one dataset. It could be expanded in the future, by additional data collection procedures. Other existing datasets do not include a combination of normal and abnormal walking in one single dataset. In such other datasets, the normal gait pattern and abnormal gait patterns are collected separately [30]–[32], [34]. Such steps, switching from normal to abnormal, could be seen in the real-life scenario, especially in former patients who can experience undesirable step patterns because of fatigue.

D. LIMITATIONS AND FUTURE RESEARCH GAPS

While the achieved results are substantial, this work has some limitations. The simulated gait deviations could be different from the gait deviations of the real patients. However, they should represent abnormal gait patterns very closely because simulations are recreating actual patients' video recordings of gait deviations and instructions from a professional physiotherapist. In real-life applications, the anomaly detection results could be influenced by the different types of terrain and walking speed. Another limitation is that a direct comparison of the new dataset presented in the paper with other gait datasets is not possible due to the lack of such datasets.

Feature engineering can be used to improve the classification results of the algorithms, by adding i.e. the stride length, gait speed, variability in steps, etc.

The main criterion in well timed gait correction is the time constraint of 50 ms to detect anomaly; if this constraint could be relaxed or met, i.e. by the CNN algorithms, then they should be a good fit for the time-series data analysis. Applying the best performing algorithms on the embedded device would give clear results about real-world usage feasibility. If they could run in real-time during the operation on the embedded devices, then it should be possible to detect gait anomalies on the fly and consider next steps: real-time anomaly detection and gait correction using the FES during the mid-swing of the step on the embedded device.

Real-time in-step anomaly detection algorithms could be used in visualization tools for real-time monitoring and feedback, which will enable physiotherapists and patients to see the gait deviations as they occur. This will be beneficial for clinicians and patients to understand and adjust their movements.

IX. CONCLUSION

In this paper, novel real-time in-step anomaly detection algorithms were proposed for real-time abnormality detection in human gait step pattern, i.e. OCSVM and SST-AD. The proposed algorithms were compared with the previously developed 1D-CNN and LSTM algorithms. All the algorithms can detect gait abnormalities in real-time during the ongoing step. Note that the results of the real-time classification, which is performed during the ongoing step, are different from results of regular classification, which is performed after the step. These results show that correct preprocessing of data and post-processing of classifiers results is enough to convert classical machine learning algorithms into real-time classification algorithms. Thus, the OCSVM algorithm is capable of detecting abnormalities with reliable performance for some subjects. This means that the proposed benchmarking framework can be used for the performance evaluation of additional new real-time in-step anomaly detection algorithms.

The presented algorithms achieve an average accuracy and F1 scores of 91% and 81% (for all gait types including Slap and Trendelenburg gait types and 89% excluding them) for SST-AD; 86.5% and 70.1% for LSTM; 95% and 88.2% for 1D-CNN; 74% and 54.9% for OCSVM, respectively. The best F1 scores for the proposed algorithms are the following: OCSVM, SST-AD and 1D-CNN algorithms achieved $64.5\pm9.8\%$, $95.8\pm5.9\%$ and $98.1\pm2.7\%$, respectively all for Hyperkinetic gait type. The LSTM algorithm achieves best F1 scores of $81.3\pm10\%$ for Hemiplegic gait type.

As can be seen from RTF results, SST-AD algorithms is able to detect gait deviation in the ongoing step in real-time. The SST-AD algorithm is computationally more effective than the 1D-CNN algorithm, while achieving similar performance.

Future work will focus on further algorithms optimization and experiments with embedded devices. Based on the current study, it is possible to develop on-demand FES devices for less intrusive gait assistance by using the SST-AD algorithm‘.

ACKNOWLEDGMENT

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Appendix 6

Unpublished results

Resistance to the time-stretching, requirements and preliminary efforts towards assistive device

Jakob Rostovski

December 2024

1 Resistance to the time-stretching of the SST-AD and 1D-CNN algorithms

In this appendix, the influence of time-stretching on gait anomaly detection algorithms is studied, followed by a description of preliminary efforts to develop a prototype assistive device. These efforts address the **RQ4**, focusing on requirements, hardware selection, and challenges.

