ARTIFICIAL INTELLIGENCE AND NEURAL NETWORK BASED MATERNAL AND FETAL HEALTH RISK LEVEL PREDICTION AND SENSITIVITY ANALYSIS DURING PREGNANCY

Zarin Tanzim

MASTER OF SCIENCE IN INFORMATION AND COMMUNICATION ENGINEERING
NOAKHALI SCIENCE AND TECHNOLOGY UNIVERSITY

SUPERVISOR'S DECLARATION

We hereby declare that we have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science in Information and Communication Engineering.

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Name of Supervisor: DR. MD. ASHIKUR RAHMAN KHAN

Position: PROFESSOR & CHAIRMAN

Date:

STUDENT'S DECLARATION

I hereby declare that the work in this thesis is my own except for quotations, references and summaries which have been duly acknowledged. This thesis has not been accepted for any degree and is not concurrently submitted for award of other degree.

Zarin Tanzim

Roll: BKH2011MSc118F

Date:

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ABSTRACT

Health of women throughout pregnancy, childbirth, and the postpartum period is referred to as maternal health. To ensure that women and their unborn children achieve their maximum potential for health and wellbeing, each stage should be enjoyable. The majority of pregnancies and deliveries are successful, but complications do happen occasionally and when they do, they can have devastating effects on both mothers and infants. Through a better understanding of risk factors, increased surveillance, and more early and suitable interventions, predictive modeling has the potential to enhance outcomes and assist gynecologists in providing better care. Dataset used for analysis is collected from the local hospitals of Noakhali District. For the analysis, the main risk factors considered are age, Blood pressure (systolic), Blood pressure (diastolic), Body temperature, maternal heart rate, blood glucose, hepatitis B, TSH, serum SGPT, serum uric acid, fetal heart rate, amount of amniotic fluid ,fetal movement and obesity. The dataset contains the details of these features of women during their pregnancy. Data preprocessing is done by mapping naming value, handling missing value by prediction, selecting important feature and feature scaling etc. Correlation is also checked for numerical values. Data is then divided for training and testing, and the best accuracy for each prediction model is then determined. These models include Multinomial Logistic Regression, Naive Bayes, K-Nearest-Neighbors, Support Vector Machine (SVM), Decision Tree, Random Forest, and Neural Network Multilayer Perceptron. Accuracy of MLR, MNB, KNN, SVM, DT, RF and MLP algorithm is 89.58%, 80.13% , 100.0%, 90.23%, 100.0%, 100.0% and 100.0% respectively. The DT, RF and MLP algorithms also gives the best precision, recall, f1-score and ROC_AUC score i.e. all are 100.0%. In comparison to other algorithms, the DT, RF, and MLP perform best in terms of accuracy, precision, recall, f1-score, and ROC_AUC score. The input and target variables will also be subjected to sensitivity analysis to determine which input parameters have the greatest impact on risk. According to sensitivity analysis, the following factors have a significant impact on the risk to the mother's and the fetus's health: blood pressure(systolic & diastolic) fetal movement, fetal heart rate, and the amount of amniotic fluid. By avoiding maternal and child morbidity during pregnancy for areas of Bangladesh, this effort will help to improve healthcare for expectant mothers and their fetuses.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
MLP	Multilayer Perceptron
SVR	Support Vector Regression
CART	Classification And Regression Tree
KNN	K – Nearest Neighbor
ROC	Receiver Operating Characteristic
TN	True Negative
TP	True Positive
FN	False Negative
FP	False Positive
TPR	True Positive Rate
DT	Decision Tree
MLR	Multinomial Logistic Regression
MNB	Multinomial Naïve Bayes
SVM	Support Vector Machine
RF	Random Forest
AI	Artificial Intelligence
ALT	Alanin Aminotransferase
MATLAB	Matrix Laboratory
WHO	World Health Organization
NN	Neural Network

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

This research study was conducted to find a model that predicts maternal and fetal health risk levels and perform sensitivity analysis to know which factors influence the risk most. This chapter discusses the impact of maternal and fetal health-related risk and the challenges of detecting the risk level and identifying the most influencing risk factors. The background, research motivation, problem statement, objectives, scope, and structure of this research are covered in this chapter.

1.2 BACKGROUND STUDY

A woman's gestational pregnancy stage is when both the mother and the fetus may have problems. The fetus's health may be impacted by the mother's adaptive changes throughout this time, her medical history, and maternal/familial traits. Therefore, monitoring fetal health and receiving prenatal care during this stage is vital for both the mother's and the fetus' health [1]. Gynecologists, in particular, want to tell parents about the health of their unborn children, and they do so based on previously studied instances and prior experiences. Therefore, identifying the potentially familial (primarily maternal) clinical information that may impact fetal health would benefit antenatal maternal care. However, several obstacles, such as a lack of facilities nearby the patient's location (outlying rural communities) or overcrowding in urban hospitals, may prevent patient-oriented healthcare from being fully implemented.

Because there is a lack of information regarding maternal health care during pregnancy and after delivery, many pregnant women pass away from pregnancy-related illnesses. The poor middle class and rural parts of developing nations are particularly affected by it [2]. For the healthy growth of the fetus and to ensure a safe birth, every minute should be watched during pregnancy. Massive traffic congestion, unfavorable weather, pollution, etc., are significant issues for the hospital's ongoing checkups. Finding the underlying causes of maternal health-related problems is crucial for early warning signs [3]. This research has ensured that pregnant women receive alternative treatment, especially those living in rural locations.

Our main goal is to provide Artificial Intelligence and machine learning along with a neural network-based system that uses a dataset of pregnant patients' clinical history and data to learn how to predict outcomes. Based on the trained dataset, the system generates a result that considers maternal and fetal health. In this approach, the system's output enables both parties to take safeguards and provides them with knowledge before delivery. The suggested machine learning system employs a unique learning strategy. The methodology section will go into great detail about these methods.

1.3 MOTIVATION FOR THE STUDY

There are many risk factors to monitor throughout pregnancy. Age, Body Mass Index (BMI), Blood Oxygen (BO), Blood Pressure (BP), Body temperature, and Physical Activity are the variables. Maternal ECG, vaginal discharge during the first trimester, nausea during the first trimester, contractions during the third trimester, fetal heart rate (FHR), abnormal fetal protein (AFP), uterine electrical activity (EUA), fetal movement activity, and so forth. We must consider these factors' cutoff points or units of measurement [4]. The critical focus for preserving excellent health throughout pregnancy is prompt diagnosis and appropriate treatment. Early prenatal care and diagnosis prevent unnecessary maternal and newborn deaths, especially in rural settings [5].

One of the benefits of Industry 4.0 technology is the significance of artificial Intelligence, machine learning, and neural networks in mission-critical industries like healthcare. However many developed countries have done much research based on this type of maternal and fetal health risk factors, but much research has been done in Bangladesh. Again, region-based research on this topic has yet to do much, which is mandatory to take necessary steps to prevent maternal and fetus morbidity. Knowing the present situation of this sector is very important to upgrade the service of this sector. Artificial Intelligence and machine learning, along with the neural network-based system, help us in this situation to predict the risk level in advance by analyzing the maternal data and helps to take necessary steps in advance according to the level of risk.

Since a majority of maternal and fetal morbidity happens in most cases due to the lack of prediction of the situation of a mother during pregnancy, and these types of unconscious condition influences the risk for both the mother and the child. Developing Artificial Intelligence and machine learning along with a neural network-based model using the maternal and fetal health data from a region will help medical specialists to understand the situation of a specific area and take proper steps. It will also help the govt. To know about the whole scenario and take necessary steps like enabling the appropriate medical facility and adequate service to prevent maternal and fetal morbidity during pregnancy and at the time of childbirth. It will also help gynecologists to make an accurate decision for a specific patient based on the previous health record of the patient. Again some risky situations can be prevented if the symptoms are known early. This research will help to ensure healthy maternal and fetal health during and after pregnancy by predicting the risk level in advance.

1.4 PROBLEM STATEMENT

According to the WHO, 810 women worldwide pass away each day due to difficulties during childbirth and pregnancy [6]. Most (94%) of maternal deaths occur in low- and lower-middle-income countries. Although the number of maternal mortality is declining as a result of recent technological advancements [7, 8], it is still difficult to ensure the safety of both mother and fetus during pregnancy. By anticipating the problems and taking preventative action, the risks associated with pregnancy in this situation can be decreased. Predictive modeling emerged as a result, saving the lives of millions of women and babies.

Such deaths are typically caused by obstetric problems such as hypertension, prolonged labor, and similar conditions [9]. Unfavorable delivery conditions, such as significant blood loss, failure to progress (FTP) labor, atypical fetal presentation, preterm birth, and others, can cause severe maternal problems [10], endangering the lives of both the mother and the unborn child. Also, the imbalanced range of the factors like age, Blood pressure (systolic), Blood pressure (diastolic), Body temperature, maternal heart rate, blood glucose, hepatitis B, TSH, serum SGPT, serum uric acid, fetal heart rate, amount of amniotic fluid, fetal movement and obesity during pregnancy influences the risk of maternal and fetal morbidity. However, most of these issues are preventable, and appropriate steps should be taken to ensure a delivery method that poses little danger.

