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SHEBA, A SPACE OF ACTION AGAINST PREGNANCY RELATED RISK FACTORS: AN EXPLAINABLE MACHINE LEARNING APPROACH TO IMPROVE QUALITY OF LIFE FOR PREGNANT WOMEN

Master's Thesis

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Tallinn 2021

TALLINNA TEHNIKAÜLIKOOL

Infotehnoloogia teaduskond

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SHEBA, RASEDUSEGA SEOTUD RISKITEGURITE VASTANE TEGEVUS: SELGITAV MASINÕPPE MEETOD RASEDATELE NAISTELE ELU KVALITEEDI PARANDAMISEKS.

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Tallinn 2021

Author’s declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature, and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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10.05.2021

Abstract

A lower-middle-income country like Bangladesh deals with lots of challenges. Providing healthcare to citizens is, unfortunately, one of them. Especially in vulnerable conditions like pregnancy where women need extra care, it is very challenging for the country to provide necessary healthcare with current infrastructure to every woman in need. This research proposes “SHEBA,” a platform targeting to make accessible service provision to pregnant women by providing necessary facilities like appointment booking, getting info and advice via the platform, and getting necessary risk assessment done via the platform. The platform is also eyeing on reducing pressure from the already stretched healthcare system by providing easy management of appointments, introductory advice, and answering frequently asked questions to the platform user without any healthcare workers’ intervention. The platform is also targeting to provide values by assessing each woman’s risk and explaining to the healthcare worker about risk so that necessary measurements can be taken against that.

This thesis is written in English and is 60 pages long, including 7 chapters, 19 figures, and 5 tables.

List of abbreviations and terms

DPI	*Dots per inch*
TUT	Tallinn University of Technology
ML	Machine Learning
NLP	Natural Language Processing
NLU	Natural Language Understanding
WHO	World Health Organisation
BMI	Body Mass Index
IPV	Intimate Partner Violence
ANC	Antenatal Care
GBDT	Gradient Boosted Decision Tree
WHO	World Health Organization
PCA	Principal Component Analysis
GDM	gestational diabetes mellitus
IVF	In Vitro Fertilization
ANN	Artificial Neural Network
PM10	Particulate Matter 10
API	Application Programming Interface
REST	Representational state transfer
UN	United Nations
AHS	Annual Health Survey
HAF	Human Chorionic Gonadotropin Associated Factor
ORT	Orthodromic Reciprocating Tachycardia
DiCE	Diverse Counterfactual Explanations
2FA	2 Factor Authentication

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1 Introduction

A lower-middle-income country like Bangladesh deals with all the developing world's problems. The proportion between scarcities and opportunities is most favoured on the side of the former, and it is vividly visible almost everywhere. I was born and brought up in Bangladesh, and like most children, I have also heard stories about my birth and birthplace repeatedly from my parents, grandparents, and relatives. I always listen to those events with wonder. I was born in the rural part of Noakhali, a humble district of Bangladesh, in 1993. I was born in my grandparent's house without any emergency medical care available nearby. Only a "*Dhai*" was present in the room to help my mother. She has not received any professional medical care during her pregnancy and solely relied on the traditional knowledge passed to her by her family. The conventional untrained nursing attendant (*dhai*) has shown from historical evidence that she uses force to carry out the baby that sometimes results in the death of the infant and mother. In rural Bangladesh, the widespread use of "*dhai*" in homes has substantially increased the vulnerability of women's lives. The biggest downside of a "*Dhai*" is her lack of formal education, medical expertise, and dependency on unsafe traditional instruments, which place pregnant women's lives in serious jeopardy (Chanda & Jabbar, 2010). My grandmother also had a similar experience with all her pregnancies. She had eleven children in her life; among them, only eight survived. She lost her children due to pregnancy and childbirth-related complications. My grandmother lost her health along the way and had a very short life. Nowadays, we cannot even think about pregnancy and childbirth without having a single consultation with doctors in the western world. When I compare my mother's and grandmother's experiences with the modern medical care facilities we enjoy here, I feel sad. I also respect and love them even more now. Fortunately, in today's date, Bangladesh has come a long way. Mother and childcare centres are well spread in most parts of the country, but it is not yet perfect. While it has been seen that with the rapid development and urbanization, this situation has improved, it is far from ideal. According to the WHO, the maternal mortality rate in 2017 was 173 among 100 000 births (World Health Organization,2019). Many rural areas still lack proper medical services. The smallest administrative section in Bangladesh is the union. While there is generally one community hospital in each union, they are sometimes understaffed and suffer from mismanagement.

When I was searching for a topic for my thesis, I looked into many. I decided that I want to research pregnancy-related risk factors and what approaches can be taken to minimize or eradicate the problem because I can relate to this topic on a personal level.

My research would aim to approach a solution in which essential prenatal care can be given, even to the remotest corners of Bangladesh by health care providers. The platform I am designing will predict potential future problems based on the health data input. A trained machine learning model will then analyse the inputs to predict the outcome. Machine learning is concerned with the proactive analysis of systems capable of recognizing distinct patterns and predicting eligible preferences based on given data. My firm conviction is that the existing situation can be changed with a solution that can eliminate or reduce the risk of pregnancy. In the long term, it would make significant positive changes in the lives of women and their families, and they could enjoy a higher quality of life.

This research tries to attempt the following questions:

1. The physical risk factors are most prevalent during pregnancy?
2. Which social risk factors are most prevalent during pregnancy?
3. What are the variables that are unique to the demographic you've chosen?
4. Is it possible to develop hypotheses to predict the risk factors for maternal death?
5. Is it possible to develop a solution that anticipates risk?
6. Can we mitigate the risk of maternal mortality by proactive measures?

The present document is designed in the following stages:

Chapter 2: Dedicated to theoretical context knowledge and the characteristics of the core demographic.

Chapter 3: Conduct a literature review on the topic, gain an understanding of the current context, and determine the scope of potential intervention.

Chapter 4: Illustrates the application of this study in practice to aid in comprehension and proposes a platform with a prototype.

Chapter 5: Demonstrates the solution's shortcomings and information gaps

Chapter 6: Addresses the suggested solution's advice and future strategy.

Chapter 7: Concluding remarks.

2 Theoretical Background

This theoretical background aims to understand the context of the current demographics of the target region. Additionally, some academic knowledge regarding the technology used in this research is also discussed briefly.

2.1 Demographics of Target Region

Bangladesh is a young country. Its history of a long period of colonization, division, and war made Bengal, once the wealthiest area of the Indian subcontinent, poor (Dutt,1992). Bangladesh has achieved its independence dated back to the 26th of March 1971 through a violent war, "*The Muktijuddho*" which left the country with over seventy percent of its population under the poverty line (Hossain,2014). Recently the Republic of Bangladesh has celebrated its 50th independent year. After the gaining of independence, the path of progress that Bangladesh made was not a smooth highway. But the country has made significant achievements too by pulling people out of poverty (Sarker et al., 2018) despite suffering from many massive natural disasters along the way (Islam, 1992). Current population of Bangladesh is around 164 million people (Walsh, 2017). Bangladesh has seen an increase in life expectancy over the time (Alam et al., 2020).

Despite some success emanating from the family planning programs, many children still go through child marriage. In Bangladesh, over fifty percent of girls are married before the age of 18 (Biswas, Khan & Kabir,2019). Over one-third of teenage girls have at least one child (Sayem, & Nury,2011). This practice has a substantial negative impact on women's health in their adult life (Paranjothy et al., 2009). Only forty-one percent of women receive skilled birth attendants during childbirth (Jo et al., 2019). Furthermore, seventy four percent of women living in urban and suburban areas get antenatal care while this percentage is reduced to only forty-nine percent of rural women having such access.

Because of all these reasons, I have chosen Bangladesh as my target region not only because it's my home country but also there is a vast space for development.

2.2 Machine learning

Machine learning (ML) is a subsection of the field of Artificial Intelligence (AI). By using computational methods, machine learning techniques learn knowledge directly from the data, rather than relying on predetermined rule-based equations to create algorithms for the prediction of output during the process of updating newly accessible data. It is a normal phenomenon that teaches computers to learn from experience to assist humans in processing large amounts of data quickly. The universal principle for data prediction is to map the learning function (f) to the input samples (X) and then process an output variable (Y) as follows: Y=f (X).

Machine learning is about how computers can be built that automatically develop with experience. It is one of the fastest growing technology fields today, bridging the gap between computer science and statistics and serving as the basis for AI and data science research. The invention of novel learning algorithms and theory, as well as the continuing boom in the rise of internet resources and low-cost computers, have fuelled recent developments in machine learning. The use of data-consistent machine-learning processes in science and technology contributes to more developed decision-making in many fields, including healthcare, manufacturing, financial modelling, and commercialization (Jordan & Mitchell, 2015).

Today, many people are familiar with internet machine learning techniques, custom advertising processed through their transactions and behaviour. It happens because ML algorithms learn data in real-time and suggest the performance based on experience from similar replicated models and behaviour. In addition to online marketing and targeted advertising, spam filtering, fraud control systems, network security detection systems, and other maintenance, monitoring, and structuring feeds are commonly used for computer teaching. These instances are just a tiny part of today's experience of using ML algorithms. Machine learning algorithms are different and are applicable depending on the exact requirements of the process: here are some following examples.

2.2 Types of Machine Learning

Machine learning methods are divided into many categories. some examples are as follows. These types can also be used in a mix-and-match fashion for a solution.

a) Supervised Learning: Supervised learning is the process of constructing a model by feeding it reliable input and output data. This pair of input/output values is commonly known as "labelled data." The processing of labelled training data is the first step in the supervised learning process. Previously acquired training data were used to train the algorithm. The validation set is distinct from the training set, which is used to assess the model's accuracy. This metric is often used in conjunction with a threshold in the training algorithm to complement the trained model's precision and avoid overfitting. And when the model on the validation set is optimal can the test set be used.

This algorithm creates a model and outputs it based on the evidence given. A supervised learning algorithm includes known inputs with the predictors (knowledge response) for the output to train the model and react rationally to new data. The function maps the information to the desired outputs with the aid of these individual variables. The model continues the training phase with the determined variables and features until the desired degree of precision is reached. Predictive models to build Regression or classification methods are used for supervised learning techniques.

- Predictions about numerical entities are made using regression algorithms. Typically, examples are used to forecast the price of various variables such as items, houses, and other goods.
- Classification algorithms are used to generate a diverse membership for a known class type. This algorithm is used in email filtering (spam, not-spam) and medical diagnosis (identifying diseases based on symptoms).

b) Unsupervised learning: This technique doesn't need a target output. It addresses more complex processing tasks by correlating multiple input variables to cluster training data into various classes. This algorithm is commonly used in image recognition, face recognition, and bank associations, and it needs a large amount of data for training.

c) Semi-Supervised Learning: This type of algorithm is created by combining supervised and unsupervised machine learning. Typically used when there is insufficient labelled data to train a model accurately. The training method may begin with labelled tools and continue with unsupervised machine learning algorithms that learn from the outcome. At the same time, detection systems are capable of detecting well-known fraud and anomalies, the remainder which slips through the cracks and remains unlabelled, which is an excellent example of this type of algorithm.

d) Active Learning: A slightly modified version of Semi-Supervised Learning. Rather than automatically learning from instances and predicting an output, Active Learning predicts an outcome by selecting unlabelled data and querying Oracle or a human expert to analyse and determine the instance's name. labelled data instances can be described more loosely than in semi-supervised learning while still maintaining a high degree of prediction model accuracy.

e) Reinforcement Learning: This algorithm trains the computer to iterate an action in a complex environment to return a particular decision based on trial and error. Each iteration teaches the system to generate a favourable outcome based on prior experience, resulting in an optimal and accurate capture. As a result, we obtain a well-known method for creating online games that include human and computer interaction.

2.3 Classification Algorithms

The primary objective of this study is to achieve a prediction of the outcome of pregnancy of a provided test subject based on data and using the data classical classification algorithms.

The primary goal of machine learning classification algorithms is to divide input data into the fewest number of distinct classes possible. The conditions that define the boundaries of each class dictate that the target label class is assigned to each particular subset. Additionally, binary, and multi-class classification is possible. A binary classifier generates output that contains only two distinct levels: normal and abnormal. A multi-class classifier can have more than two usable classes and be capable of predicting the outcome for a wide range of separate categories. In the example presented in this study, a multi-class classifier was used to distinguish between various types of attacks within the anomalous behaviour.

Although all classification algorithms share a common purpose, their mathematical and logical approaches to problem-solving differ. Several well-known and frequently used classification algorithms are mentioned below, along with a brief description.

- **Decision Trees:** By segmenting the data into smaller subsets, decision trees classify it into a tree structure. Thus, using consecutive rules dependent on the most important differentiators in the input variables is accomplished.
- **K-nearest neighbour:** This technique classifies objects based on their closest neighbours' majority vote weight. Among its nearest k neighbours, the targeted object is assigned to the most convenient and familiar class.

- **Random forests:** This method identifies objects by building multiple decision trees and assigning them to the class that receives the most votes from all of the trees.

- **Support Vector Machines:** This classification algorithm plots training data points in n-dimensional space with a simple distance between them (depending on the number of features set). New examples are predicted based on the closest group to where they appear on the map.