1.1 Influence of Time-Stretching on Algorithms

To evaluate the real-world performance of the SST-AD and 1D-CNN algorithms, their resistance to changes in walking pace was assessed. Walking pace can vary in real-life scenarios. To simulate these changes, the original dataset was resampled to reflect a range of slowdown or speedup up to 20%. Models trained on the original dataset were tested under these conditions, following the same procedures described in **Publications III and IV**. No testing on training data was performed. In Fig. 8 and 2

As seen in Fig. 1, the SST-AD algorithm is sensitive to reduced gait speeds, except for Hyperkinetic, Parkinsonian, and Trendelenburg gait types, where performance remains consistent. Increased speeds negatively impact performance, particularly for Hyperkinetic, Parkinsonian, and Slap gait types. On average, speed changes reduced the SST-AD algorithm's F1 score from 80.1% to 71% (Table 1).

The 1D-CNN algorithm is less affected by speed variations. As shown in Fig. 2, speed changes impact all gait types except Hemiplegic and Steppage gaits. The average F1 score decreases from 88.2% to 83.4%.

Earliness is unaffected by time-stretching for both algorithms (Table 2). Similarly, real-time operation remains stable (Table 3).

As a conclusion of this section, both of the SST-AD and 1D-CNN algorithms anomaly detection capabilities are slightly affected by the change of gait speed, however, the algorithms are still able to detect gait deviations in real-time.

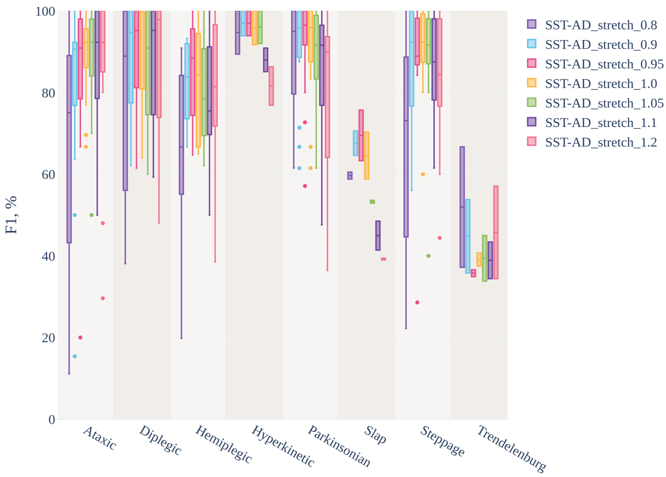

Figure 1: F1 scores of the SST-AD algorithm depending on the gait speed. The y-axis represents the F1 scores in percent, while the x-axis represents the different anomalies. The most frequent values are placed in the boxes, and outliers are shown by the whiskers and dots.

Table 1: Comparison of average F1 scores by SST-AD and 1D-CNN across time-stretch percentages

Time-Stretch (%)	**SST-AD**	**1D-CNN**
-20	71.4±18.6%	85.6±10.0%
-10	79.8±12.1%	86.4±10.8%
-5	80.2±11.4%	87.0±10.4%
0	80.1±9.8%	88.2±8.8%
+5	77.4±10.6%	86.6±10.2%
+10	74.2±11.4%	87.5±9.8%
+20	72.7±14.8%	83.4±12.1%