Studies have been conducted in recent years to forecast potential pregnancy risks and forecast the delivery technique most appropriate for the moms' pregnancies. The preterm birth risk factors were predicted by Chen et al. [11] using a Neural Network (NN) and Decision Tree (DT) approach. Similarly to this, Rawashdeh et al. [12] used Random Forest (RF), DT, K Nearest Neighbors (KNN), and NN to predict the probability of premature birth. These studies used several ML approaches and displayed a range of performances. Again, the sort of information employed in this research varied. Examples include demographic data, maternal information, obstetric characteristics, medical and obstetric history, ultrasound measures, behavioral data, and the like. The primary objective of this study is to examine contemporary theories of research and development that center on machine learning (ML) to predict and identify various risk levels of maternal and fetal health during pregnancy.

1.5 RESEARCH OBJECTIVES

The focus is to find the best performance by providing an algorithm for the prediction of maternal and fetal health risk levels. Hence the main objectives of this research are:

I. This research will propose a computerized method of predicting the risk level of maternal health in the context of the Noakhali District.

II. To contribute to reducing maternal mortality by predicting the risk level in advance and taking necessary steps.
III. Work with a method that will be less prone to errors because it is automated and machine learning-based.
IV. To contribute to the fulfillment of the Bangladesh govt. Sustainable Development Goal (SDG) by predicting the risk level of maternal health and taking the necessary steps to reduce maternal mortality.

The rest of the paper describes several related works, methodology to reach the desired target, desired outcomes, and conclusion. The methodology chapter describes the way of data collection and preprocessing, using the procedure of the algorithms and process to analyze performances. After the methodology chapter, there is an expected outcome chapter. In this chapter, interpret the predicted outcome. The final chapter, the conclusion, narrate this paper and describe a different perspective.

1.6 SCOPE OF THE STUDY

This study's data for prediction came primarily from one source. The information is gathered from pregnant women treated at hospitals in Noakhali. Pregnant women's information is collected utilizing a form. Matlab and Anaconda3 are necessary tools for carrying out this work.

1.7 THESIS OUTLINE

There are five chapters, including this Introduction chapter. Figure 1.2 shows all chapters.

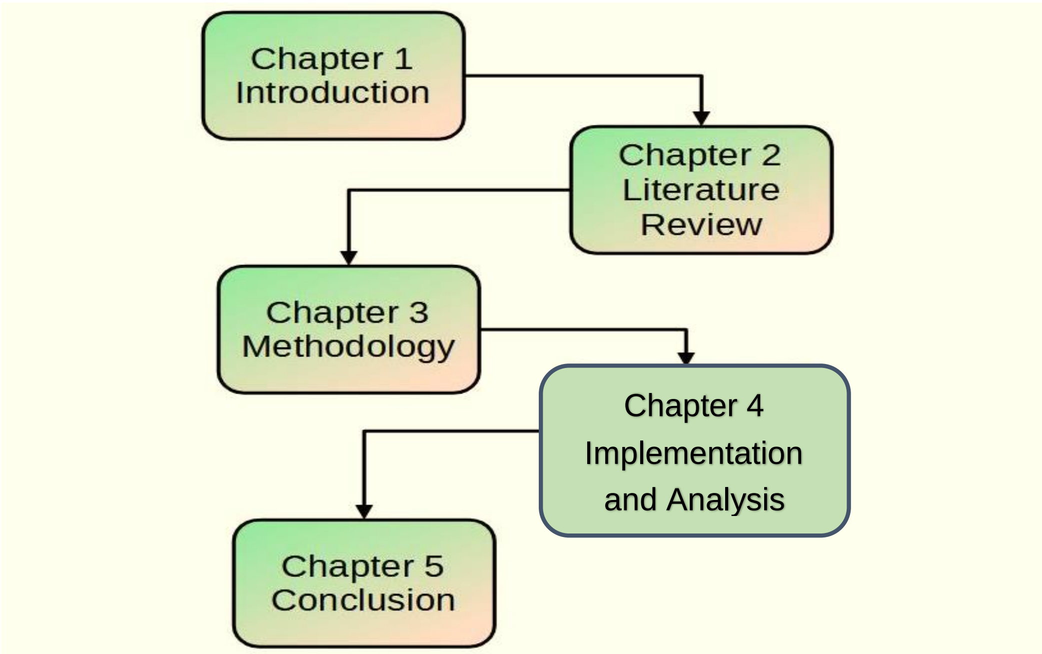


Figure 1.1: Chapters in this thesis report.

The introduction chapter explained the problem statement, the objectives, and the limitation of the thesis. The rest of the paper describes several related works and methodologies to reach the desired target, result, and conclusion. The methodology chapter describes the way of data collection, using the procedure of the algorithms and process to analyze performances. After the methodology chapter, there is a chapter named Result and Discussion. In this chapter, interpret the outcome of the model. The final chapter, the conclusion, narrate this paper and describe a different perspective.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Risk factors associated with maternal and fetal health must be monitored throughout pregnancy. Many countries are becoming more aware of its impact and taking proper care of pregnant mothers. Additionally, much research work has also been performed based on maternal health. The issue is that most of the work is performed abroad and the basis on online data. Only a few studies have been based on real data collected from Bangladesh. This literature review examines the previous work those have been performed on maternal and fetal health and prevention techniques held in different countries.

2.2 LITERATURE REVIEW

Artificial Intelligence and Machine learning are becoming increasingly widely used in practically every field. These techniques enable researchers to address diagnostic and prognostic issues across various medical specialties [13]. Emerging themes in next-generation healthcare applications include automatic treatment systems or patient recommendation services, medical signal analysis, long-term patient tracking and analysis, medical image and sound processing, drug development, and assistive robotic surgery. Medical diagnosis is arguably the most promising use of machine learning in the healthcare industry. The most well-known implementations involve developing decision support systems for analyzing brand-new cases utilizing training data sets and dealing with improper medical data, such as noise or missing data.

This section discusses some of the most well-known research initiatives on applying machine learning techniques to predict pregnancy risks and fetal health. Low birth weight (LBW) risk in pregnancy was predicted by Yarlapati et al. using machine learning techniques as a significant indicator of fetal health. [14]

Based on Indian health care data, they could predict the fetal state as LBW or NOTLBW with a 96.77% accuracy by applying the Bayes minimal error rate classifier. In another study [15], the right needle insertion site is identified using ultrasound scans of pregnant individuals' lumbar spines. A Support Vector Machine (SVM) with a Gaussian kernel is used to identify the interspinous region. The suggested model had a 95.00% success rate when tested with 640 photographs from a different group of 16 pregnant patients after being trained with 800 images from 20 pregnant participants.

The impacts of risk factors such as age and hematocrit over the gestational age of pregnant women were examined by Cheng et al. [16]. This study's main contribution is that it shows how different recognized risk variables affect 412 pregnant women with gestational hypertension and preeclampsia groups, comprising 1874 clinical follow-up records. Woolery and Grzymala-Busse researched predicting the probability of preterm birth [17]. They employed 18,890 subjects and 214 factors to develop an expert system to assess the probability of preterm birth. For 9419 cases, their suggested approach was 53–88% accurate in predicting premature delivery.
Antepartum cardiotocography (CTG) data was employed with eight machine learning algorithms, such as ANN, SVM, k-NN, RF, and CART, to investigate predicting fetal health [18].

C4.5 decision tree classification algorithm and Naive Bayes kernel algorithm are two examples of previous research on machine learning in medical diagnosis and prediction; applications of these algorithms include predicting and presenting gestational risks [19, 20] and normal or abnormal stages of pregnancy[21].
Making a prognosis for preeclampsia disease in pregnant women was the goal of Kenny et al. [22]. Using 97 plasma samples, they employed genetic programming to confirm the patterns of metabolites that separate plasma from patients with preeclampsia. Smyser et al. study .'s [23] used

multivariate pattern analysis on data from neonatal functional MRI to predict brain maturity and neurodevelopmental outcome in neonates. Individual babies' birth gestational age was accurately predicted by SVM 84% of the time (p b 0.0001).

Cardiotocography (CTG) was the main topic of Czabanski et al. [24] .'s study for the biophysical evaluation of the fetal condition. The classification of fetal heart rate (FHR) signals using a fuzzy approach is done as the initial stage. The proposed method is successful in the second phase, with the maximum CC = 92.0% and Q.I. = 88.2%, utilizing Lagrangian Support Vector Machines (LSVM). In the study [25] that models fetal brain development, 105 preterm newborns had their whole-brain functional connectivity examined. Using the SVM approach, connections were estimated with an accuracy of 80%.
Results were produced in this regard for regions where the analysis of magnetic resonance images (MRIs) could not adequately interpret. In their CTG analysis of infants, Krupa et al. [26] used empirical mode decomposition and SVM.