- **Naive Bayes:** The Naive Bayes classifier was influenced by the Bayes theorem. The fundamental principle of the probabilistic classifier is that features are uncorrelated.

- **Logistic Regression:** This classification is a statistical approach that uses binary label outputs to perform binary classification. An output calculated by identifying one or more independent variables and analysing the dataset.

- **Gradient Boosting:** Gradient boosting is a technique for creating additive regression models by fitting a simple parameterized function (base learner) to current "pseudo"-residuals iteratively using the least-squares process. It is a process that progressively improves loss functions until it converges to the best-fit classifications. The pseudo-residuals are the gradient of the loss function being reduced concerning the model values at each training data point evaluated at the current level. By incorporating randomization into the methodology, gradient boosting approximation accuracy and execution speed can be significantly increased. For each iteration, a subsample of the training data is randomly selected (without replacement) from the entire set of training data (Friedman, 2002).

- **LightGBM Classifier:** LightGBM is a high-performance, low-memory-consumption gradient-boosting platform that employs tree-based learning algorithms. It outperforms traditional gradient boosting in terms of precision and data handling capacity on a wide scale. Parallel and asynchronous learning are both supported.

- **Cat boost Classifier:** Cat boost is a Supervised ML open-source Gradient Boosted Decision Tree (GBDT) implementation that provides Ordered Target Statistics and Ordered Boosting. Cat boost excels at machine learning tasks involving categorical, heterogeneous data (Hancock & Khoshgoftaar, 2020).

- **Neural Network**: In machine learning, a neural network is a mechanism in which the algorithm is given the trained data set and the expected performance, and the algorithm extract characteristics. The idea was inspired by the way the human brain functions. It usually has more than two layers, with each layer being referred to as a neuron. In simple terms, a neuron accepts inputs, performs math on them, and outputs a single value. Artificial intelligence expert systems based on machine learning and neural networks can be used to assist dentists in making tooth extraction decisions related to orthodontic care (Jung & Kim, 2016). It offers a generalized approach to problem-solving, and the applications of this method are virtually infinite. Pattern recognition, facial recognition, email spam screening, and medical diagnosis are only a few examples.

2.4 Natural Language Processing (NLP)

"Natural Language Processing is a theoretically motivated range of computational techniques for analysing and representing naturally occurring texts at one or more levels of linguistic analysis to achieve human-like language processing for a range of tasks or applications" - (Liddy, 2001)

As previously said, an NLP framework strives for human-like language processing. Previously, the field of NLP was referred to as Natural Language Understanding (NLU); however, we now recognize that although the goal of NLP is real NLU, that goal has yet to be accomplished.

NLP has more realistic aims, many relevant to the specific application it is used in . For example, an NLP-based IR system aims to provide more accurate and comprehensive information to meet user information needs. NLP has a range of foundations: computer sciences and information technology, linguistics, mathematical engineering, electrical engineering, robotics, and artificial intelligence, as well as psychology. NLP applications include various fields of research such as computer translation, processing and summary text in natural languages, user interfaces, speech recognition, artificial intelligence and specialist systems, and other fields of analysis (Chowdhury, 2003)

Inductive Learning: Inductive learning is a method for acquiring information used in the NLP process to extract knowledge in the method of if-else laws. It is a technique for automatically acquiring information. Typically, an inductive learning program needs a collection of examples as input. Each model is described by a set of attribute values and the class to which it belongs (Pham & Pham,1999). It is a commonly used technique for natural language processing.

Knowledge Base: In natural language processing, a knowledge base is described as the data, documents, or material that the NLP model uses to learn. In a typical NLP-based system, the system progressively accumulates data of responses, usually in the form of questions and answers, to make sense of the incoming context from real-world users.

2.5 Feature Engineering

Many real-life examples that machine learning is applied to are often applied to massive datasets. Specifically supervised learning specifically depends on data. Feature engineering means understanding and extracting features that are important from the dataset that probably consists of lots of unnecessary data. The effectiveness of a trained model is highly dependent on the consistency and reliability of its functionality. The process of feature engineering is mainly to write code that takes raw data objects collected from real life as an input and extract feature that are suitable for a machine learning algorithm for its specific purposes (Anderson & Cafarella, 2016). According to a survey that took the opinion of around eighty data scientists, feature engineering and extraction take almost eighty percent of total development time (Press, 2016). Feature Engineering has been categorized into multiple types. Data scientists use one or more of these techniques for extracting features. Following are some techniques of feature engineering.

Imputations: Imputation is a method for dealing with missed values, which are popular when processing data for machine learning. Missing values may be caused by human error, data flow interruptions, or privacy concerns, among other factors. Missing values, for whatever reason, have a negative effect on the performance of machine learning models (Abayomi, Gelman & Levy, 2008). Depending on the conditions, many imputation methods are used, such as falling throws all together or replacing them with any acceptable values.

Handling Outliers: An outlier in a data set is a finding or a point that is substantially different from or conflicting with the rest of the data (Ramaswamy, Rastogi & Shim, 2000). Outliers in machine learning pose problems in classification algorithms when they are usually far from the classification line. Outliers also trigger philosophical quandaries, such as the possibility that dropping those outliers all along would result in classification errors. A delicate balance of managing outliers is needed for classification algorithms to work properly.

One-hot encoding: The most frequently used technique for converting categorical features to a format suitable for use as input to a machine learning model is a one-hot encoding (Seger, 2018). Using a single hot encoding, categorical variables are replaced with finite integer values. By converting categorical data, which algorithms understand, to a numerical format, the algorithm gains precision, as the methods used do not result in information loss.

Scaling: In most cases, some numerical features of the dataset do not have a specific range, and they differ from each other. as an example, it won't be very reasonable to expect age as a categorical variable. Scaling solves this problem. The continuous features have given ranges as part of the scaling process.

3 Methodology

A target context analysis reveals previously unknown viewpoints, circumstances and thus provides a deeper understanding of the context. Both background, similarities, inequalities, and areas of consensus may be used in theoretical analysis, thus simplifying current circumstances and achievements. It extends the view and reference frames to facilitate the connection of points. I have tried to get an idea of the current circumstances and the explanations behind them. Many academic scholars noticed that the multiple questions were addressed from diverse theoretical perspectives and understanding levels. A wide variety of experimental, statistical, physical, and semi-quantitative analyses were conducted (e.g., desktop research, proof of concept solutions). The study is carried out to understand the past writers' views on pregnancy and the risk status of new mothers in Bangladesh. In addition, various methods suggested by different writers are considered in this study. There are also various machine-based learning solutions specific to the target context.

3.1 Literature Review

An attempt has been given to analyse and explain various authors' perspectives and suggestions about the target meaning context. This section aims to clarify how and why we ended up in these circumstances. The situation varies according to geographical region. This research's primary target region is Bangladesh.

Let us begin by looking at the underlying definition of maternal death. Maternal death is described by the World Health Organization (WHO) as "the death of a woman during pregnancy or within 42 days after the termination of pregnancy, regardless of the date or place of the pregnancy, from any cause related to or induced by the pregnancy or its management, but not from accidental or incidental causes" (World Health Organisation, 1992). According to WHO statistics, nearly 295 000 people died during and after pregnancy and childbirth in 2017. The vast majority (94 percent) of these deaths happened in low-resource settings, and the vast majority could have been prevented (World Health Organization,2019).

Many years of study have been conducted worldwide by many scholars to understand more about how to reduce maternal mortality locally and globally. The researchers discovered an obvious inverse association between childbirth weights and maternal cardiovascular disease mortality. This procedure is initiated by three key causes. Adverse social conditions will lead to low birth weight as well as an elevated risk of death. Second, maternal fitness, nutritional status, and behavioural traits may all influence birth weight and cardiovascular mortality. Third, intergenerational factors, such as genomic and epigenetic mechanisms that result in a favourable association between mothers' and offspring's birth weights, may have an impact on cardiovascular danger (Smith, Harding, & Rosato,2000). This research found a close link between maternal health and socioeconomic, mental, and dietary factors, which could influence morbidity.

Furthermore, it has been shown that the long-term consequences of former births and obstetric conditions can be harmful in the long run and are associated with an expanded danger of long-term neonatal mortality. Any, if not all, of these cases are most likely the result of common risk factors in these patients. In order to increase women's welfare and avoid problems, all patients and the caregivers must be mindful of these risks (Neiger, 2017).

The effect of maternal BMI and gestational weight gain on pregnancy complications is examined (Santos et al., 2019). The term "gestational weight gain" refers to the amount of weight gained between pregnancy and the time of the infant's birth. Parental pre-pregnancy BMI and preterm excess weight are linked with an increased incidence of pregnancy complications, according to a meta-analysis of 2,65,270 births. According to the analysis of the results mentioned above, obese, overweight mothers who gain much weight during pregnancy are at the greatest risk of pregnancy complications. Morbidity increases by up to 30% during pregnancy (Santos et al., 2019).

The relationship between advanced maternal age and pregnancy-related complications has been studied in China's demographics, and it has been concluded from the collected data that advanced maternal age, identified as over 35 or 40, does increase the risk of risk for both mother and child (Shan et al., 2018). Various authors have also observed this phenomenon. A similar conclusion is reached that pregnancy at an advanced maternal age is linked to increased incidence to the mother and foetus (Yogev et al., 2010; Seoud et al., 2002).

Now, looking back to the target demographics of Bangladesh, all the reasons mentioned earlier do apply here. On top of that, some more social factors do make the situation direr for new mothers.

Intimate Partner Violence is thought to have a major negative effect on the health of pregnant mothers, and several scholars have reported that witnessing IPV during pregnancy is common in Bangladesh and has a negative impact on mothers' reproductive health. Furthermore, the findings of these authors suggest that IPV is a major contributor to pregnancy complications (Ferdos et al., 2018).

Besides that, locally confined conditions that may lead to maternity risks can be observed. A research in rural *Rajshahi* found that the prevalence of asymptomatic bacteriuria would advance to more symptomatic bacteriuria. Persistent asymptomatic bacteriuria during pregnancy can lead to a variety of severe complications, such as pyelonephritis, low birth weight, premature labour, and anaemia, both of which are major causes of maternal and child morbidity and mortality in Bangladesh (Ullah et al., 2007).

When looking up the typical complications that occur, It was discovered that complications during pregnancy and childbirth cause 75% of maternal deaths. haemorrhage, severe vomiting, convulsions/fits, and anaemia of the face, foot, or body are found to be high-risk pregnancy risks (Chakraborty et al., 2003). According to a survey performed in Dhaka's slums, postpartum haemorrhage and pre-eclampsia were the leading causes of maternal mortality (Khatun et al., 2012).

Another research examined the possibility of maternal health problems in teenage females. Early marriage is still prevalent in rural Bangladesh. Premature pregnancy is a side effect of early marriage. A study conducted in one district of Bangladesh demonstrated unequivocally that teenage girls lack sensitivity and decision-making abilities in their homes and can be classified as a risk category due to their age and lack of awareness (Shahabuddin et al., 2017)

These authors provide an in-depth understanding of the different contributing factors to the problems. Now let us examine the current state of e-Health services in developing countries, emphasizing the target area.

Bangladesh's government has previously taken steps to raise awareness about maternal health care. One significant move was the establishment of the voucher program in 2004. The voucher program's objective was to promote maternal health services, especially eligible birth attendance, and alleviate some of the financial burden associated with delivery. The owner may receive maternal treatment at publicly run hospitals by presenting the freely obtained voucher. It aided in the spread of knowledge across vast populations (Nguyen et al., 2012).

In the aspect of private-public partnership for better health care, it has been analyzed and found that private-sector, when coupled with the public sector, can work successfully to deliver services in underserved communities. Potential private-public partnerships will improve quality of life in general and, as a by-product, improve pregnancy health care services (Hossain et al., 2020).

It is often observed that a solution that works in one developed country also works in another developing country. With this thought process in mind, it is demonstrated that by using e-Health solutions, delays in maternal healthcare can be reduced in remote communities of Ghana. This model identifies poverty, cultural values, organizational problems, connectivity, and a shortage of human capital as the primary barriers to eHealth solution implementation in Ghana (Pagalday-Olivares et al., 2017). Similar conclusions can apply to Bangladesh as well.

Now, let us look at the technical contributions to this aspect. Numerous scholars have discussed these problems and advocated for using technology to analyse and explain the situation and improve it.

Advanced machine learning techniques have also been used to attempt to ascertain the causes. The author used principal component analysis (PCA) to investigate a potential association between thyroid abnormalities and gestational diabetes mellitus (GDM) in pregnant women. Their findings imply that thyroid hormones should be used in conjunction with a more sensitive GDM diagnosis (Araya et al., 2021).

Numerous authors also employ a machine learning-based approach to outcome prediction. One unique approach is to predict the outcome of pregnancy following in vitro fertilization (IVF) treatment using the artificial neural network (ANN) prediction technique (Hassan et al., 2020).

Image recognition, a widely used machine learning technique, is used in this domain. Authors appear to be using image feature extraction and analysis to predict pregnancy test outcomes following embryo transfer (Chavez-Badiola et al., 2020).

One author explored the connection between maternal exposure to particulate matter (PM10) during pregnancy and an increased risk of congenital heart defects using machine learning models. In a dataset of 39,053 births, they discovered strong evidence that maternal exposure to PM10 during weeks 3–8 of pregnancy was associated with an increased risk of CHDs (Ren et al., 2018).