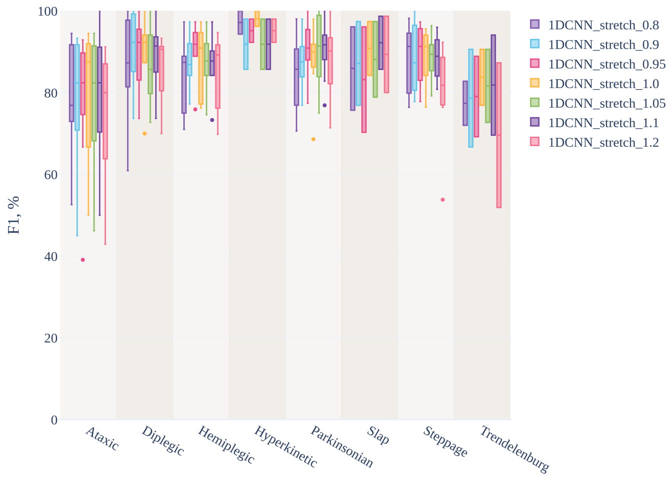

Figure 2: F1 scores of the 1D-CNN algorithm depending on the gait speed. The y-axis represents the F1 scores in percent, while the x-axis represents the different anomalies. The most frequent values are placed in the boxes, and outliers are shown by the whiskers and dots.

Table 2: Comparison of average earliness in seconds by SST-AD and 1D-CNN across time-stretch percentages

Time-Stretch (%)	**SST-AD**	**1D-CNN**
-20	0.6±0.2	0.3±0.1
-10	0.5±0.2	0.4±0.1
-5	0.6±0.2	0.4±0.1
0	0.6±0.2	0.4±0.1
+5	0.6±0.2	0.4±0.1
+10	0.7±0.2	0.5±0.1
+20	0.7±0.3	0.5±0.2

Table 3: Comparison of average real-time factor by SST-AD and 1D-CNN across time-stretch percentages

Time-Stretch (%)	SST-AD	1D-CNN
-20	0.3±0.1	0.2±0.1
-10	0.3±0.1	0.2±0.1
-5	0.3±0.1	0.2±0.1
0	0.3±0.1	0.2±0.1
+5	0.3±0.1	0.2±0.1
+10	0.3±0.0	0.2±0.1
+20	0.3±0.1	0.2±0.1

2 Requirements and preliminary efforts on how to develop comfortable personalized gait assistive device

To deploy comfortable and user-friendly gait assistive device, it should have personalized gait correction routines, which take into account the gait normalcy in real-time. The patients, who have successfully finished the rehabilitation process, can walk without assistance for short periods of time [1]. This means, that only occasional interventions are necessary to correct the gait of the patient.

Ease of use of the gait assistive device is the second important topic in development of the device. This includes the placement of the electrodes, which most often are attached with specialized gel pads. This requires training and finding the correct points, where to connect the electrodes. Built in electrodes, i.e. embedded into the sock, might improve the ease of correct alignment of the electrodes in very short time.

The assistive device should have two main parts: the algorithm and the stimulation hardware with appropriate stimulation parameters. In this section, I describe the process of optimization of the FES parameters, used to stimulate the ankle dorsiflexion. After that, I discuss the possible alternatives to the commonly used gel pads to conduct the stimulation to the muscles. Next I describe the preliminary software and hardware development path, requirements and challenges. I conclude this section with future works, which are out of the scope of this thesis, regarding further development of the software and hardware, to create a gait assistive device with real-time gait deviation detection.

2.1 FES parameters evaluation

First the stimulation parameters should be determined, to evaluate the stimulation hardware parameters, which are suitable for the FES of the leg muscles. The stimulation should start when the anomaly detection algorithm outputs the alarm signal. To estimate the correct parameters for the stimulation, I had

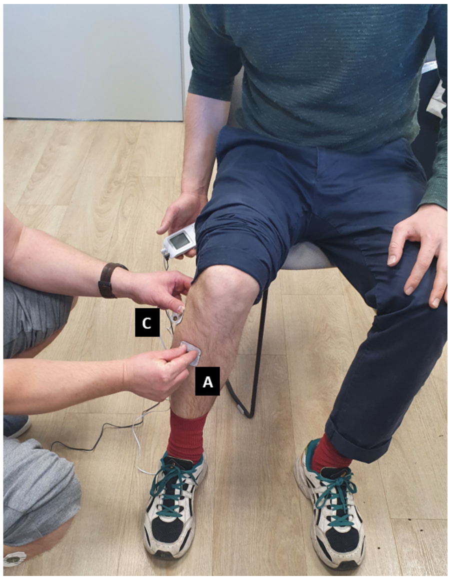

Figure 3: Placement of the gel electrodes and configuration process of the Sanitas 43 EMS/TENS stimulation device