With a UCI dataset [27] made up of fetal heart rate and uterine contractions, Ocak [28] conducted a CTG analysis and proposed an SVM-based model for estimating fetal health. Enabling the genetic algorithm to remove the irrelevant characteristics from the dataset improves the classification performance of the SVM. His suggested method correctly predicted whether a prenatal condition was abnormal or normal with 99.3% and 100% accuracy, respectively. Using a modular neural network, research using a separate UCI dataset with 2126 fetal CTG recordings makes a complete prediction of pathologic cases [29]. On the same dataset, the traditional neural network method also produces results with high accuracy [30].

Much research is being done in the Artificial Intelligence and machine learning field for biological decision-making. A machine learning-based approach that uses supervised machine learning algorithms to predict neonatal death has been put out by Mboya IB et al. [31]. Numerous aspects of childbirth are predicted using ML-based models. For instance, Abraham, Abin, et al. developed a new method for extracting data from EHRs to use several machine learning models to predict singleton preterm delivery [32]. Recent research on childbirth modes has been presented by Islam, Muhammad Nazrul, et al., with two main findings: first, the potential highlights for selecting the labor mode, and second, machine learning algorithms for determining the most appropriate labor mode (vaginal birth, crisis cesarean, cesarean birth) [33].

Table 2.1: A survey on existing research in maternal and fetal health

Author And Year	**Source of data**	**Method**	**Advantage and limitation**
N.S.Prema et al.(2019)[34]	Local hospitals of Mysuru, Karnataka state, India.	support vector machine (SVM) with linear and nonlinear kernels and logistic regression,	**Advantage:** Accuracy range between 70% to 90%. **Limitation:** the risk factors considered are limited, and the data sample size is also small.
Kowsar et al. (2021)[35]	Trail Upazilla Health Complex, a specialized clinic for maternal care located in Trail, Kishorganj, Bangladesh	•Decision Tree •Extra Tree •AdaBoost •Bagging •Gradient Boosting •Enable Hist Gradient •Random Forest •Radios Neighbor •K-Nearest Neighbor	Advantage: Accuracy range between 75% to 98%. Limitation: The dataset used in this project is not very robust.

Author And Year	**Source of data**	**Method**	**Advantage and limitation**
M. Nazrul Islam et al.(2022)[36]	The primary articles or studies were searched in different sources such as Google Scholar, SpringerLink, IEEE Xplore, ScienceDirect, etc.	A systematic literature review (SLR) approach provided by Kitchenham et al. was followed to attain the review objectives.	**Advantage**: This will help scholars and practitioners (health professionals) understand ML's significance in real-time decision-making regarding pregnancy and can be a prominent aid in reducing maternal threats. **Limitation:** The search keywords may not encompass all the relevant articles. Again, the inclusion criteria used for selecting the articles may not be able to cover all the related articles.
Yuhan Du et al (2022)[37]	Clinical data collected at the PEARS randomization visit (14.91±1.66 weeks gestation, also referred to as the baseline)	Machine learning algorithms, namely logistic regression, random forest, support vector machine (SVM), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost) for data modeling	**Advantage:** At approximately 28 weeks gestation, 71 (14.67%) were diagnosed with GDM, and 413 (85.33%) were not. The AUC-ROC score is 79.2%. **Limitation:** further cross-cultural/ethnic testing, preferably on much larger sample size, is needed to investigate the optimal decision threshold for different minority cultural or ethnic groups.

Author And Year	Source of data	Method	Advantage and limitation
Tomas M. Bosschieter et al.(2022)[38]	The real-world clinical data used in this analysis are from the Foundation for Health Care Quality's Obstetrical Care Outcomes Assessment Program (OB COAP).	• EBM • Logistic Regression • XGBoost • Random Forests • DeepNeural Network(DNN)	**Advantage:** ROC-AUC score range is between 74% to 76%. **Limitation**: The sample of data should be increased.
N. Imtiaz Khan et al.(2020)[39]	Used the dataset prepared by Campillo-Artero et al. [40] to build efficient and effective ML models.	• AdaBoost • CatBoost • XgBoost	**Advantage**: Accuracy is between 85% to 90%. **Limitation**: As for limitation, three ML methods were used, which is narrowly adequate, and only 11 features were considered for developing the ML models
V.Madhusri et al.(2019) [41]	Data was collected through Hospitals, Healthcare centers, and Personal Interviews.	Naive Bayes, KNN, and SVM (support vector machine) predicting algorithm to predict the outcomes of the complications in pregnancy.	**Advantage**: Accuracy is between 78% to 90%. **Limitation:** Dataset is not robust.

2.3 SUMMARY

In big data science, data mining and machine learning have the most significant and rapidly expanding features for knowledge discovery from a dataset. This advantage is frequently used to predict risk after mining steps like classification, pattern prediction, clustering, attribute selection, etc. [42]. In contrast to their previous research, this research will demonstrate and evaluate multiple supervised classifiers, Deep Neural Networks, and Artificial Intelligence methodologies using a real dataset of maternal health reports to determine the most effective model for predicting the risk level in the context of Noakhali District.

Several risk factors for maternal mortality have been thoroughly examined and demonstrated in this study. Risk factors are those things that make getting sick more likely. The classification and forecasting of pregnancy risk intensity is a complex issue. The risk parameter gathered and displayed here is very important.

Few methods have been developed to categorize, examine, and forecast maternal and neonatal health risk.

CHAPTER 3

METHODOLOGY

This methodology chapter explains how information was gathered from various Noakhali hospitals. Manual data collection was done at numerous hospitals. This chapter provides an explanation of the data gathering formula. Discussions also include the feature extraction method and classification models. The parameters for the model performance study are mentioned at the end of the chapter.

3.1 INTRODUCTION

The work of researchers during the preceding several years was described and evaluated in the previous section.

To develop our proposed model, we went through four crucial steps: dataset development, data preprocessing, model training, and model performance evaluation. The steps involved in our proposed study are shown in Figure 3.1:

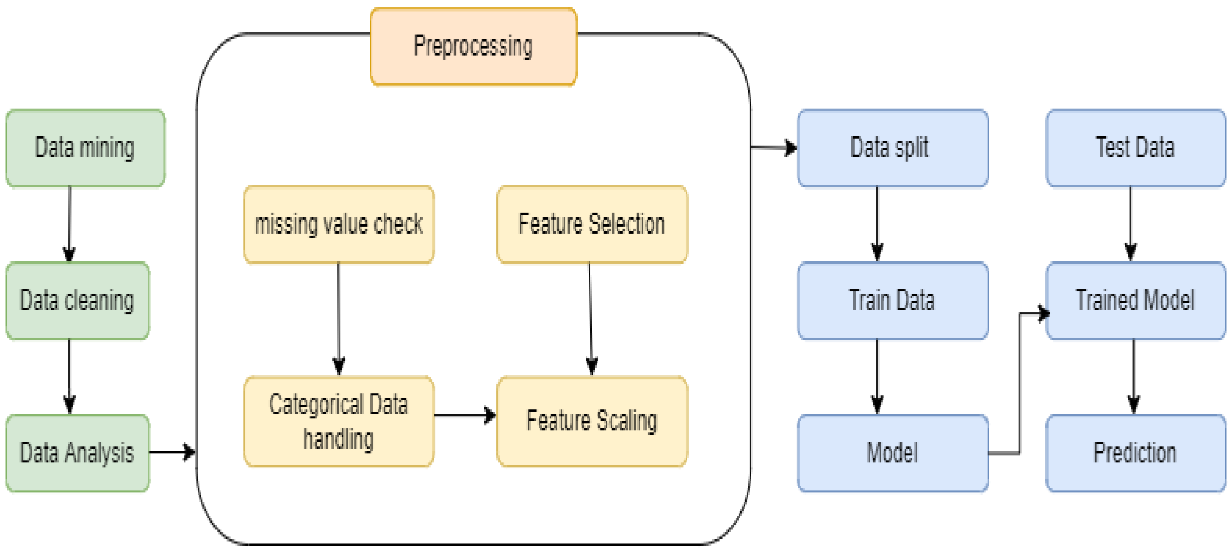


Figure 3.1: Phases involve in our research work.

3.2 DATASET PREPARATION

The first step of this research work was dataset creation. Complete attribute description of the dataset is given below.

1. **Age:**

Age of the patient. Age can be numeric value like 10 – 45.

2 Systolic Blood Pressure:

Systolic blood pressure (the first number) measures the force that the heartbeats' blood exerts against the artery walls. Blood is pushed via arteries to the rest of the body when the heart beats. Systolic blood pressure is the result of the pressure that this force puts on certain blood vessels. Systolic pressure should be under 120. A value between 120 and 129 is considered high. It could take the form of a number.