3.2 Understanding of Literature Review

From the start of the literature review, we can see that there are many factors involved in pregnancy in general. Age, Weight, Morbidity, BMI, Hypertension are some of the common attributes that are often coming. Premature pregnancy and pregnancy at late age both pose risks for both the mother and the baby. These common features, if present, should be considered as risk factors according to the literature review.

When we examine domain-specific concerns concerning the target population, we see that abuse against women by intimate partners, the widespread practice of early marriage, and even oddly specific cases such as asymptomatic bacterial infections all contribute to the mother's risk during pregnancy.

When considering the actions taken by local governments, government initiatives such as voucher schemes, public-private partnerships, and even eHealth systems can have a beneficial impact on the subject.

When we examine the technical solutions considered in the literature review, we see that several machine learning methods have already been demonstrated to apply to the subject matter. As an example, the use of PCA in the case of gestational diabetes mellitus, predicting the outcome of pregnancy following IVF treatment, image analysis of the embryo to better understand the success rate following IVF, or even the attempt to establish a connection between the existence of particle PM10 in the air and pregnancy. All of these techniques demonstrate the feasibility of applying machine learning techniques to the subject at hand.

3.3 Constructions of Hypothesis

According to the article 'The Role of Hypothesis in Constructive Design Research,' the methodology of constructive design research allows a planner to generate information based on the ability of the design field (Krogh et al., 2012). After being inspired by this comment, I started developing theories based on my review of the literature and comprehension of the topic.

Hypothesis 1: The first hypothesis is derived from the literature review, followed by an in-depth examination of the research question through experimentation.

Hypothesis I: It is possible to identify pregnancy related risk factors of a certain geographical location. **Research Question I:** How to identify all the risk factors in the interested region

Table 1: Hypothesis 1

Hypothesis 2: The second hypothesis is also derived from the understanding of literature review, followed by an in-depth examination of the research question.

Hypothesis 2: It is possible via eHealth solution to improve quality of service towards pregnant women. **Research Question 2:** How can we identify the features of an eHealth solution that address existing issues and provide easier service towards citizen

Table 2: Hypothesis 2

Hypothesis 3: The third hypothesis is also derived from the understanding of literature review, followed by an in-depth examination of the research question.

Hypothesis 3: It is possible for machine learning algorithm to assist health worker via identifying risk up-to certain degree. **Research Question 3:** What machine learning technique can be used to fulfil the purpose

Table 3: Hypothesis 3

3.4 Probable Solution space

Potential interventions are identified after a detailed understanding of the problem domain is attained. I identified a need for an eHealth solution that considers the demographics of the target region and effectively delivers eHealth services to remote areas of Bangladesh. The platform's ultimate objective is to increase resource accessibility for rural residents of Bangladesh and to create a machine learning model capable of predicting risk factors during pregnancy. The fundamental goal is to decide if the risk can be anticipated. It can aid in the implementation of adequate precautions and, eventually, risk avoidance. I planned my probable solution using the knowledge acquired through research and personal experience. The following segment is outlined in detail.

4 Practical Implementation

4.1 Proposed Solutions

This research is proposing "SHEBA (CARE)" as a platform that will simplify the process of accessing hospital services while also adding value to health care staff by offering a convenient way to handle appointments, automatically answering frequently asked questions, and warning and explaining difficult pregnancy cases so that precautions can be taken sooner.

The solution proposed here is considering two types of user

User groups 1: Pregnant women and their families.

Provided Feature for User group 1:

1. Signup and Registrations
2. Appointment taking facility to the nearest hospital.
3. Consultation via NLP trained chatbot in Bangla and English
4. Receive alert if falls in the risk zone.

User group 2: Healthcare workers

Provided Feature for User group 2:

1. Appointment management facility
2. Prediction of outcome based on provided data of the subject using the trained model. Take necessary precaution according to the provided explanation.

The solution is available for web and mobile-based platforms. The solution is a cross-platform solution that is targeting to work on both android and IOS-based systems. A simplified block diagram is given below for the proposed solutions.

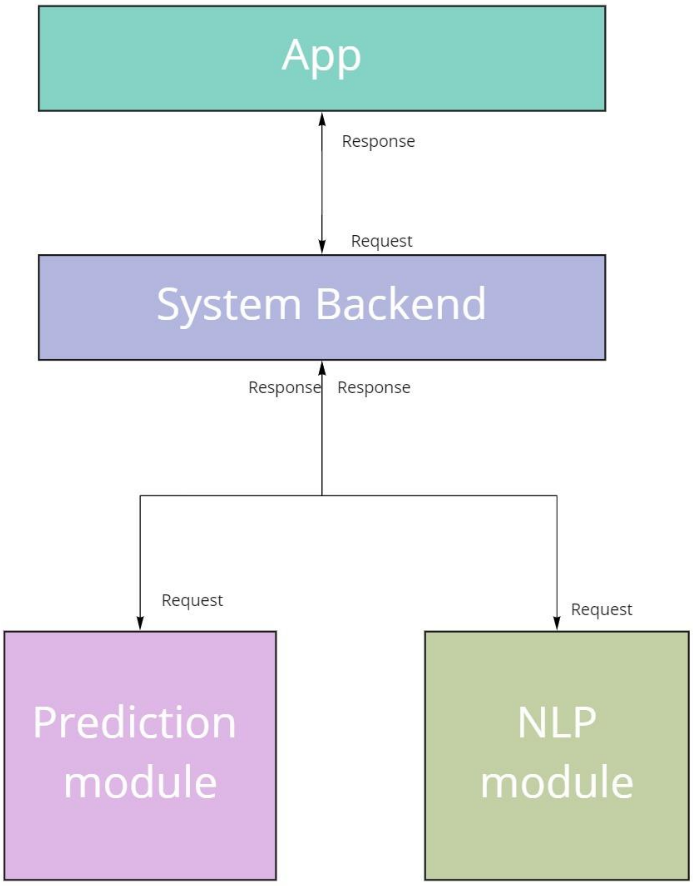

Fig 1: Block Diagram of The Platform

The user may submit various types of requests through the app, such as login, appointment scheduling, etc. The platform backend service will handle this request and return an answer to the application. If the device backend detects that it has received a consultation request for the app, it will request a relevant response from the NLP-powered chatbot. After receiving the answer, the backend system will return it to the app. Similarly, if the system receives a request for outcome prediction, it will forward the request to the prediction model, which will provide the outcome. After that, the backend system would simply deliver it to the app. Respected pregnant women can obtain notifications through the app if necessary. The following subsection consists of the description of the targeted platform features.

4.2 Login and Signup Facility

4.2.1. Purpose of This Feature

The proposed solutions would include user-friendly login and registration processes that will be accessible in several languages. During registration, the user will be required to provide only one piece of information: a unique digital smart ID number. Bangladesh's government provides each citizen with a smart ID card linked to a centralized database of citizen information. A safe API is available for development purposes. By using those APIs, it is possible to retrieve citizen information using just an ID card. Providing only an ID card number in this manner should theoretically suffice to retrieve the requisite details to proceed with the sign-up process. Citizens will then receive an SMS containing a One Time Password (OTP) allowing them to access the system. The phone number will be collected per the NID issued. If no phone number can be extracted from the NID data, the user will be prompted for one.

4.2.2 Values Provided.

- Simple to use login method that requires little user interaction.
- Facilitate educationally challenged individuals' use.

4.3 Appointment Facility

4.3.1 Purpose of This Feature

This feature aims to provide less educated individuals with an easy-to-use and user-friendly appointment scheduling system. The solution will be available in both Bangla and English. The proposed component's value proposition is to allow the user to access this function through an intuitive interface. Additionally, the process will interact with the consultation capabilities and will be able to schedule appointments based on the context of the consultation module's performance for that particular use.

4.3.2 Values Provided.

- Appointment booking at the nearest hospital becomes easy.
- Integration with chatbots and appointment scheduling from the user's conversation on the mobile-based platform to provide convenience.

4.4 Consultation Using NLP

4.4.1 Purpose of This Feature

This feature enables developing a knowledge-rich, Natural Language Processing-enabled Chatbot that the user can use to seek consultation. The bot will be bilingual in Bangla and English and will be able to provide information based on its knowledge base. This functionality will also be added to the appointment module, allowing users to make appointments directly from the chat window.

4.4.2 Technique Used.

Chatterbot: It is a Python library that simplifies the process of automating the generation of responses to user input. Chatterbot generates a variety of different types of responses by using a variety of machine learning algorithms. Chatterbot simplifies the process of developing chatbots and automating interactions for device users in my use case. Chatterbot’s language-neutral nature enables it to be taught to communicate in any language (In this case, English, and Bangla). Additionally, since Chatterbot is a machine-learning system, an agent instance can develop its knowledge of potential responses as it communicates with humans and other insightful data sources. Chatterbot is a very easy-to-use and robust library where it can be trained with a custom knowledge base vital for this implementation.

4.4.3 Knowledge Base of the chatbot

The knowledge base used for chat is in Bangla and English. The knowledge base consists of usual greetings like hi, hello, and subject-specific knowledge like introductory consultation, hospital information etc. A Sample knowledge base of the chatbot is given below.

```
- - please help
  - Yes , how can i help you
- - help me
  - Yes , how can i help you
- - Give me the phone number of nearest hospital
  - phone num of nearest hospital is +8801680522618
- - phone number of nearest hospital
  - phone num of nearest hospital is +8801680522618
- - phone number  hospital
  - phone num of nearest hospital is +8801680522618
- - phone num of hospital
  - phone num of nearest hospital is +8801680522618
- - I dont feel well. what can I do
  - please contact nearest hospital
```

Fig 2: Sample chatbot knowledge base

Multiple question forms are added to improve the confidence for the chatbot provided answer.

4.4.4 Values Provided.

- Human like interaction with automatic consultation based on Knowledge base.
- Appointment from chat context
- Usage of Speech to text for user who face writing challenge.
- Multiple Language supported knowledge base

4.5 Prediction Model

4.5.1 Purpose of This Feature

The purpose of this feature is to predict the outcome of a test subject (e.g., predict the outcome of pregnancy based on a trained model) collected by the healthcare professional during initial and trimester visits by the test subject. This feature is the core of the system as the whole purpose is to increase preparedness and awareness regarding the risk of the prenatal and neonatal stage of pregnancy.

4.5.2 Block Diagram of the prediction model

A simple block diagram of the built model is shown below. The collected data was pre-processed in order to remove the correct features from the dataset. This dataset is split into two parts for training and evaluating the prediction model. The dataset that was used to train different machine learning classifier models is then used to predict the outcome using test results. The most important step is to calculate the error associated with the prediction, since this will help us choose the best model for predictions. After that, the best one is saved for future use. When further input sets are needed to predict the result, the saved model can be reloaded and used to make the prediction. Following that, human-readable counterfactual interpretations are generated and modified.

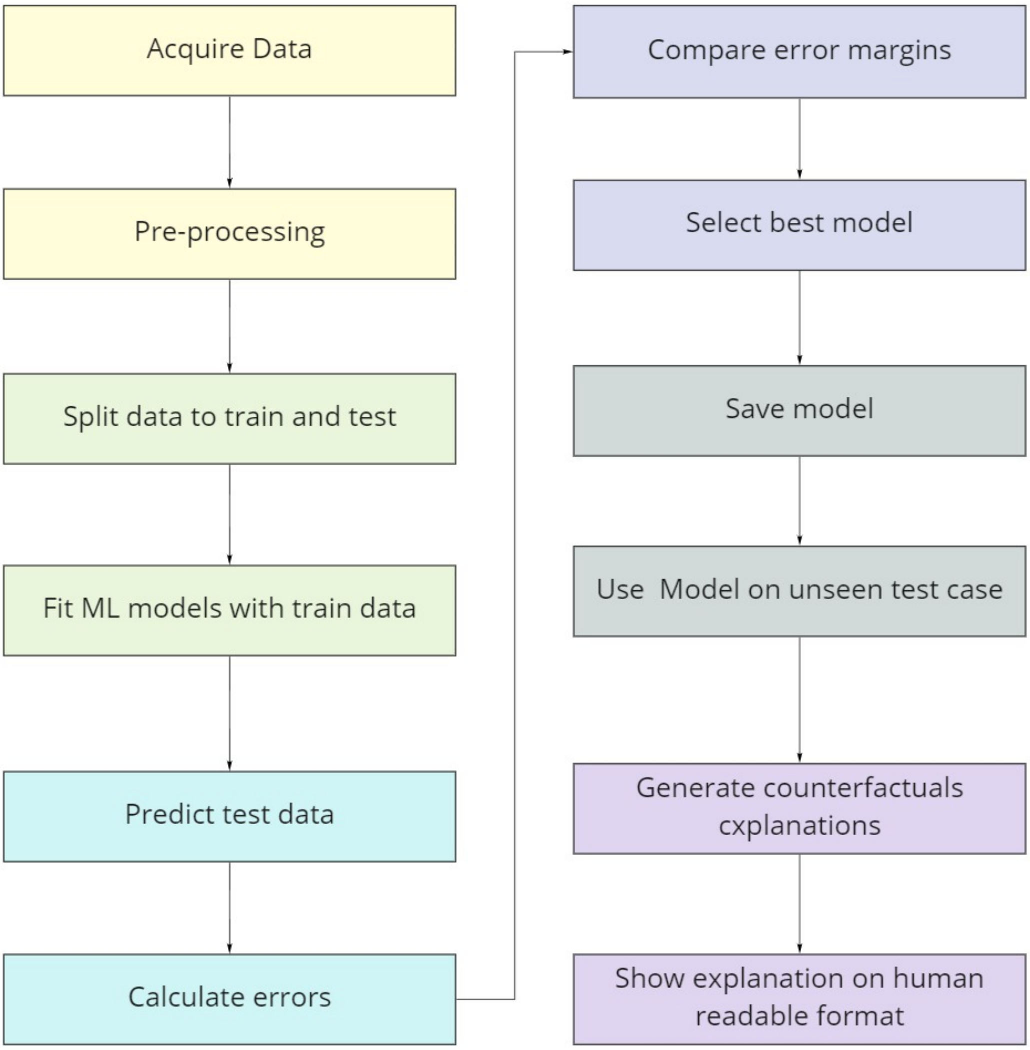

Fig 3 : Block Diagram of prediction model

4.5.3 Data Acquisitions

Obtaining a dataset of pregnancy-related variables is not a simple process. Frequently, data is available in summary or analytics form in a variety of large non-profit organizations, such as the WHO or UN. Health data collection is a significant problem in developing countries (Alam et al., 2012).