consultation with a physiotherapist. The potential logic of the stimulation was tested by using the off-the-shelf FES device: Sanitas 43 EMS/TENS. Gel pads were used as the conductors, placed on the appropriate muscles to stimulate the ankle dorsiflexion (fig. 3). By using the 30mA stimulating current amplitude, 310 microseconds pulse width, and 60 Hz repetition frequency, the ankle dorsiflexion was achieved. These parameters will help with the development of the stimulation part of the device.

One of the potential alternatives to the gel electrodes were tested as well, which are using so-called "smart socks" with integrated electrodes (fig. 4).

2.2 Stimulation tests using socks with integrated electrodes

Manufacturing the sock with integrated electrodes is challenging. The developed prototype of sock with integrated electrodes did not fully fit the physiotherapist, which it was supposed to fit (Fig. 5. Thus, the stimulation tests were performed by resting the electrodes on the correct positions on the leg. During the experiment with the electrical stimulation, it was found, that the dry electrodes do not provide enough conductivity and cause uncomfortable "burning" sensation on the skin. After applying water as a conductor to the electrodes, it

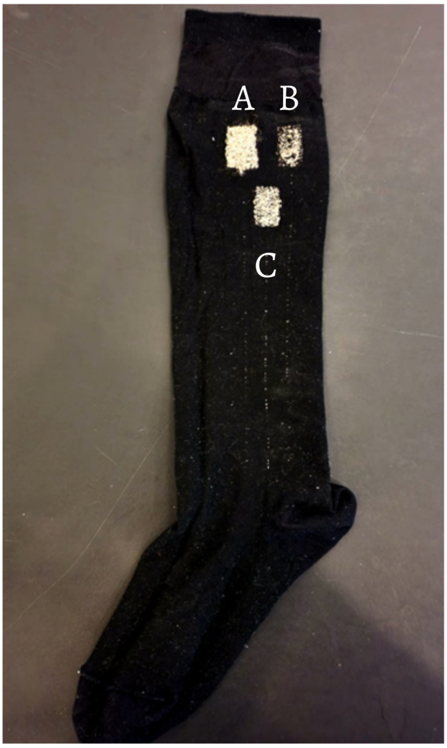

Figure 4: Example of the developed socks prototype with integrated electrodes for FES usage.

Figure 5: Example of the wearable electrodes integrated into the sock

was possible to use electrodes and achieve stimulation of the ankle dorsiflexion. This is a limitation of the developed sock and should be considered in future works.

2.3 Evaluation of the embedded devices platforms

As it was stated in **Publication II**, the gait anomaly should be detected under 50ms. To test the parameters for contraction of the muscles, of the shelf FES device was used, to evaluate the correct stimulation parameters (section 2.1).

Selected hardware should be capable of: 1) collecting the data from IMU with sufficient frequency of at least 100Hz; 2) able to preprocess data for the algorithm; 3) run the algorithm in real-time with timely anomaly detection; 4) be energy efficient.

First device, which was evaluated as potential candidate for the deployment of real-time gait deviation detection was esp32 based development board. The ESP32 WeMos Lolin32 Lite at the time was one of the boards, which was widely available, easy to get, relatively cheap, with built-in Wi-Fi and Bluetooth for testing, I2C interface and dual core processor. It can be programmed with Micropython and C. Micropython was chosen for fast development and to port the model from existing python code.

ESP32 devices are widely used and deployed in similar topics, like speech recognition [2], which uses time-series data and image recognition [3], using convolutional neural networks.

In the assessment of the devices capability, first the data collection speed and stability were estimated. This is required to be able to train the algorithm for the particular person and deploy the trained algorithm on the device afterwards. Thus such approach should provide personalized gait deviation detection.