3. Blood Pressure Diastolic:

` The second number, or diastolic blood pressure, describes how much force blood is applying to artery walls while the heart is at rest in between beats. A healthy diastolic blood pressure reading is under 80. It might have a numerical value.

4.Maternal Heart Rate:

The number of times a person's heart beats each minute is known as heart rate or pulse. While everyone's definition of normal heart rate is different, people often fall between the range of 60 to 100 beats per minute. It might be a number.

5.Fever,cough or cold :

An abrupt increase in body temperature is known as a fever. It is a portion of the immune system's overall reaction. An unexpected expulsion of air through the wide breathing passages during a cough can help rid them of fluids, irritants, foreign objects, and bacteria. An inhale, a forced exhalation against a closed glottis, and a violent expulsion of air from the lungs after opening of the glottis are the three phases of the cough reflex, which can be recurrent and usually accompanied by a characteristic sound. It could have a notional value, such as yes or no.

6.Body Temperature:

Body temperature is 98.6 F on average (37 C). However, the typical range for body temperature is between 97 F (36.1 C) and 99 F. It might be a number.

7. Fetal Movement:

In a typical 2-hour period, there should be at least 10 motions. Anything different from this is abnormal. It might have a numerical value.

8. Obesity:

A person is considered underweight if their BMI is under 18.5. A person is within the healthy weight range if their BMI is between 18.5 and 25. When a person's BMI is between 25.0 and 30 it is considered to be overweight. One is considered obese if their BMI is 30.0 or greater. It might be a simple yes/no answer.

9. BMI(Body Mass Index):

Simple math is used to determine a person's body mass index using their height and weight. BMI is calculated as follows: kg = weight in kilograms/m2, where m2 equals height in meters squared. It might be a number.

10. Blood glucose (2-h glucose):

Impaired glucose tolerance refers to a 2-hour result between 140 and 200 mg/dL (7.8 and 11.1 mmol/L). One of the results is tolerance. It denotes a higher long-term risk of getting diabetes. The value may be numerical.

11. Blood glucose (Fasting glucose):

For non-diabetics, a fasting blood glucose level of between 3.9 and 7.1 mmol/L (70 and 130 mg/dL) is considered normal. The value may be numerical.

12. Blood glucose (HbA1c):

The A1C test, sometimes called a HbA1c test or a hemoglobin A1C test, is a quick blood test that assesses a person's average blood sugar levels over the previous three months. One of the often utilized tests to identify prediabetes and diabetes, it serves as the primary test for assisting the patient and her healthcare team in managing their diabetes. The value may be numerical.

13.HBsAg (Hepatitis B surface antigen):

Hepatitis B surface antigen (HBsAg) test results that are "positive" or "reactive" signify that the subject has hepatitis B. The "surface antigen" of the hepatitis B virus, which is detectable by this test, can be found in a specific person's blood. The value may be nominal and either positive or negative.

14. TSH(Thyroid Stimulating Hormone):

The term TSH refers to thyroid stimulating hormone. This hormone is measured by a blood test called a TSH test. A thyroid issue may be indicated by TSH levels that are either high or low. It might have a numerical value.

15. ALT, SGPT (serum):

Alanine aminotransferase, also known as ALT or SGPT, is measured by an ALT test. One of the enzymes that aids the liver in turning food into energy is ALT. These enzymes can leak out of the liver cells when it is wounded or irritated, which can be indicated by high levels of these enzymes. The value may be numerical.

16. Uric acid (serum):

A serum uric acid measurement, commonly known as a uric acid blood test, measures the amount of uric acid in a person's blood. The examination can reveal how well a person's body manufactures and excretes uric acid. When the body breaks down foods that contain purines, an organic substance, uric acid is created. The value may be numerical.

17. Fetal Heart Rate:

Fetal heart rates typically range from 110 to 160 beats per minute. 5 to 25 beats per minute can be different. The fetal heart rate may fluctuate as your unborn child adjusts to the environment in your uterus. Your baby may not be getting enough oxygen or may be experiencing other issues if the fetal heart rate is irregular. The value may be numerical.

18. Amniotic Fluid Index :

Using the accepted evaluation method, an amniotic fluid index of normal range is between 5 and 25 cm. Oligohydramnios, or less than 5 cm, and polyhydramnios, or more than 25 cm, are both medical terms. The value may be numerical.

19. Risk Level:

This number represents the level of risk that the pregnant woman and her fetus are at. determination of risk level (0: low risk, 1: mid risk and 2: high risk). Risk ranges are described in the table below:

Table 3.1 : Pregnancy-related medical parameters with corresponding values and their weights

Parameters	Low risk	Mid risk	High risk	References
Blood pressure	Systolic 120–139 mm Hg, diastolic 80–89 mm Hg	Systolic 140–159 mm Hg, diastolic 90–99 mm Hg	Systolic 160 mm Hg or greater, diastolic 100 mm Hg or greater	[43]
Maternal Heart rate	Heartbeat 75–80 bpm	Hear beat 90–140 bpm	Heartbeat >70 and <140 bpm	[44]
Fever, cough or cold	no	no	yes	[45].
Body temperature	Averages about 98.6 F (37 °C)	<98.6 F (37 °C) and > 102 F (38.9 °C)	102 F (38.9 °C) or higher and (>35 °C or > 95 F) = Hypothermia	[45].
Fetal movement	10 movements such as kicks, flutters, or rolls. within 12 h; 6 k/2 h	10 movements flutters, or rolls. within 12 h; 6 k/2 h	>10 movements such as kicks, flutters, or rolls. within 12 h; >6 k/2 h	[45].
Age	20–29	30–35	35–45	[45].
Obesity	no	no	yes	[45].
BMI	(18.5–24.9 kg/m^2)	(18.5–24.9 kg/m^2)	Underweight (18.5 kg/m^2) overweight (25–29.9 kg/m^2), obese (30–34.9 kg/m^2)	[45].
Blood glucose (2-h glucose)	<7.8 (<140) mmol/l (mg/dl)	<7.8 (<140) mmol/l(mg/dl)and ≥ 7.8 (≥140)	≥mmol/l (mg/dl)11.1 (≥200)	[46]

Parameters	Low risk	Mid risk	High risk	References
Blood glucose (Fasting glucose)	<6.1 (<110) mmol/l(mg/dl)	≥6.1 (≥110) and < 7.0(<126) mmol/l(mg/dl)	≥7.0 (≥ 126) mmol/l(mg/dl)	[46]
Blood glucose (HbA1c)	<42 mmol/mol	42–46 mmol/mol	≥48 mmol/mol	[46]
HBsAg (Hepatitis B surface antigen)	negative	negative	positive	[46]
TSH	2.5–3.5 mIU/L	3.5–4.5 mIU/L	>4.87 and <0.25 mIU/L	[47]
ALT, SGPT (serum)	3 – 30 U/L	30 – 35 U/L	>45 U/L	[48]
Uric acid (serum)	375 – 393 µmol/L	393 - 400 µmol/L	>400 µmol/L	[49]
Fetal Heart Rate	110 – 160 bpm	160– 200 bpm	>200 bpm	[50]
Amniotic Fluid Index	5-20 cm	20-25 cm	>25 cm and <5 cm	[51]

3.2.1 Data Collection

We had a challenging time collecting the data. We gather information over the course of three months from various hospitals and clinic facilities. Our goal is to collect 1,000 sets of data with a variety of features. We then choose those attributes that are significant and prevalent among the greatest number of patients. We choose 20 qualities, of which 19 are independent and 1 is dependent on the desired value (low risk, mid risk, or high risk). The information is gathered from many hospitals, including Ma o Shishu, Goodheal, Motherland, Janani General, and Noakhali Sadar. Basically, people that are admitted to the hospital are where we gather the most data. Patients are questioned, their test results are analyzed, and significant attribute data is gathered. But several of the values for the various properties were slightly absent. The quantity and caliber of the data that we gather have a significant impact on the proposed model's efficacy. Our model will perform better the more data we gather. However, our objective is to compile data on at least 1000 patients' test results along with their responses to various questions. Collecting information from various sources proved to be a difficult issue for us. The process of gathering data was iterative; throughout time, we visited several different hospitals. Finally, we obtained data from various Noakhali locations. After removing the abnormalities, our data set has 930 rows and 20 attributes. Data is used for training by 80%, testing by 10%, and validation by 10%.The sample of raw dataset is shown in Appendix A-1.