After overcoming obstacles to collecting a dataset suitable for the planned model, a dataset that is publicly accessible is captured. The data set used in this study was compiled from a health survey conducted in nine Indian states. The dataset was gathered from publicly accessible sources on the internet (Annual health survey AHS,2011–12). The training and test datasets are generated by neutrally combining a dataset of five states. The initial datasets contain 204 columns of values separated by a pipe ("|"). Several columns are given below as an example.

Field Name	**Field Descriptions**	**Codes Used**
state	State	Uttarakhand-05 Rajasthan-08 Uttar Pradesh-09 Bihar-10 Assam-18 Jharkhand-20 Odisha-21 Chhattisgarh-22 Madhya Pradesh-23
rural	Rural/Urban	Rural-1 Urban-2
result_of_interview	Result of Interview	Completed-1 Not-Completed: -Refused-2 Incapacitated-3 Partly Completed-4 Not at Home-5 Others-6
sex	Sex	Male-1 Female-2
religion	Religion	Hindu-1 Muslim-2 Christian-3

		Sikh-4 Buddhist-5 Jain-6 Others-7 No religion- 8
chew	Chew	Pan with tobacco-1 Pan without tobacco-2 Pan masala with tobacco-3 Pan masala without tobacco -4 Tobacco only-5 Ex – Chewer -6 Never chewed-7 Not known-0
alcohol	Consume Alcohol	Usual drinker-1 Occasional drinker-2 Ex – drinker-3 Never drank-4 Not known-0

Table 4 : Sample column definition of the dataset

After careful consideration, It is identified that all these field-collected is not necessary for the prediction algorithm to work.

4.5.4 Data Pre-processing

Pre-processing data is vital for the machine learning techniques used in the algorithm. The model's performance and ability to extract useful information are directly related to the quality of the data, which is often insufficient, inconsistent, or lacking in some patterns or overloading. Therefore, this stage is crucial before data is trained and fed into the primary algorithm model. This move has been demonstrated to enhance efficiency by converting raw data into cleaner representations by eliminating unnecessary noise and information during the data collection process.

Prior to being used in the subsequent stages, data must undergo a few steps to ensure the most efficient and clean process. Since feature selection has a significant impact on the model's performance, it is a critical step in the process. This approach automates the identification and processing of the most valuable and informative features for the learning pipeline. Not all features perform in the same way as the most informative ones; some additional features have a detrimental effect on the entire process, slowing computation and training, reducing model interpretability, and, most importantly, decreasing the model's overall performance.

The selected models have a range of effects on the features obtained during data acquisition. Particular characteristics may be irrelevant to the label class, whereas others may be critical. Certain factors have a one-of-a-kind value or are associated with the model. As a result, this technique is used to exclude redundant features from the data collection that are less informative for the forecasting class and to increase the model's accuracy using the data found in the selected variables and attributes.

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Feature Name	**Description**
rural	Rural/Urban
age	Age

marital_status	Marital Status
delivered_any_baby	Have you delivered a live baby?
born_alive_female	Female children born alive?
born_alive_male	Male children born alive?
born_alive_total	Total children born alive?
mother_age_when_baby_was_born	When did you first give birth? (In completed years)
outcome_pregnancy	Outcome of pregnancy(s) results - yes -1, no -0
is_tubectomy	Modern Method-Tubectomy
is_copper_t	Modern Method-Copper-T/IUD
is_pills_daily	Modern Method-Pills(Daily
is_piils_weekly	Modern Method-Pills (weekly)
is_emergency_contraceptive	Modern Method-Emergency contraceptive Pill
is_moder_methods	Modern Method-Other Modern Method
is_contraceptive	Traditional Method-Contraceptive Herbs
is_periodic_abstinence	Traditional Method-Rhythm/periodic abstinence

is_withdrawal	Traditional Method-Withdrawal
is_amenorrahoea	Traditional Method-Lactational Amenorrhoea Method(LAM)
is_other_traditional_method	Traditional Method-Other Traditional Method
is_currently_pregnant	Are you currently Pregnant?
pregnant_month	Record number of months of completed of pregnancy
when_you_bcome_mother_last_time	When you became a mother last time, or did you not want to have any children at all?
anm_in_last_3_months	Healthcare workers visited during the last 3 months?
during_pregnancy	Have you got childcare services during the pregnancy
during_lactation	Have you got childcare services during lactation?
aware_abt_rti	Have you heard of RTI/STI?
aware_abt_hiv	Have you heard of HIV / AIDS?
aware_of_haf	Familiar with the use of HAF/ORT/ORS during diarrhoea?
aware_of_the_danger_signs	Are you familiar with the red flags of Acute Respiratory Infection (ARI) / Bronchitis?
highest_qualification	Highest educational qualification

occupation_status	Occupation / Activity Status
disability_status	Whether having any form of disability?
injury_treatment_type	Treatment type for injury during last 1 year
illness_type	Type of illness
symptoms_pertaining_illness	Symptom of illness for more than one month
sought_medical_care	Sought medical care
diagnosed_for	Has Diagnosed for
diagnosis_source	Source of Diagnosis
chew	Chew habit (e.g - paan with tobacco)
smoke	Smoke
alcohol	Consume Alcohol
drinking_water_source	Main Source of Drinking water
is_water_filter	Does the household treat the water to make it safe
water_filteration	What does the household usually do to make water safer to drink?
toilet_used	Type of toilet facility mainly used(code)
is_toilet_shared	Whether the toilet facility is shared?

ever_conceived	Have you ever conceived?
no_of_times_conceived	If Yes, how many times have you conceived?
age_at_first_conception	age at first conception?
is_injectable_contraceptive	Modern Method-Injectable Contraceptives
months_of_preg_first_anc	How many months pregnant during first ANC visit
is_husband_living_with_you	Is your husband living with you?
health_prob_afters_fp_use	Have you or your husband experienced any health issues as a result of using this method?
counselled_for_menstrual_hyg	Counselled for menstrual hygiene?
aware_abt_haf	Aware about HAF during diarrhoea?
aware_abt_ort_ors	Know about the process of ORT / ORS in the situation os diarrhoea?
aware_abt_ort_ors_zinc	Aware about ORT / ORS and Zinc during diarrhoea?
aware_abt_danger_signs_new_born	know the danger signs of new-born children?
wt	Weight

Table 5: Features used in the model.

The attributes in this section were chosen after careful consideration. Weight, for example, has a major effect on the outcome of a pregnancy. Obesity in women during their reproductive years is a major public health issue, particularly in "developing countries." Maternal obesity has been linked to an heightened risk of preterm birth and low birth, and pregnancy weight gain/excess weight has been linked to an increased risk of pre- and gestational hypertension in children. We have already seen authors try to explain this phenomenon. Obesity before pregnancy increases the risk of developing diabetes, hypertension, and preeclampsia (PNEC) early in pregnancy.

Additionally, it increases the probability of caesarean and instrumental deliveries and the likelihood of preventing sterility, sickness, and maternal mortality if childbirth happens during it. Ventilatory complications before pregnancy or having required ventilatory assistance earlier, or both, can both increase the need for ventilatory support before and during labour and delivery, or have a substantial impact on the duration of hospitalization, and can also be the cause and effect of a higher incidence of these adverse outcomes. This increases the likelihood of the infant becoming overweight or obese since the mother will pass it on to the fetus. According to experts, alcoholism or other bad habits, such as smoking, may also harm a person's health. Numerous pre-existing morbid conditions can also damage the mother's health during pregnancy. Awareness is beneficial in reducing risks.

Additionally, antenatal care visits assist women in reducing their risk of complications. Sanitation and living arrangements can also play a role. Unsanitary living conditions can result in severe illness that can affect new mother and her child. All of this reasoning contributes to the selection of this trait in general.

4.5.5 Balancing Unbalanced dataset

Since the experiment is essentially a binary classification problem, it is susceptible to unbalanced data. In binary classification problems, an unbalanced dataset occurs when the two groups are not fairly represented in the dataset. In intrusion or fraud detection, for example, fraudulent transactions are usually outnumbered by legitimate ones. When one class in a dataset is underrepresented, the data is said to be unbalanced. Typically, the minority class is the focus of attention in such situations. Since there are few instances of one type, the classifier often fails to generalize the characteristics of the minority class well, leading to poor predictive accuracy. (Pozzolo et al., 2015).

There are two main types of schemes to balance an unbalanced dataset.

Under-sampling: Under-sampling is used to minimize the representation of members of the majority class in the training data. Consequently, the total record count of the training set is significantly decreased. This means that the time required for planning is reduced considerably during classification. Additionally, significant memory savings are realized because we are dealing with highly high-dimensional datasets. However, since we're excluding members of the majority class, we're likely to lose out on a lot of valuable data if we discard documents that might help our classifier build a more accurate model (Liu, 2004).

Oversampling: Oversampling is intended to improve the representation of ethnic groups in the training kit. Oversampling has the benefit of retaining both minority and majority classes, since no data from the original training collection is missing. The downside is that we have significantly expanded the size of the training set. As a result, training time and the amount of memory required to maintain the training set are increased. Because we are dealing with highly high-dimensional datasets, we must exercise caution to keep time and memory complexity within acceptable bounds. If the time taken to resample is overlooked, under sampling outperforms oversampling in time and memory complexity. Consequently, for oversampling to be viable, it must beat under sampling in terms of classification performance. Previous research has not established conclusively whether under sampling or oversampling is more efficient for classification. The conflicting results are most likely due to the use of several datasets and classification algorithms. Additionally, the process of resampling is almost certainly domain- and problem-specific (Liu, 2004). Synthetic Minority Oversampling Technique or SMOTE is a common oversampling technique.

SMOTE: SMOTE is a technique of over-sampling where the minority class is over-sampled by generating "synthetic" instances rather than substitution sampling (Chawla et al., 2002). Synthetic samples mean the algorithm generates similar new samples of the minority class rather than copy the samples. SMOTE does not produce lots of synthetic examples because it operates in "function space" rather than "data space.". Based on the requirement of oversampling, randomly chosen neighbours from the nearest point are chosen along the classification line (Chawla et al., 2002). By inserting synthetic instances from which each minority class sample is drawn, SMOTE oversampling the minority class. The instances are placed along with the line segments that link the majority, if not all, of the minority class's k-nearest neighbours. neighbours are randomly chosen from the k-nearest neighbours based on the level of oversampling needed. SMOTE is introduced by using the five nearest neighbours. For instance, if the oversampling factor is 400 percent, only four neighbours are chosen from the ten nearest neighbours, and a synthetic sample is created (Chen 2009). In a nutshell, the SMOTE algorithm multiplies the difference between the considered function vector and its nearest neighbour (case of minority class) by a random number between 0 and 1 (Jishan et al., 2015). This thesis used the oversampled minority class using the SMOTE technique.

4.5.6 Analysis of the Prediction Model

The research model was built in Python, using the Scikit Learn library for data extraction and feature engineering, as well as auxiliary libraries such as panda for feature extractions. Scikit-learn is a simple-to-use and reliable open-source data mining and analysis tool. This library is intended to be used for various purposes and is based on common numerical and scientific libraries such as NumPy, SciPy, and matplotlib. Scikit-learn provides methods for creating groups, performing regressions, clustering, pre-processing, selecting models, and dimension reduction. Scikit-learn is the primary library that was used in this research to develop the machine learning algorithm. Pre-processing and preparation were accomplished using the Scikit-learn library and classification models (Decision Tree, Random Forests). Additionally, I used the XGBoost library to implement the xgb Classifier. XGBoost is a distributed gradient boosting library that has been configured to be extremely powerful, scalable, and portable. It utilizes Gradient Boosting to incorporate machine learning algorithms. Additionally, two classification techniques are used: LightGBM and the cat boost classifier.

Normality of Data: The normality distribution or Gaussian distribution of the used dataset will aid in comprehending the data set's structure and the amount of data close to the mean or standard deviations.