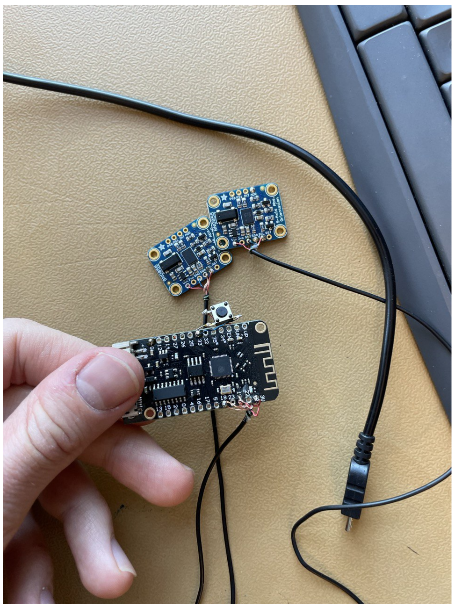

Figure 6: ESP32 board with two BNO055 IMU's

Two IMUs were connected to the ESP32 board to collect the data from the forefoot and under the knee, mimicing the data collection procedure from **publication I**. Bosh BNO055 IMU sensors were chosen initially due to availability, good performance and low price (Figure 6).

Figure 7: Raspberry Pi Zero 2W and MPU6050 IMU

During the experiments it was possible to record 20 seconds of continues time-series data to the flash with frequency of 100Hz and several minutes of data could be recorded using Bluetooth transmission with frequency of 50Hz. Faster recording speed was not possible on the selected platform with micropython, due to instability and data drops.

Regarding the algorithms, it is possible to run simple 1D-CNN models on the ESP32 running micropython, but there are compatibility issues with bigger and more complex networks. This limitation does not fulfill the requirements of data collection samplerate of more than 100Hz and possibility to run the algorithms in real-time. Thus, the research efforts switched to the Raspberry Pi Zero 2W.

Raspberry Pi Zero 2W is widely available microcontroller, provides more computational power to deploy the algorithms on the device, compared to the ESP32. By switching to the Raspberry Pi Zero 2W and changing IMU to the MPU6050 due to python library availability, it was possible to collect data with the frequency of 125Hz (fig. 7).

Raspberry Pi zero still has some limitations, i.e fewer python libraries available, thus requiring to adapt the in-step anomaly detector code to accommodate these limitations. Initial tests showed, that it is possible to collect the data and

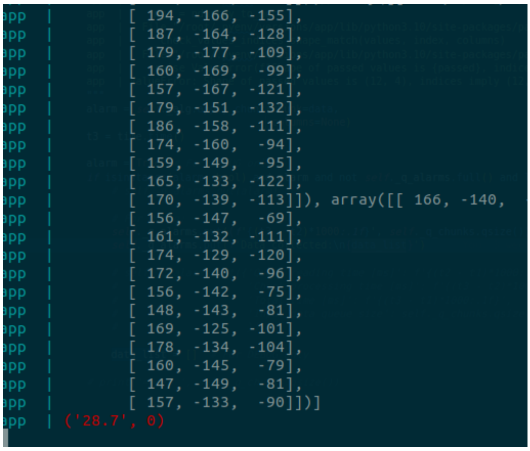

Figure 8: Example of chunks collection on the Raspberry Pi and alarm from the algorithm

to run the SST-AD algorithm on the device (Fig. 8). However, to evaluate the quality of the anomaly detection is challenging and requires more effort.

As a conclusion to this section, a development of the assistive device is ongoing, showing how nontrivial the solution can be. From the standpoint of the patient, the easy-to-use, comfortable device, which provides intervention only when necessary, would be the answer to the **RQ4**.

Future work, which is beyond the scope of this thesis, will focus on the development of a prototype assistive device that incorporates real-time gait deviation detection algorithms. Currently, the evaluation of classification performance for algorithms deployed on the device requires further refinement. Gait data and classification results should be recorded during the device's operation to accurately assess the performance of the deployed algorithms. Future efforts will involve gathering such data to evaluate the classification quality of the device. Additionally, the prototype assistive device should be assessed by physiotherapists and real patients to validate its ability to detect true gait deviations and determine its potential benefits for patients.