3.2.2 Data Preprocessing

There are discrepancies in the range and measure units of the variables, which should be noticed before adding the obtained data to the classification algorithm for training. Convergence might be significantly delayed if this data were used directly to train a classification algorithm. The training and validation data can be preprocessed before use as a remedy to this issue. Following the collection of all raw data, samples are first added to an excel file and saved with the 'csv' extension. There are various arguments with string values that were initially transformed to numbers using Python. In addition to dealing with missing values and categorical values, data preprocessing also entails these tasks. The created code for preparing data is shown below:

Code:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
dataset = pd.read_csv("final.csv")

#converting string value into numeric value
fever_cough_cold_mapping = {"no": 0, "yes": 1}
dataset['fever'] = dataset['fever'].map(fever_cough_cold_mapping)
obesity_mapping = {"No": 0, "yes": 1}
dataset['obesity'] = dataset['obesity'].map(obesity_mapping)
HBsAg_mapping = {"negative": 0, "positive": 1}
dataset['HBsAg'] = dataset['HBsAg'].map(HBsAg_mapping)
risk_level_mapping = {"low risk": 0, "mid risk": 1,"high risk": 2}
dataset['risk_level'] = dataset['risk_level'].map(risk_level_mapping)
#finding missing values in the dataset
dataset.isnull().sum()
#showing missing values in the heatmap
sns.heatmap(dataset.isnull(), yticklabels = False, cbar = False, cmap = 'viridis')
# impute missing numerical values with median of the column
dataset["temp_fah"].fillna(dataset.groupby("Age")["temp_fah"].transform("median"),
inplace=True)
dataset["MHR"].fillna(dataset.groupby("Age")["MHR"].transform("median"), inplace=True)
dataset["fasting_BG"].fillna(dataset.groupby("Age")["fasting_BG"].transform("median"),
inplace=True)
dataset["HbA1C_BG"].fillna(dataset.groupby("Age")["HbA1C_BG"].transform("median"),
inplace=True)
dataset["uric_acid"].fillna(dataset.groupby("Age")["uric_acid"].transform("median"),
inplace=True)
```

Sample of preprocessed dataset is shown in appendix A-2.

3.3 TOOLS USED

3.3.1 Framework

There are various machine language platforms that enable programming in various computer languages. For instance, the Java-based Weka software, the C++ and Python-based TensorFlow, the Python-based PyTorch and Sci-Kit Learn, and the C, C++, C#, Java, FORTRAN, and Python-based MATLAB program. With the aid of the Anaconda distribution and MATLAB tools, the Python-3.9 programming language will be used for this research project. The choice of python and MATLAB tools was made for their abundance of libraries and frameworks.

Different tools are used for this study. All of them are free and open source.

1. **Python:**

   In many kinds of fields, including general programming, web development, software development, data analysis, machine learning, etc., Python is a very popular high-level generic programming language. Python was chosen for this project because it is relatively user-friendly, flexible, and has a large community of support[52].

2. **NumPy**:

   The extremely powerful software NumPy gives us the ability to perform scientific computing. It has advanced functionalities and can execute N-dimensional array, algebra, Fourier transform, and other operations. Numerous more libraries are created on top of NumPy and use NumPy as their basic stack, making it widely used in data analysis, image processing, and other areas. [53].

3. **Matplotlib:**

   A Python 2D plotting package called Matplotlib creates publication-quality graphics in a range of hardcopy formats and interactive settings across several platforms. Python scripts, the

Python and IPython shells, the Jupyter notebook, web application servers, and four graphical user interface toolkits can all use Matplotlib[54].

4. Pandas:

Open source software with a BSD license called Pandas was created specifically for the Python programming language. It offers a full suite of tools for data analysis in Python and is the best rival to the R programming language. Pandas makes it simple to carry out tasks like reading data frames, csv and excel files, slicing, indexing, merging, handling missing data, and more. The capability of Pandas to perform time series analysis is its most significant feature. [55].

5. Seaborn:

Python programming was used to construct the data visualization library known as Seaborn. Matplotlib is stacked on top of this high level library. Compared to matplotlib, Seaborn is more visually appealing, more informative, highly user-friendly, and strongly integrated with NumPy and Pandas. For virtually side-by-side use, Seaborn and Matplotlib can be used to draw inferences from the datasets[56].

6. SciPy, Scikit-learn:

Scikit-learn is a third party modification to SciPy and is a widely used popular library for machine learning. SciPy is a collection of essential mathematical functions built on top of Numpy. All the tools and algorithms required for the majority of machine learning tasks are included in Scikit-learn. Regression, classification, clustering, dimensionality reduction, and data pre-processing are supported by Scikit-learn. Scikit-Learn is utilized for this study since it is based on Python and can communicate with the NumPy library. Using it is also pretty simple. [57].

7.MATLAB:

The most natural approach to use MATLAB is to express computational mathematics because the language is matrix-based. With the aid of its computational capacity, the platform is highly tuned for tackling technical and scientific challenges. The platform primarily focuses on three disciplines: mathematics, graphics, and programming. All mathematical tools can be used for calculations, and built-in graphics can be used to illustrate data. A large collection of pre-built toolboxes can be used to practice rigorous algorithms and programming. And by working together, all of these things may be accomplished. Working with other languages including C, C++, C#, Java, FORTRAN, and Python is possible with MATLAB. One can scale up his web, enterprise, or production systems to clusters and clouds and work with massive amounts of data.