For the datasets, quantile-quantile map, or QQ plot was used to generate normal distributions for continuous attributes. QQ plot produces its Gaussian distribution sample. The QQ plot provides a much more accurate visualization of my data, assuring us of its normality.

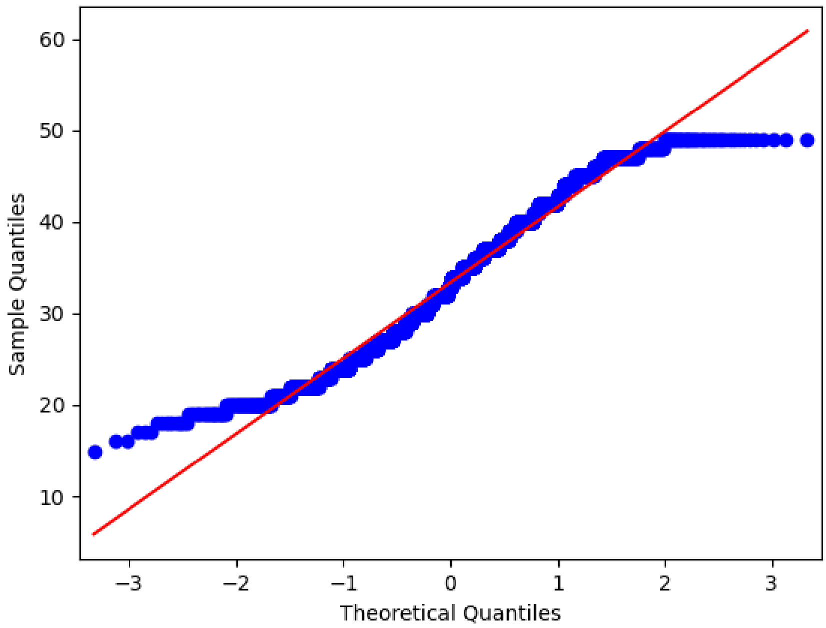

Fig 4: Normality distribution of 'age' feature

We can see that the normal distribution looks like a gaussian distribution as most of the data points are relatively evenly spaced.

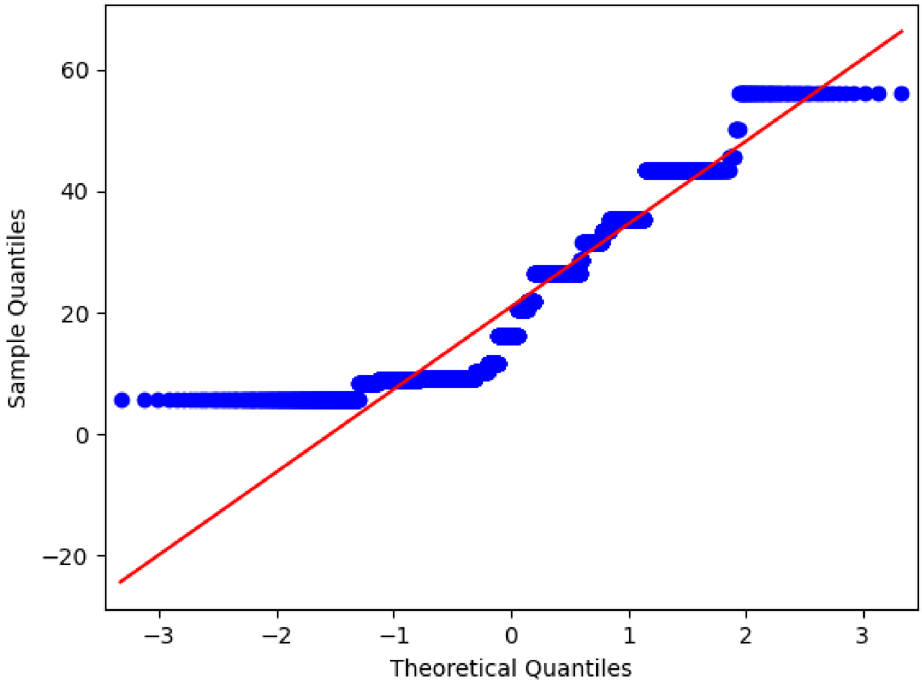

Fig 5: Normal distribution of 'weight' feature

The normal distribution of the weight variable seems to have similar or identical weight for multiple data points based on the understanding of the graph.

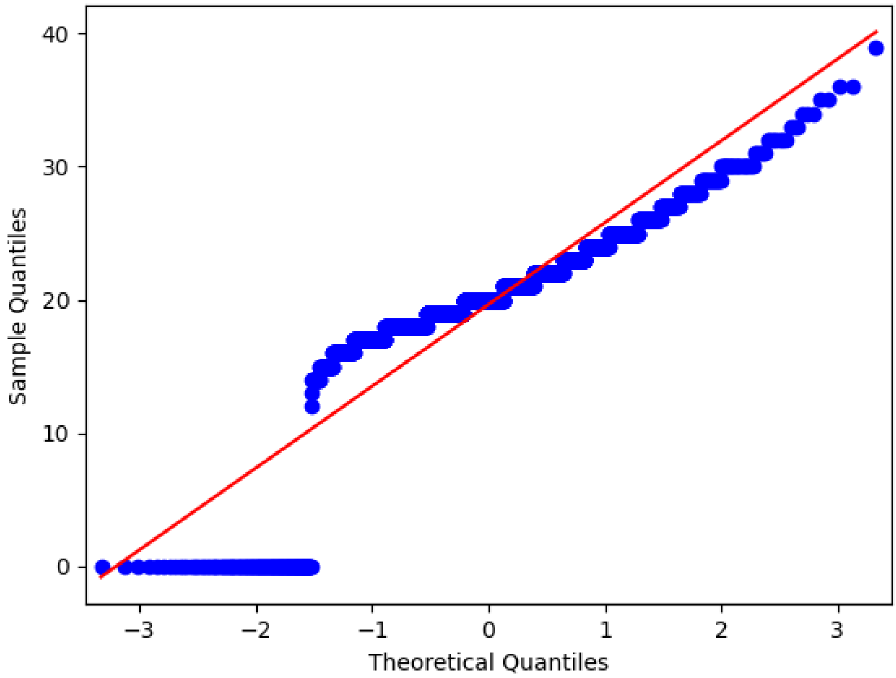

Fig 6: Normal distribution of 'mother_age_when_baby_was_born' feature.

We can see that lots of data points in the normal distributions have 0 values; this is normal as the data points also represent women with no child as the value of zero.

After analysing the data, it is the part where it is needed to split the data set via train-test split. The train-test split procedure is a prevalent technique used to measure machine learning algorithms' accuracy via splitting the data set in the train set and test set and using the test set to predict the outcome and then measure accuracy. In this experiment, The data divided between training and testing set according to the 80-20 rule, where 80 % of the data used to train the model and 20 percent were used to test the trained model's performance. After splitting the dataset, it has been observed that the minority class has a minimal amount of data. SMOTE technique is used to oversample minority sets with synthetic minority generation.

Then different ML classifiers to train the dataset are used. The following classifiers are used in this experiment.

- Gaussian Naive Bayes
- K Nearest Neighbours Classifier
- Random Forest Classifier
- Gradient Boosting Classifier
- XGB Classifier
- LightGBM Classifier
- Cat boost Classifier

At first, all these classifiers are trained with the same dataset. Later, the test samples are used to predict the output variable 'outcome_pregnancy.' Cross-validation scores have been generated to analyse the model performance.

Cross Validation: Cross-validation is a method that is often used to verify machine learning models. In simpler terms, cross-validation is the division of a data set into train and test databases and the test database for prediction. Following the forecast, the model's accuracy is evaluated by examining the dataset's actual outcome. The cross-validation score is expressed as a percentage; for example, a score of 0.90 indicates that the model can predict with 90% accuracy. As a bar graph, the cross-validation centre of the model used in this experiment is shown below(Ramezan, Warner& Maxwell,2019).

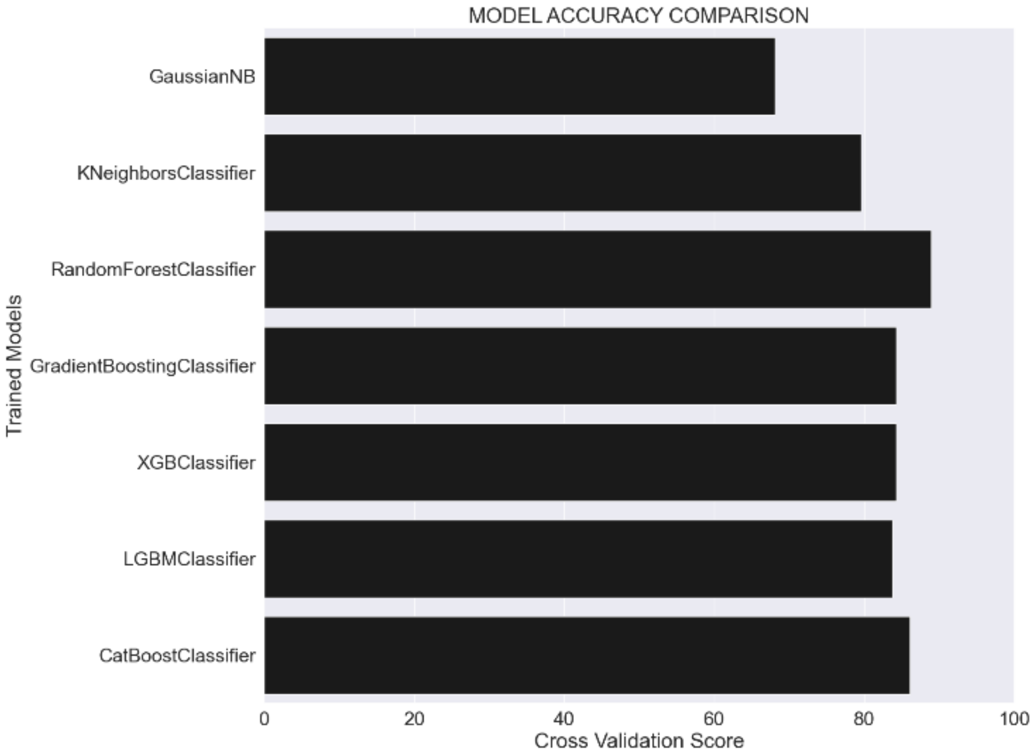

Fig 7: Cross-validation score of models

For the dataset used in this experiment, five of the seven classifiers generate a cross validation score that is very close to the one shown in the graph. However, Random Forest Classifier outperforms other classifiers on this training dataset. This graph is only applicable to the subset of the dataset that was used in this study. Changing the dataset or increasing the amount of data used to train the model can result in a different outcome.

After comparing the outcome of the solution according to cross validation score random forest classifier have been favoured to choose for future predictions. After that I decided it is important to learn the magnitude of importance for the feature, I have selected to know which feature is contributing the most to the outcome and for this I have used SHapley (SHAP) values for this part of analysis.

SHAP values: SHAP Values (an acronym for SHapley Additive exPlanations) decomposes a forecast into its constituent features and illustrates the effect of each. SHAP assigns a significant value to each function for each prediction (Lundberg & Lee, 2017). In simpler terms, consider a football team competing in a competitive league. Each footballer will have some SHapley values, and the team's chances of scoring a goal will be based on all those SHapley values. Initially developed for game theory, SHAP values are now commonly used in machine learning models to determine the significance of features. The Summary plot of SHapley values of the top 20 most crucial feature is given below