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Curriculum Vitae

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3. Education

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2015–2017	Moscow Institute of Physics and Technology (State University), Faculty of Molecular and Chemical Physics, Applied Physics and Mathematics, MSc *cum laude*
2011–2015	Moscow Institute of Physics and Technology (State University), Faculty of Molecular and Chemical Physics, Applied Physics and Mathematics, BSc

4. Language competence

Estonian	native
Russian	native
English	fluent
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5. Professional employment

2021–2025	Tallinn University of Technology, School of Information Technologies, Thomas Johann Seebeck Department of Electronics, Junior Researcher
2019–2020	MTS, Lead Specialist
2016–2018	Federal Research Center Crystallography and

	Photonics RAS, Engineer
2015–2016	Photochemistry center RAS, Engineer
2014–2015	A.N. Frumkin Institute of Physical Chemistry and Electochemistry, Engineer

6. Voluntary work

2022–2022 Ericsson, Test Product Manager Trainee

7. Computer skills

- Operating systems: Windows, Linux
- Document preparation: Microsoft Office, LibreOffice, LaTeX
- Programming languages: C, C++, Python, microPython
- Scientific packages: MATLAB, TensorFlow, scikit-learn, tslearn, Keras

8. Defended theses

- 2017, Investigation of the effect of volatile organic analytes on the spectral properties of dyes embedded in silica gels, MSc, supervisor Dr. Alexander Koshkin, Moscow Institute of Physics and Technology (State University), Department of Molecular and Chemical Physics, Physics of supramolecular systems and nanophotonics.
- 2015, "Development of chemical informatics methods adapted to work with unbalanced data", supervisor Dr. Natalia Kireeva, Moscow Institute of Physics and Technology (State University), Department of Molecular and Chemical Physics, Physics of High-temperature processes.

9. Field of research

- Gait analysis
- Signal processing
- Electronics
- Machine learning methods

10. Scientific work
Papers

1. J. Rostovski, A. Krivošei, A. Kuusik, U. Ahmadov, and M. M. Alam. SVM time series classification of selected gait abnormalities. In *Body Area Networks. Smart IoT and Big Data for Intelligent Health Management*, pages 195–209, Cham, 2022. Springer International Publishing

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Patent application

1. A. Krivošei, A. Kuusik, J. Rostovski, and M. M. Alam. Real-time motion abnormality detection method and device, 2024. PCT Patent No: PCT/IB2024/055807

Conference presentations

1. J. Rostovski, A. Krivošei, A. Kuusik, U. Ahmadov, and M. M. Alam. *SVM time series classification of selected gait abnormalities*, 16th EAI International Conference, BODYNETS 2021, Virtual Event, October 25–26, 2021,
2. J. Rostovski, A. Krivošei, A. Kuusik, M. M. Alam, and U. Ahmadov. *Real- time gait anomaly detection using SVM time series classification*, International Conference on Wireless Communications and Mobile Computing, 19–23 June 2023, Marrakesh, Morocco
3. J. Rostovski, M. H. Ahmadilivani, A. Krivošei, A. Kuusik, and M. M. Alam. *Real-time gait anomaly detection using 1D-CNN and LSTM.*, Nordic Conference on Digital Health and Wireless Solutions, 7–8 May 2024, Oulu, Finland

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8. Kaitstud lõputööd

- 2017, Uuring lenduvate orgaaniliste analüütide mõju kohta värvainete spektraalomadustele, mis on kinnitatud silica geelidesse, MSc, juhendaja Dr. Aleksandr Koškin, Moskva Füüsika- ja Tehnoloogiainstituut (Riiklik Ülikool), Molekulaar- ja Keemilise Füüsika teaduskond, Supra- ja nanofotonika süsteemide füüsika.
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