3.4 DATA ANALYSIS

This thesis demonstrates what factors have the most impact on risk level. Sensitivity analysis and a Microsoft Office Excel sheet are used to complete this work.

3.4.1 Sensitivity Analysis

Sensitivity analysis is a technique for carefully altering model input and assessing the effects of these changes on the model output. This approach displays the model's responsiveness to these modifications as well as the effects of specific characteristics on the model's functionality. Determine the interactions between the input and target factors

Age, blood pressure (systolic), blood pressure (diastolic), body temperature, maternal heart rate, blood glucose, hepatitis B, TSH, serum SGPT, serum uric acid, fetal heart rate, amount of amniotic fluid, fetal movement, and obesity are 19 attributes of the dataset that will be used as input variables in the risk level prediction for maternal and fetal health. The output variable will be divided into three groups based on the risk to the maternal and fetal health: low risk (number = 1), mid risk.

The sensitivity analysis for this study will be calculated using a mean-based approach. Sensitivity is determined while all input and output parameters are fixed in their reference state. The means of the experimental variables are chosen as the reference condition. Using this analysis method, we have changed one variable at a time to observe how it impacts the expected result. The maximum and lowest values of the input variable are often used to determine the change in the anticipated output, with all other input variables being held constant at their reference values. The input variable is fluctuated at random from the mean value between its minimum and maximum variables[58]. The percentage of change of an input variable has been determined using the following formulas if the mean, maximum, and minimum values of the input variable are Xmean, Xmax, and Xmin, respectively:

~ ((Xmax - Xmean)*100)/ Xmax) (from mean to maximum value) ………………………(3.1)

~ ((Xmin - Xmean)*100)/ Xmin) (from mean to minimum value)………………………...(3.2)

The sensitivity is calculated by dividing the percentage change in input by the percentage change in output. Then, by repeating those procedures, the output's sensitivity to each of the independent variables.

3.5 DISTINCT TECHNIQUES

A subfield of artificial intelligence called "machine learning" studies how computers can learn new information, develop new skills, and recognize previously learned information. Data mining, computer vision, natural language processing, biometrics, search engines, credit card fraud detection, securities market analysis, DNA sequence sequencing, speech and handwriting recognition, strategy games, and robotics have all made extensive use of machine learning. A computer program learning from experience E with respect to a task T and a performance metric is what machine learning is exactly defined as. P if E increases its performance on T as judged by P[59]. For a deeper understanding of the human world, it is essential to comprehend facts and gain insights. Today's data volume is too large for conventional ways to handle. In some circumstances, manually analyzing data or creating predictive models is not only time-consuming and less effective. On the other hand, machine learning generates accurate, repeatable outcomes and gains knowledge from prior calculation. It is also frequently referred to as predictive modeling or predictive analytics. In order to learn from data and create generalizable models that make accurate predictions or to uncover patterns, particularly with fresh and previously unexplored similar data, it is necessary to develop new algorithms or to make use of those that already exist.

Imagine a dataset as a table, with each observation (also known as a measurement, data point, etc.) represented by a row, and its features and their values represented by a column. The initial dataset for a machine learning project is typically divided into two or three subsets. The training and test datasets are the required subsets, and frequently a third validation dataset is also created as an optional subset. A predictive model or classifier is trained using the training data after these data subsets have been extracted from the main dataset, and its predictive accuracy is assessed using the test data. As was already established, machine learning uses algorithms to automatically model and identify data patterns, frequently with the intention of forecasting some specific output or response. These algorithms heavily rely on mathematical optimization and statistics. Types of Machine Learning are :

1) **Supervised learning**:

Supervised learning is the process by which an algorithm learns from example data and associated target responses, which might take the form of numeric values or string labels, such as classes or tags, in order to later predict the correct response when asked with new instances. This method does resemble human learning that is guided by a teacher. The student develops general rules from the specific instances that the teacher offers and helps them memorize.

2) **Unsupervised learning**:

When an algorithm picks up new information from simple samples without any accompanying feedback, allowing the program to discover the data patterns on its own. Typically, this kind of algorithm restructures the data into new features that might indicate a class or a new set of uncorrelated values. They are very helpful in giving people understanding of the significance of the data as well as fresh, beneficial inputs for supervised machine learning algorithms. It is a form of learning comparable to how humans identify objects or events as belonging to the same class, for example, by assessing how similar two objects are to one another. Some marketing automation suggestion systems that you can obtain online are based on this type of learning.

3) Reinforcement learning:

Provide the model with data as feedback, focusing on how to behave in accordance with the surroundings to optimize the anticipated benefits. It differs from supervised learning in that it does not call for precise correction of sub-optimal behavior or the proper input/output combinations. Online planning is the main focus of reinforcement learning, which calls for a balance between compliance and exploration (in the unknown).