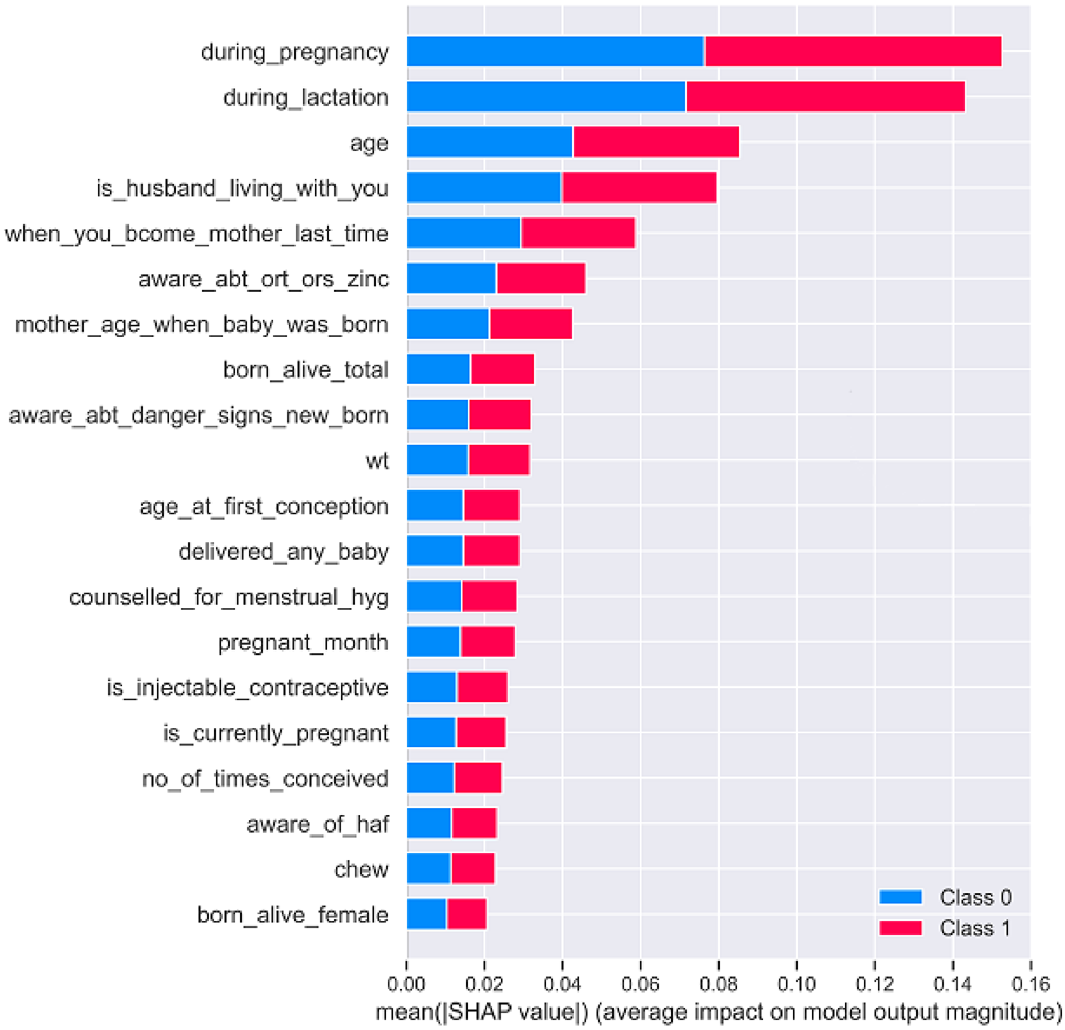

Fig 8: SHAP values for top 20 features

From the graph, we can see that the top two attributes contributing to the prediction are receiving childcare services during pregnancy and lactation. This conclusion is reasonable because usually, receiving childcare services reduces chances of complications because of check-ups and early detection of reason resulting in complications. The next most important feature as per the SHAP value is age. This conclusion is also very logical because we see that both have a high chance of complications early and late stages of life, as researchers concluded. It can also be noticed that factors like weight and bad habits like chewing "pan with tobacco" has also contributed to the outcome.

Generation of Counterfactuals: A counterfactual explanation is essential to machine learning models to generate a what-if scenario in simple terms what factors changing can produce an alternate outcome. Counterfactual situations can be considered when asking what would have happened if the patient had undergone a new medication or reacted differently in a different context. What if the patient had undergone a new kind of treatment? Every bit as subject to every inference made by the conclusion(s) based on it is [is by definition contingent on] these numbers, and none of the assumptions could be formed even though all of that is presumed to be valid (Dawid, 2000). There is a need for clear explanations for machine learning systems, given their current use in social domains such as economics, education, criminal justice, and the health sector as advanced predictive applications. As an illustration of how historical evidence demonstrates that pregnant women have a higher rate of miscarriage, consider a woman who is almost seven months pregnant. Although recognizing counterfactuals can be highly beneficial, obtaining an example of an alternative outcome and tracking the input variables for that outcome can potentially minimize the risk of miscarriage or complications by offering additional insight. DiCE is a strategy that uses counterfactual (CF) explanations by viewing feature-perturbed copies of the variables that contributed to the alternate result. In Simple terms, it generates "what-if" reasons for model success and may be a helpful complement to other interpretation approaches for both model users and model developers (Mothilal, Sharma & Tan, 2020).

In this experiment, after selecting the model based on the cross-validation score, the subsequent experiment is tried to provide a counterfactual explanation for the experiment. The main plan to include counterfactuals' explanation in the bigger picture will be to provide the health care professions in a human-readable format to assess what can be done differently to alternate the outcome in the risk cases.

Attributes Name	Original Dataset value	Counterfactuals value	Counterfactuals Value	Description of the meaning of the value
is_withdrawal	2	2	1	Traditional Method-Withdrawal Yes-1 No-2
during_pregnancy	0	1	0	Have you availed Anganwadi Services during the pregnancy and/or lactation for the last surviving child?-During Pregnancy Yes-1 No-2
during_lactation	0	1	1	Have you availed Anganwadi Services during the pregnancy and/or lactation for the last surviving child?-During Lactation Yes-1 No-2
outcome_pregnancy	0	1	1	outcome of pregnancy - 0 means negetive

Fig 9: Counterfactuals outcome with explanations

The above in the picture only shows the factors contributing to different outcomes for one test case. From this example, taking childcare services during pregnancy and lactations causes change mostly when other factors remain the same. changing the use of the traditional method of pregnancy care is also contributing to a different outcome for one alternative explanation of counterfactuals.

Saving the model for future use in the platform is identified as the next critical step, as rerunning the train set for each prediction in the platform is neither ideal nor feasible. For these purposes, Python's Joblib library is used. Joblib is a set of Python tools for performing lightweight pipelining. Joblib enables the avoidance of repeated computations on the same dataset and disk persistence. Joblib can easily save models to the system's storage area and load them when required. Joblib's simplicity of use contributes here to save the qualified model for future use.

4.6 Prototype of the Solutions

4.6.1 Coding Works

All the code that was written as part of the solution is available on GitHub. This study utilizes two repositories. Both repositories' URLs are included in the appendix parts. The aim of using two repositories is to create a solution that is loosely coupled by software development fundamentals (Orton & Weick, 1990). Both solutions software packages are self-contained. Additionally, although both the prediction model and the backend API are written in Python, they are not tightly coupled. The following section will expand on the overall understanding of the platform's development process.

4.6.2 Backend Repository

This repository contains the code that was written as part of the research model, as well as the backend Rest API implementation (URL on Appendix 1).

REST APIs are now the de facto standard for device integration on the Internet (Sohan et al., 2017). It is now the de facto architecture for web-based solutions. REST API using the Flask framework is used in this case. Flask is a Python microframework that offers the fundamental features of a web framework. It enables the addition of plug-ins to take the usability of the framework to new heights. It is referred to as a Python microframework because it simplifies core functionality while remaining extensible in terms of growth (Aslam, Mohammed & Lokhande, 2015). The ease of use of Flask allowed developing APIs at a faster pace. For the sake of keeping simplicity for the proof-of-concept solutions, any Database is not used. To provide functionality like user login and appointment, the power of panda is used to create a database like a scenario with CSV.

4.6.3 Front end Repository

This repository contains the source code for the app and is publicly available through GitHub (URL on Appendix 1)

The Ionic framework leverages the power of JavaScript to create a cross-platform compatible application. Ionic is an open-source, cross-platform framework for creating high-quality mobile and desktop apps using web technologies. Given the familiarity and ease of use of JavaScript, this framework is chosen to construct the app from the ground up. Using a simple command such as "ionic cordova run android," it can create an entire apk file with the JavaScript code. The intensity of this structure has been instrumental in the application's development. Although the system can also be used to deploy iOS apps, developing an Android-compatible app as part of this research is done due to the difficulty of testing and deployment.

4.6.4 Description of the Interface

Login/Registration UI:

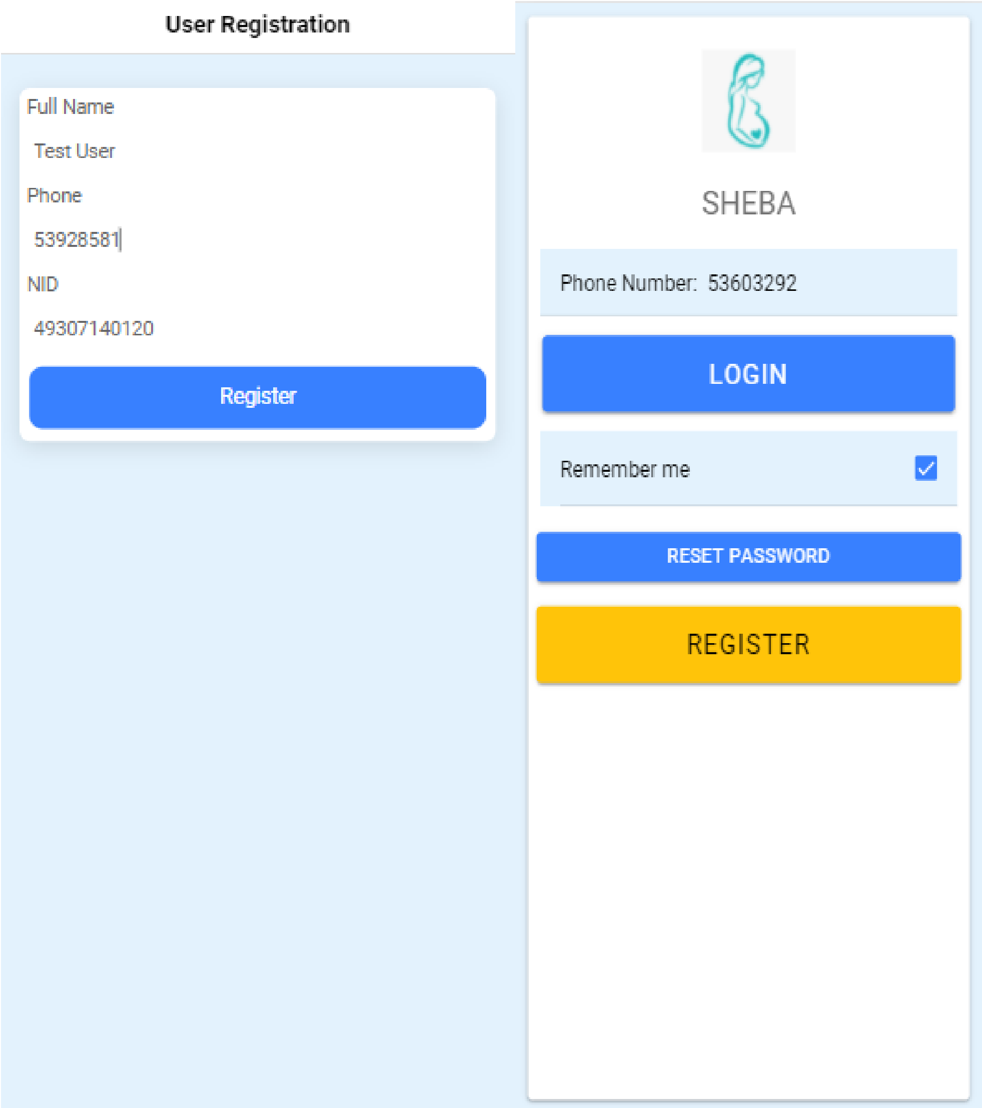

Fig 10: Login and registration UI

Users can use the register option to register in the system, as shown in the above example. After registration, the system takes only phone numbers to log in to the system. After the user inserts the phone 2FA method will be initiated (to be implemented).

Appointment UI: Users can make appointments to a hospital after inserting the date and time. Current users' appointments will be shown in the dashboard.

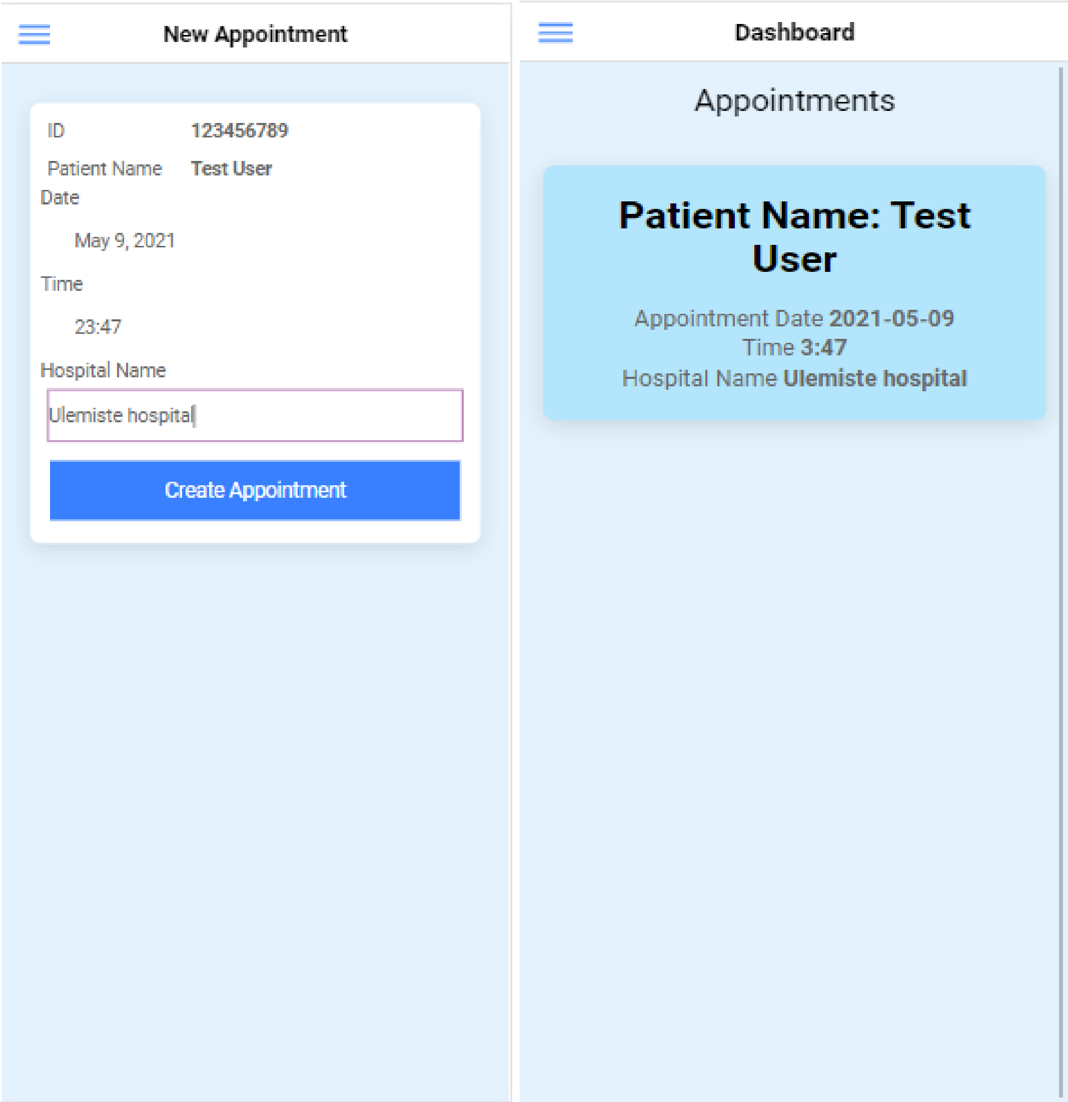

Fig 11: Appointment UI

All appointments UI: This UI is for health care workers. Health care workers can see all the appointments for the hospital in this menu.