3.5.1 Techniques Used For The Prediction Model

Predicting the class of a set of data points is the process of classification. Targets, labels, and categories are other names for classes. Approximating a mapping function (f) from input variables (X) to discrete output variables is the problem of classification predictive modeling (y). Classification falls under the supervised learning category, where the targets are also given access to the input data. Following that, we'll talk about a few

a) Multinomial Logistic Regression:

Following the application of a transformation function, the predictions of logistic regression are discrete values (i.e., whether a student passed/failed), but the predictions of linear regression are continuous values (i.e., rainfall in cm). The transformation function that is used in logistic regression is known as the logistic function, and its formula is h(x)=1/ (1 + ex). An S-curve is created as a result.

The results of logistic regression are probabilities for the default class (unlike linear regression, where the output is directly produced). Given that it is a probability, the result falls between 0 and 1.

The logistic function h(x)=1/ (1 + e -x) is used to log-transform the x-value to get this output (y-value). The probability is then forced into a binary categorization using a threshold[60].

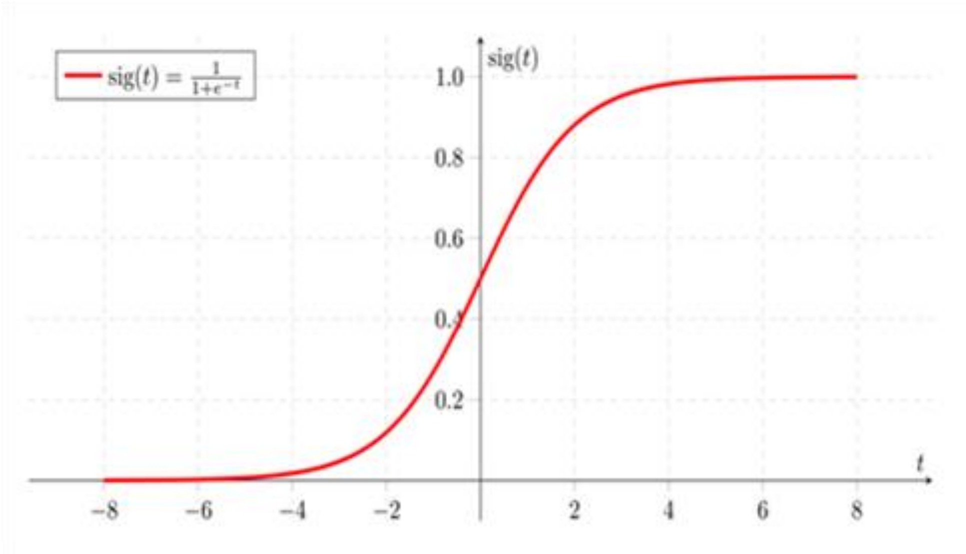


Figure 3.2: Logistic Regression algorithm graph

(Source: Wikipedia)

In a modified form of logistic regression, known as multinomial logistic regression, each input example is predicted to belong to more than two classes, or multinomial probability. One-vs-rest techniques and one-vs-one wrapper models are examples of this type.

b) Naive Bayes:

It is a classification method that relies on the independence of predictors in the Bayes theorem. A Naive Bayes classifier, to put it simply, believes that the presence of one feature in a class has nothing to do with the presence of any other feature. A fruit might be categorized as an apple, for instance, if it is red, rounded, and around 3 inches in diameter. A naive Bayes classifier would consider all of these traits to independently contribute to the likelihood that this fruit is an apple, even though these attributes depend on one another or the existence of the other features. Simple to construct and especially helpful for very big data sets is the naive Bayesian model. Along with being straightforward, Naive Bayes is known to perform better than even the most complex classification techniques. From P(c), P(x), and P(x|c), the posterior probability P(c|x) can be calculated using the Bayes theorem. Look at the equation below:

Likelihood class prior probability

$$P(c \mid x) = (P(x \mid c)P(c))/P(x)$$

Posterior probability Predictor prior probabilty

$$P(c|X) = P(x1|c) \times P(x2|c) \times \ldots \times P(xn|c) \times P(c)$$

…...…………….(3.3)

c) KNN (k- Nearest Neighbors):

Both classification and regression issues can be solved using it. It is, however, more frequently employed in classification issues in the sector. K nearest neighbors is a straightforward algorithm that sorts new instances according to the consensus of its k neighbors and stores all of the existing examples. The example that is being classified is the most prevalent among its K nearest neighbors as determined by a distance function.

These distance measures can be measured using the Euclidean, Manhattan, Minkowski, or Hamming methods. For continuous functions, the first three functions are utilized, while for categorical variables, the fourth function (Hamming). If K is equal to 1, the instance is then merely put into the class of its closest neighbor. Choosing K can occasionally be difficult when using kNN modeling[60].

Figure 3.3: K- Nearest Neighbors visualization
(Source: Wikipedia)

d) Support Vector Machine (SVM):

It is a technique for classification. This algorithm plots each data point as a point in an n-dimensional space, where n is the number of features you have and each feature's value is a specific

coordinate value.

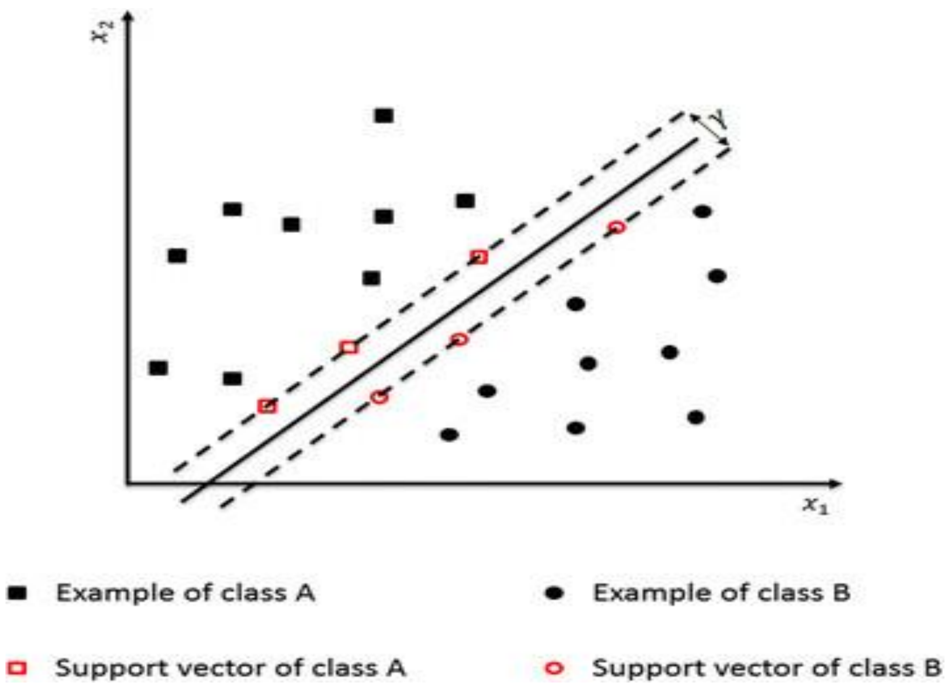


Figure 3.4: Support Vector Machine algorithms visualization
(Source: Wikipedia)

e) Decision Tree:

A decision tree is a classifier that uses recursive instance space partitioning. There are nodes and a root in this paradigm. Every node aside from the root has just one incoming edge. After conducting a test, intermediate nodes generate outgoing edges. Leaves are nodes without outgoing (also known as terminal or decision nodes). Each internal node in a decision tree divides the instance space into two or more sub-spaces according to a certain discrete function of the values of the input attributes.

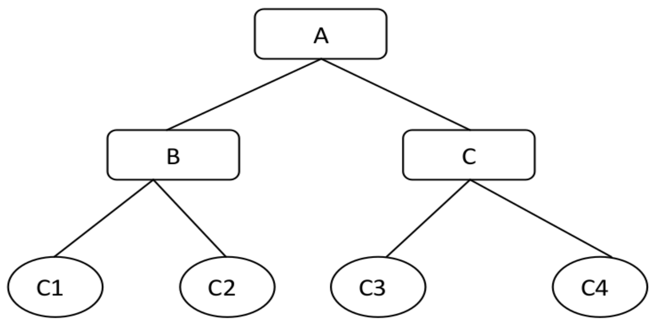


Figure 3.5: Decision Tree algorithm visualization
(Source: Wikipedia)

f) Random Forest:

It is an algorithm for supervised classification. A random forest algorithm, or collection of numerous classification trees, is made up of a large number of decision trees. Every decision tree has a rule-based system in it. The decision tree method will have a set of rules for the provided training dataset with targets and features. Unlike decision trees, finding the root node in a random forest does not require performing an information gain calculation. It predicts the outcome using the rules of each decision tree that is generated randomly and records the result. Additionally, it determines the vote total for each forecast target. The final forecast from the random forest method is therefore the one with the highest number of votes.

Artificial Neural Network algorithm used:

g) Multi-Layer Perceptron:

More than one linear layer can be present in the Multilayer Perceptron (combinations of neurons). If we use a three-layer network as a simple example, the input layer will be on the top layer, the output layer will be on the bottom layer, and the middle layer will be referred to as the hidden layer. The input layer receives our input data, and the output layer receives our output. To make the model more complex in accordance with our purpose, we are free to increase the number of hidden layers