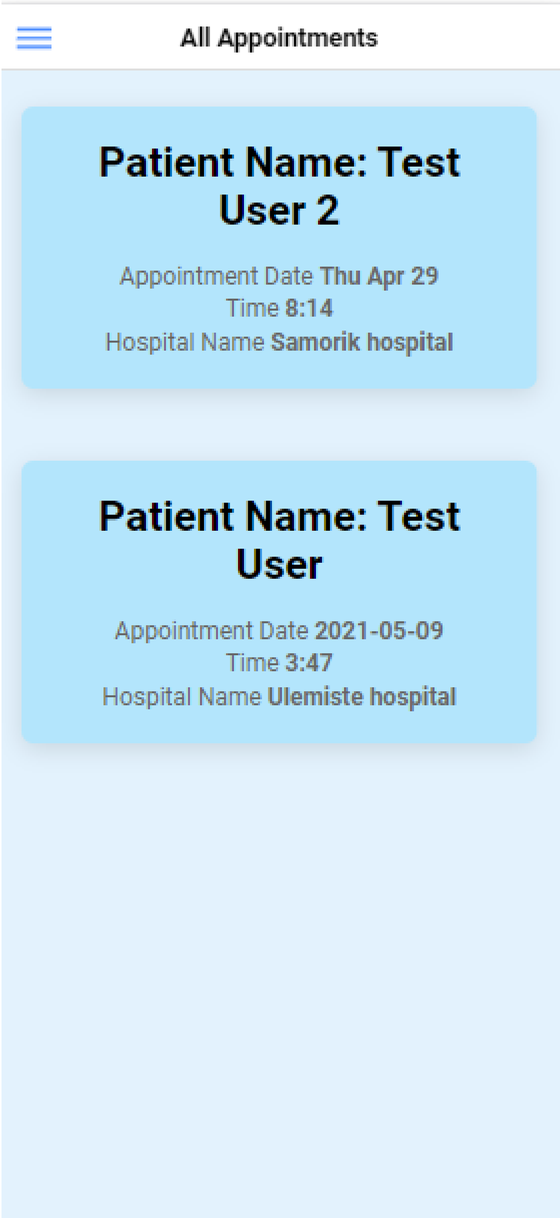

Fig 12: All Appointment UI

Consultation UI: Logged in, users can find answers for frequently asked questions from this menu with NLP trained chatbot. It is also possible to provide general advice if the chatbot is trained to do so.

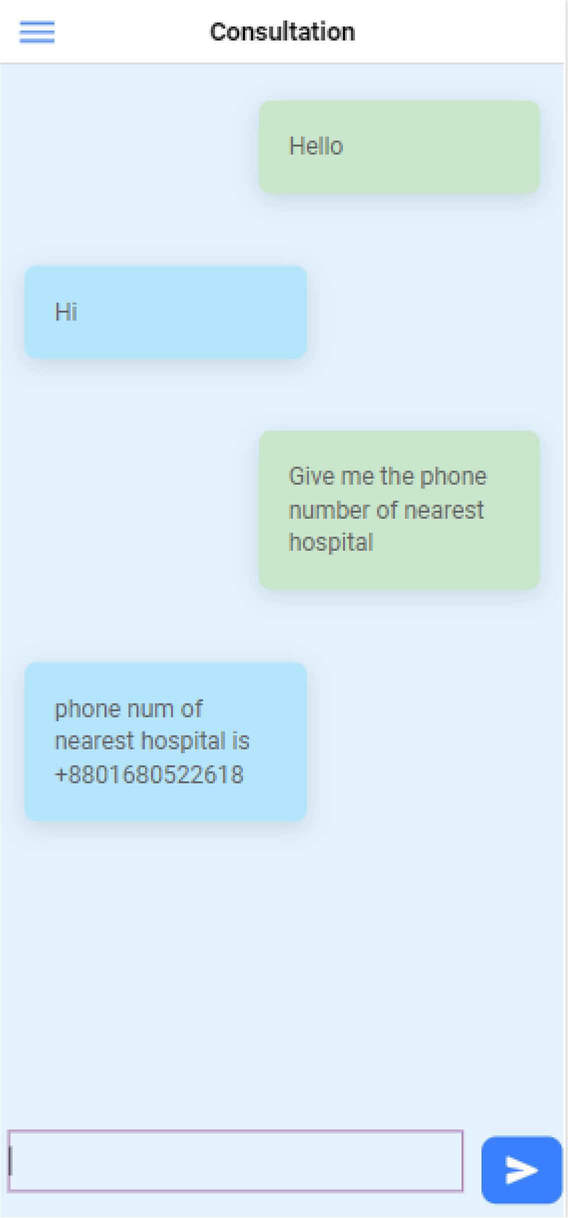

Fig 13: Consultation UI

Prediction UI: The prediction UI also is conclusive to the health care workers where the health care worker will input data of the patient. Based on the input data, the saved model will provide a prediction with an explanation.

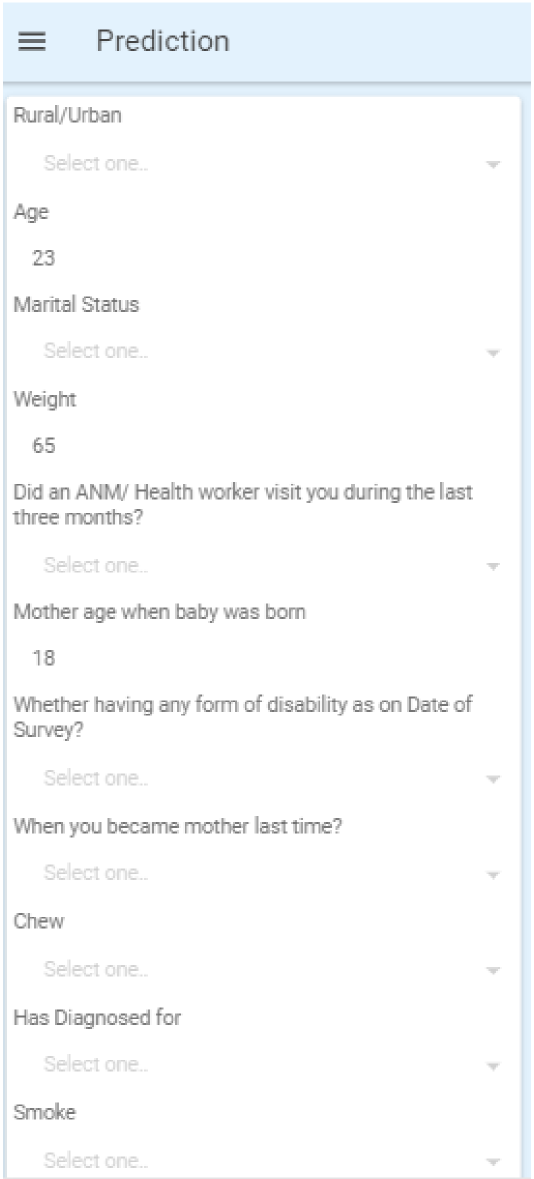

Fig 14: Prediction UI

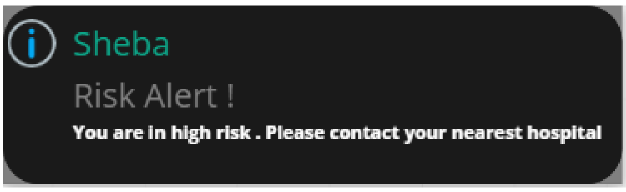

Fig 15: Notification example from the platform

If the prediction model predicts that the women fall in the risk zone based on the data provided, then a notification will be sent to the respected women's smartphone.

4.7 User Journey

To explain the user journey to the platform following is a sample persona one design based on the demographics of the target region.

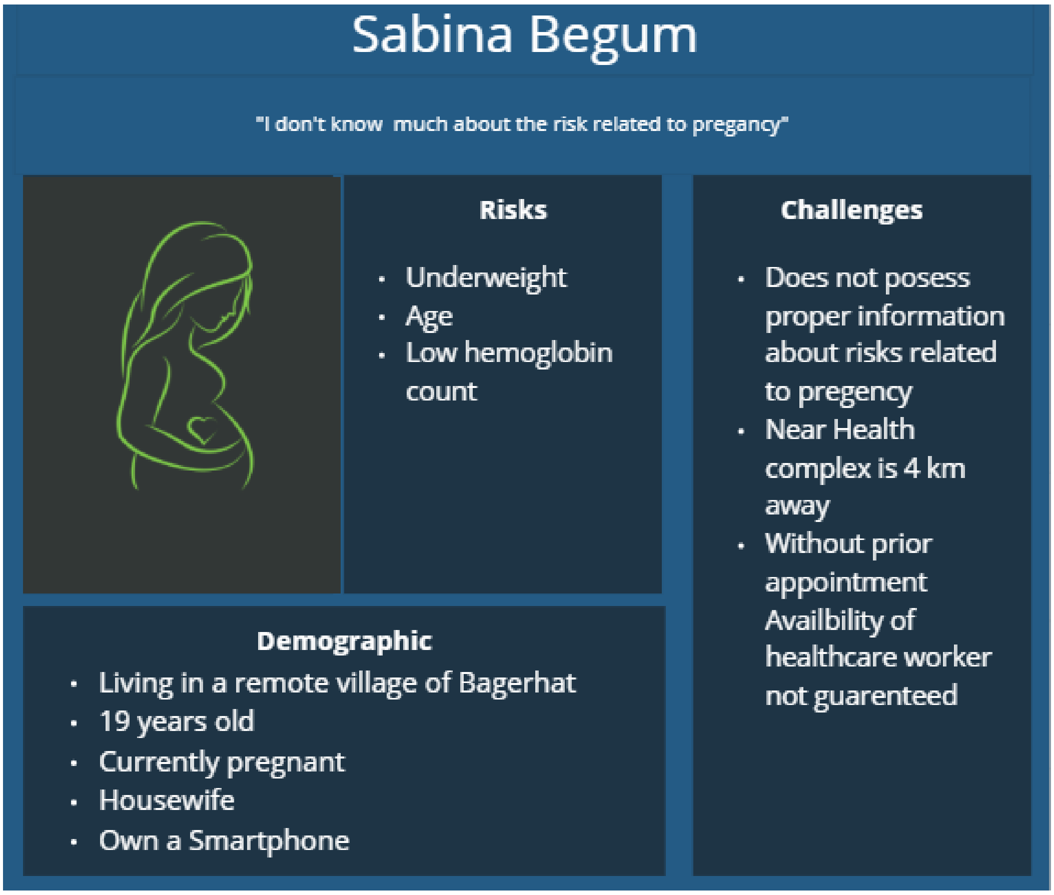

Fig 16: Sample Persona

Designed sample persona according to the design lives in remote areas in rural Bangladesh. There is one union hospital, but there were no healthcare workers to help her at that time when she visited the hospital. She was not aware of the availability. With this platform proposed, she can make appointments before visiting the hospital. This will ensure the availability of health care workers for consultation. Also, via the app, she can know essential advice. This will raise more awareness in her. As she has some pre-existing risk factors with each trimester visit, the healthcare worker can assess and save her condition in the platform. Then the prediction model can predict the risk, and if she falls under the risk category, she will get notifications and get advice from the platform. The healthcare worker will also be notified so that she can assess and take necessary precautions. This will help with the preventive measures.

4.8 User Testing

I believe that a solution that is unable to meet the needs of the users is unsuccessful. User testing often reveals personal requirements or flaws in the feature, rendering the solutions ineffective in a real-world scenario. With this in mind, I have shifted my focus to user testing.

4.8.1 Means of Testing

I intended to perform user testing with actual users after developing the initial solution. I've planned to schedule two workshops for a total of 25-30 participants. However, due to a pandemic, my nation was put on lockdown. I hoped for an improvement in the situation, but the lockout persisted. Despite these significant impediments, I was able to connect by phone with eleven correspondents. Throughout those discussions, I explained all of the solutions' functionality and how they can bring value to their lives.

4.8.2 Feedback

The overwhelming majority of them were ebullient and open to the platform. The user demonstrates a deep commitment to the site. One of the concerns they expressed was their inability to write fluently due to educational constraints. This is a legitimate issue from the user's perspective. I later intended to solve this by using native Speech to Text engines (STT) on smartphone platforms. This capability is rapidly maturing as tech giants work tirelessly to advance STT in a variety of languages. Bengali being one of those languages, I'm hoping that users will encounter no difficulties or errors in the future while using these features on the platform.

4.9 Provided values.

Without specific values, it is almost futile to build a platform. The solution tried to incorporate values based on the analysis's results and existing knowledge of the situation. Observing the challenges that pregnant women face today, I attempted to provide elegant solutions to one or more of these problems. I divided the platform's values into three categories.

4.9.1 Values for App Users

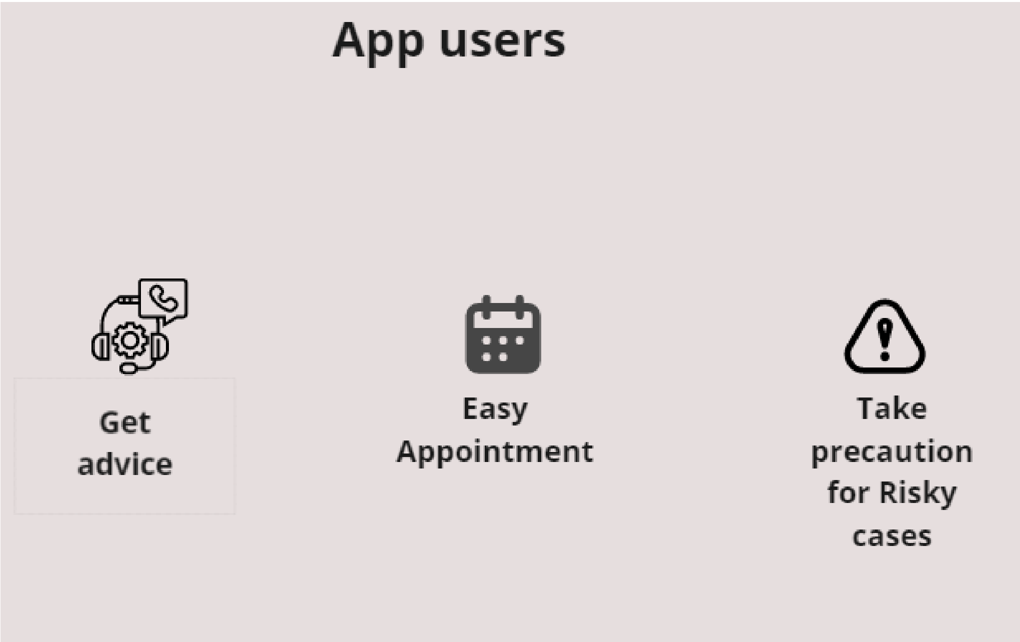

Fig 17: Values for app user

This platform is primarily aimed at pregnant women and their families. The platform's worth can be summarized in three distinct categories. With the help of the NLP-powered chatbot, one can obtain essential advice on a subject discussed and basic information such as the contact information for the nearest hospital. Each trimester visit will benefit from the convenience of an appointment. Users will be alerted if they fall into a risk category based on the health information they have given. This way, users can conveniently obtain assistance if they receive alerts from the platform, such as meeting with doctors immediately. These principles can easily have a beneficial impact on one's quality of life.

4.9.2 Values for Healthcare Professionals

Fig 18: Values for healthcare professionals

For health care professionals, the platform added value by facilitating appointment scheduling. Users can receive essential advice and information through the app's chat feature. In exchange, it would alleviate pressure on health care staff. Most significantly, understanding a patient's vulnerability enables health care professionals to take appropriate precautions to mitigate risk before anything disastrous occurs.

4.9.3 Values for Government

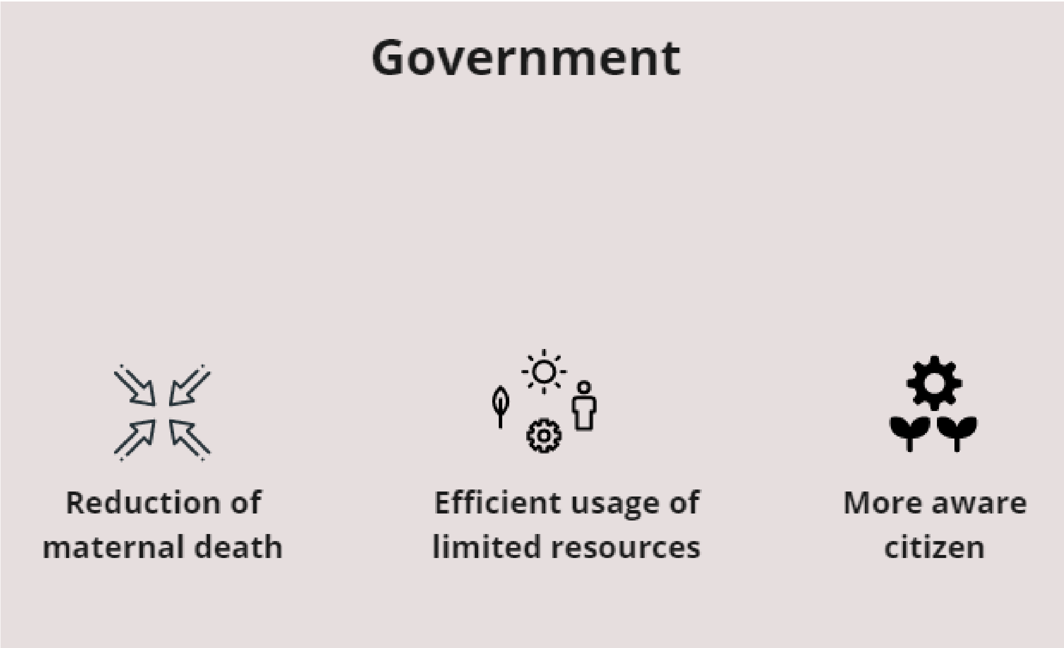

Fig 19: Values for government

The platform can contribute positively to the reduction of maternal mortality. This is a critical component of the government's Sustainable Development Goals (SDG) program (Rahman et al., 2016). Reduced pressure on healthcare staff through the consultation function ensures productive use of scarce resources. Eventually, the platform would contribute to the incremental development of more knowledgeable citizens in general, which is a significant gain for any government.

4.10 Challenges of the Platform

4.10.1 Security Issues

Since the solution relies on data to run the machine learning models, it is vulnerable to abuse or unintentional disclosure of confidential health data. Appropriate protection measures will be implemented to resolve these concerns. The targeted platform's primary objective is to act as a non-profit organization in collaboration with the Bangladeshi government. As a result of the platform's cooperation with the government, any applicable local laws about behaviour violations will apply.

4.10.2 Manipulating Model

It is possible to build a synthetic dataset on which the model performs exceptionally well and reports on the model's accuracy. Such a model will perform poorly in a real-world situation and, when implemented, will result in a more significant error margin in predictions, thus eroding the model's practicality. Synthetic model modification for overfitting is avoided and will continue to be avoided in the future.

4.10.3 Adoption of The Platform

Unfortunately, Bangladesh is one of 57 countries worldwide with an unequal healthcare system. It is on the verge of a severe healthcare crisis due to inadequate funding and a shortage of qualified health staff (Alam et al., 2019). There is frequently a perceived lack of interest in adopting digital platforms in general (Sarker et al., 2018). As a result, the adoption of this eHealth platform could face general disinterest. Proper marketing and government initiatives will help mitigate this problem.

5 Limitations

5.1 Limitations of the Implemented Features

The implemented function is limited by its nature as a proof-of-concept solution. No validation is performed during the user registration process due to a lack of time. Additionally, while the ideal solution would link to the national Smart-ID database to retrieve information, this functionality would take additional time and effort to incorporate due to its third-party dependence. As a result, this feature is not available. With little or no exposure to user interface design, the UI design is uninspiring. At the moment, the introduced consultation does not support history retention, which means that when a user logs out of the system, he or she will be unable to view any previous chat history during the subsequent session. The form for the prediction functionality is huge and tedious to complete. The focus was not on UX but rather on functionality.

5.2 Limitations Due to Datasets

This analysis was derived from vital statistics censuses conducted in nine states of India between 2010 and 2020. The dataset's accuracy is not out of doubt. It has been observed that the dataset has a disproportionately high rate of stillbirth as a pregnancy outcome. Additionally, some categorical data, such as "diagnosed for," contains information about other diseases. Rather than using generic "other" choices as categorical variables, the model's output can be improved if additional categories are given. It is possible to compensate for these limitations over time by gathering other data from real-world examples after implementing and incorporating it into the model's training data. Due to the model's current restrictions imposed by the dataset, there is less belief in the model's accuracy. Additionally, due to the model's limited computing capabilities, complete datasets cannot train it. This has likely resulted in the development of personal prejudice.

5.3 Limitations of Knowledge

As I am not directly involved in the health field, my expertise is derived from theoretical research. There is a possibility that there is an information gap about the attributes chosen for this analysis. Additionally, the demographics of the target region are rapidly changing. The knowledge applied to the target area is accumulated over time, and some of that knowledge may be obsolete today. In that case, the solution presented here could perform inadequately in a real-world scenario.

6 Recommendations and Future Works

Most implemented solutions make use of supervised learning to build the prediction model. It is possible to boost the models' accuracy by feeding them real-world data continuously. Real-world data can be collected continuously while solution is live. To accomplish this, the proof-of-concept approach must be matured with more robust functionality, and current shortcomings addressed.

Additionally, it is intended to incorporate models of artificial neural networks into this solution. For an answer to reach its optimal level, mass acceptance within the target population is critical. This can be accomplished only with the assistance of the government. Before that, the solution's absence would be reduced. Complete app features, including access control, will be introduced and an enhanced user interface and a more educated chatbot. The prediction model's accuracy should be evaluated further using real-world use cases. When these objectives are met, they will help to solidify the design solutions. Following that, the solution can be presented to the government for implementation. The implementation process will be conducted following the industry-standard software development life cycle. Although the future is challenging, I believe that it can accomplish the objectives of this study with the proper measures.

7 Conclusions

In this research, the main focus was on improving service quality for pregnant women. The focus was circled pregnancy risk identification and facilitation of accessible service provision in the local community. The platform is targeting to enhance the quality of primary health systems in Bangladesh, focusing on rural Bangladesh. Initially, the effort was given to understand the area of possible intervention. The practical aspect of machine learning was the main focus while researching for a solution. Most of the tools and technologies implemented as part of the platform have been learned chiefly as part of this research work. Online learning platforms like Kaggle initially assisted in a big way for the learning curve.

How the platform will work in the real scenario is yet to be tested. The effort is given to address the current gap. So, in theory, the platform will provide concrete values.

Although the accuracy of the ML models is not out of the question due to the quality of the dataset, it is possible to increase the correctness of the trained model with real-life data collected when the solution is implemented in a mass way. That is the beauty of ML models that it gets more accurate over time. Ease of use of the platform should address educational gaps and learning obstacles to some degree. The platform requires digital literacy. So it can not address or target digital illiterate people. The focus point was not on addressing that issue. However, efforts were given to make the learning curve as small as possible with the platform planning to take most responsibility. Taking minimalistic user info and using the NID database of Bangladesh will also use the STT engine that usually defaults to any smart device.

This topic was chosen because of the personal connection with the demographic. A careful effort is given to address and propose an improvement to the existing situation, and I believe the potential of this solution is enormous. It can create a significant impact on the life of pregnant women. In a domino effect, it will result in the overall improvement of the quality of citizens' life.

Summary

This research is divided into seven chapters that are discussed. Initially, in the introduction section, the connection and reason to choose this topic were given. The next section discussed some theoretical knowledge about the demographic of the target region and some technical topics like machine learning, NLP, feature engineering. In the next chapter, the focus was given to understand why the current situation exists based on research of the work of previous authors. After that Hypothesis is constructed, and possible intervention areas are identified. Chapter 4 is dedicated to explaining the features of the solution in detail, as well as a description of the prototype designed. This chapter also discussed user journey and user feedback. Next to that, the values the solution is proposing and the challenges to the proposed platform were discussed. The next chapter discussed the limitations of the solution; after that, recommendations and future work are provided. In concluding remarks, a holistic picture of the overall process is described in the solution context.

The practical part of the implementation of this research was very challenging. Creating an app with the features mentioned earlier was not a menial task. I am very grateful to my supervisor Pr. Sadok Ben YAHIA, for all the guidance provided that drove me towards the proposed platform.

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Appendix 2 – URL of Project Repositories

Backend system URL : https://github.com/sharifulbony/thesis-backend

Frontend system URL : https://github.com/sharifulbony/thesis-frontend