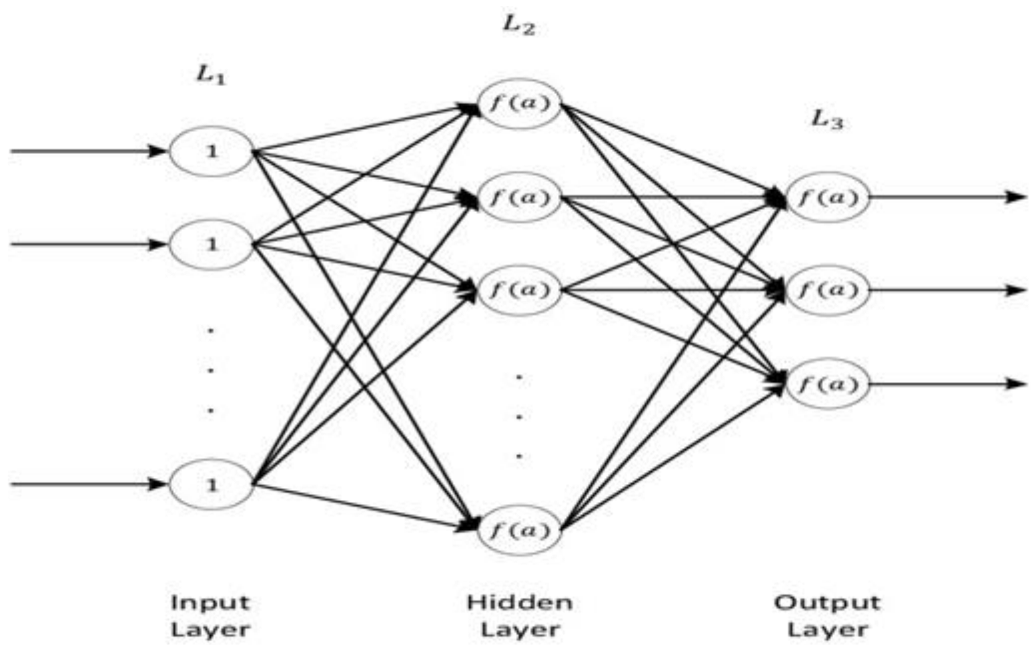


Figure 3.6: Multi-Layer Perceptron neural network
(Source: Wikipedia)

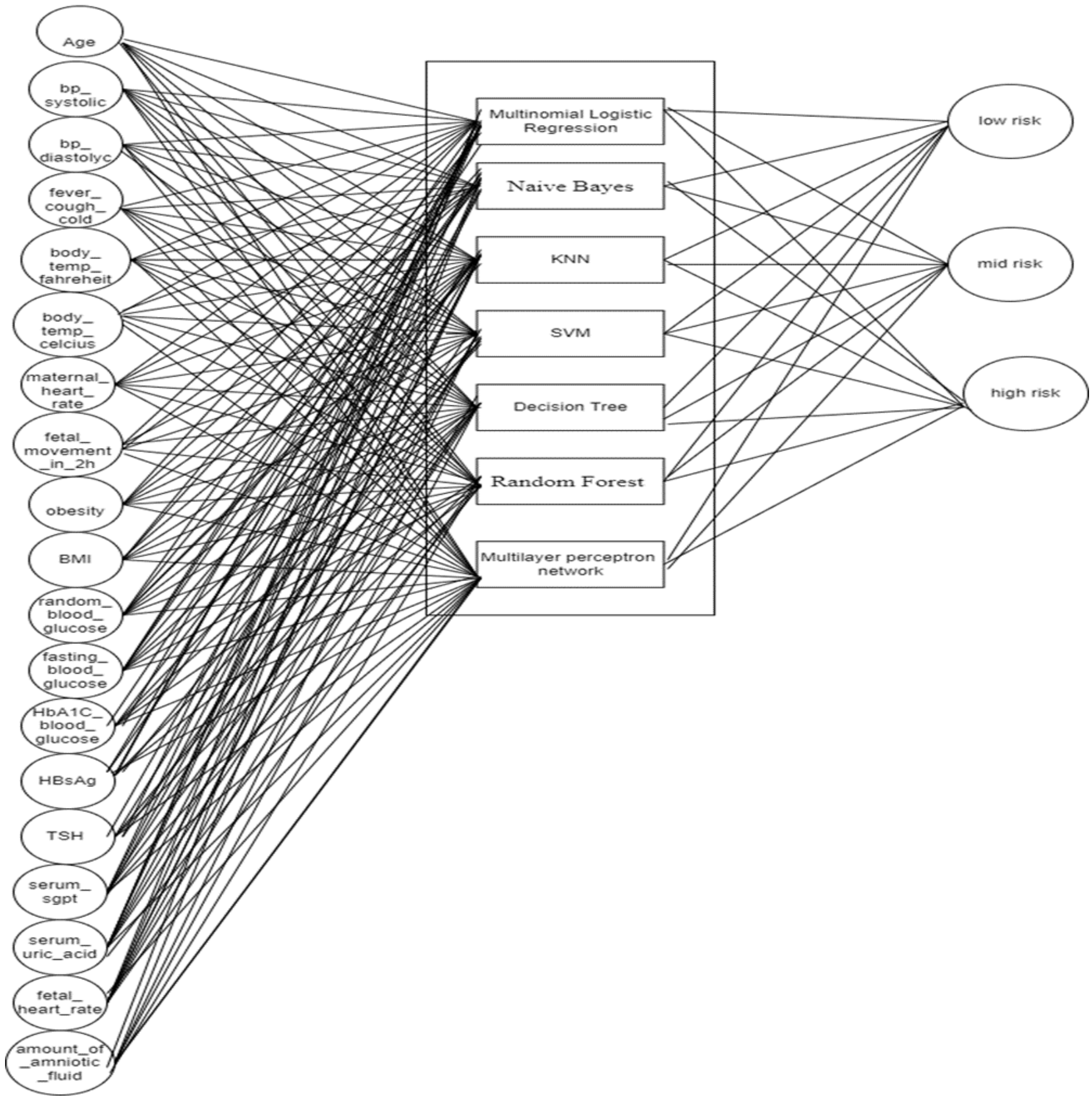


Figure 3.7: Input attributes, used algorithms and output of the thesis.

3.6 PERFORMANCE METRICS OF ALGORITHMS

Performance metrics in the context of machine learning are measurements of how well an algorithm performs depending on various criteria, such as accuracy, precision, recall, etc. The discussion of several performance measures follows:

Confusion Matrix:

Confusion Matrix, as its name suggests, produces a matrix and summarizes the overall effectiveness of the approach. It is the simplest approach to gauge how well a classification problem is performing when the output can include two or more different sorts of classes. A confusion matrix is nothing more than a table having two dimensions, Actual and Predicted, as well as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each dimension.

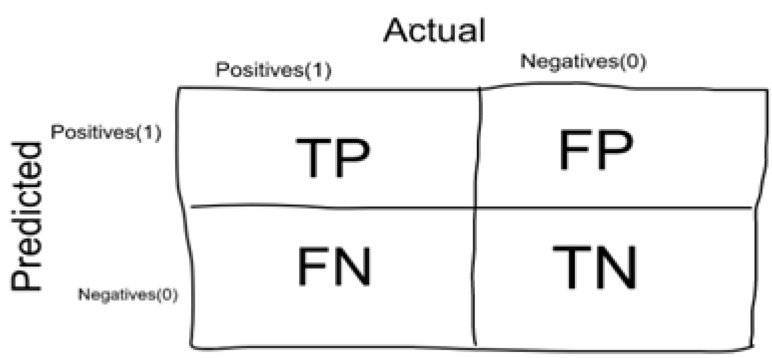


Figure 3.8: Confusion Matrix Structure

Explanation of the terms associated with confusion matrix are as follows −

- True Positives (TP) − It is the case when both actual class & predicted class of data point is 1.
- True Negatives (TN) − It is the case when both actual class & predicted class of data point is 0.
- False Positives (FP) − It is the case when actual class of data point is 0 & predicted class of data point is 1.

- False Negatives (FN) − It is the case when actual class of data point is 1 & predicted class of data point is 0.

1) Accuracy:

When we say something is accurate, we usually mean it to be accurate. It represents the proportion of accurate predictions to all input samples. Its use as a performance metric for classification algorithms is very widespread. It can be described as the proportion of all forecasts made to the number of accurate predictions made.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

……………………………………….(3.4)

It works well only if there are an equal number of samples belonging to each class.

2) Precision:

The percentage of cases that are classed as true positives for determining precision. It displays how closely expected values match one another. The following formula is used to calculate precision..

$$Precision = \frac{TP}{TP + FN}$$

` ………..……………………….(3.5)

How closely or nearly the projected values match the actual values is a measure of precision. For instance, if a person's actual height is 6 feet and their measured or predicted height is 5.5 and their height fluctuates between 5.4 and 5.6 each time their height is measured, the prediction is quite precise but not accurate.

3) **Recall** :

The percentage of positive events that are accurately identified as positive is known as recall. Recall is frequently referred to as sensitivity. Formula for calculating recall is given below.

$$Recall = \frac{TP}{TP + FN}$$

……………………………………(3.6)

Recall is simply the measure of how many true samples are predicted from the all the samples.

4) **F1 Score:**

The F1 Score is the Harmonic Mean of memory and precision. The F1 Score ranges from [0, 1]. It provides information on the accuracy and durability of your classifier, including the proportion of correctly classified cases (it does not miss a significant number of instances).

High accuracy but low recall results in exceedingly accurate results but misses many occurrences that are challenging to classify. The performance of our model improves as the F1 Score increases. Mathematically, it can be expressed as :

$$F1 = 2 * (precision * recall)/(precision + recall)$$

…..………………………(3.7)

F1 Score tries to find the balance between precision and recall.

5) **AUC (Area Under the ROC curve):**

AUC-ROC is a performance statistic for classification issues that is based on shifting threshold values. ROC stands for Receiver Operating Characteristic. AUC measures reparability, whereas ROC is a probability curve as its name implies. Simply said, the AUC-ROC metric will inform us of the model's capacity for class distinction. The model is better the higher the AUC.

Plotting TPR (True Positive Rate), also known as sensitivity or recall, vs. FPR (False Positive Rate), also known as -Specificity, at different threshold values can be used to produce it mathematically.

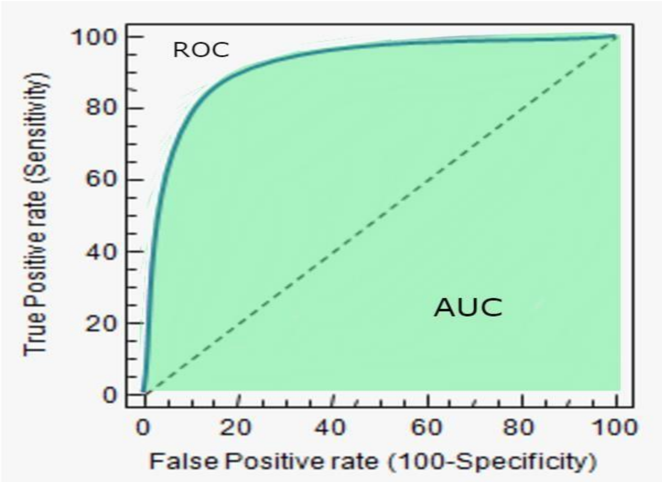


Figure 3.9: AUC and ROC curve
(Source: Geek Culture website)

3.7 WORKFLOW OF THE PROPOSED WORK

Through Figure 3.10, depict workflow from start to end of the proposed research work.

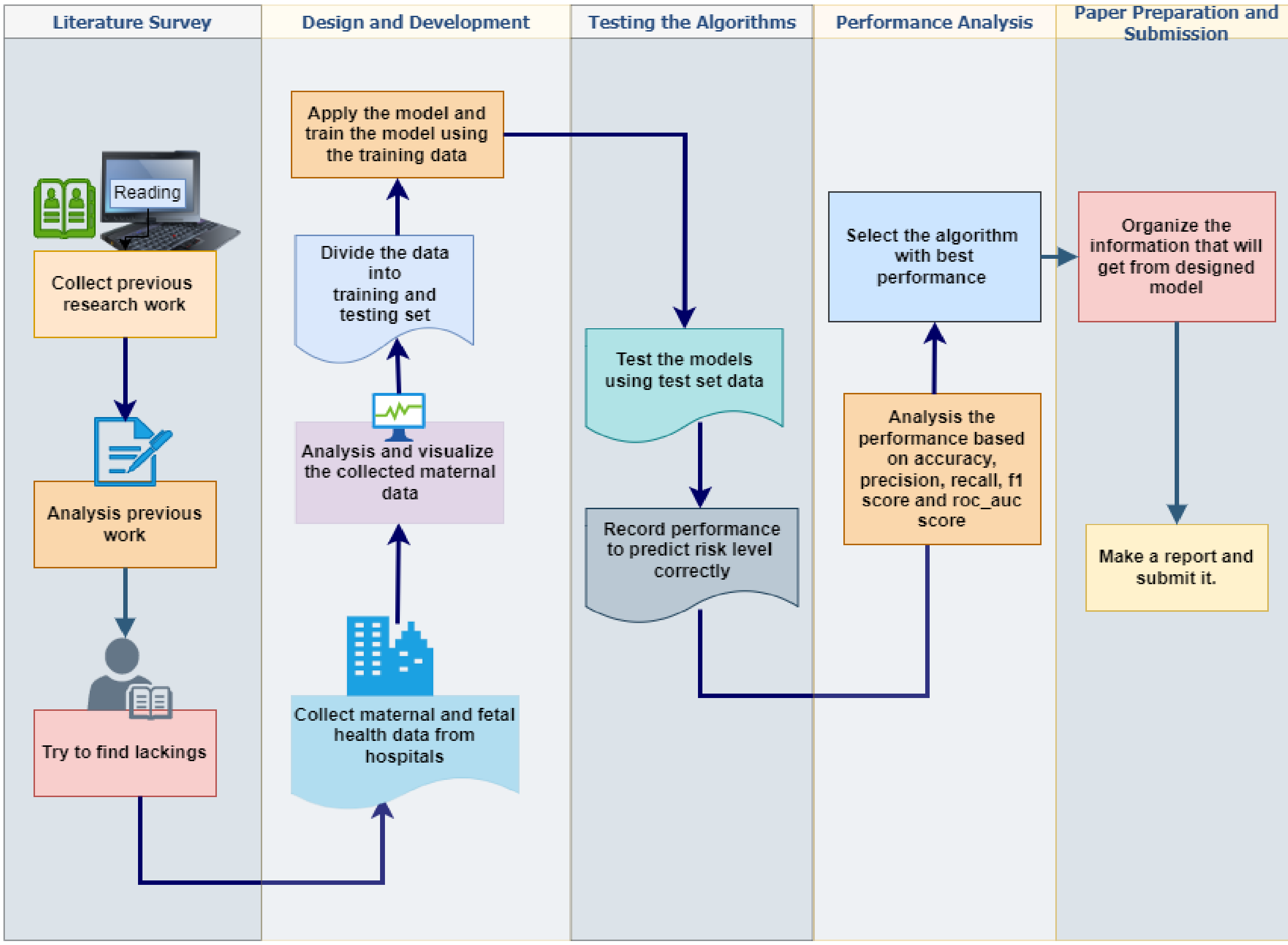


Figure 3.10: Workflow of this thesis study

The part on the literature review gathered information from earlier studies and made an effort to identify any gaps. Data were collected and prepared for use as input by neural network and artificial intelligence algorithms. Data from the training set and testing set were collected separately. Utilize the training dataset to train the model during the design and development process. During the testing phase, the testing dataset was used to track how accurately the system forecasts the risk level for maternal and fetal health. Choose the best performing algorithm for risk level prediction based on the best performance with the highest precision and accuracy. We then produced a report based on the findings.

3.8 CONCLUSION

It is possible to improve the precision of risk assessments for maternal and fetal health. The method used to gather the data and the features chosen to train the model both affect how accurate the model is. Reduced maternal and fetal morbidity during pregnancy and childbirth can be achieved through early identification and risk level prediction. Additionally, it aids the gynecologist in making decisions regarding the patient in light of their prior medical history. Our findings and the implications of our research study are discussed in the following chapter.

CHAPTER 4

IMPLEMENTATION AND ANALYSIS

In this chapter, the performance of the Artificial Intelligence and Neural Network model is analyzed. This chapter mainly has three sub-sections: performance analysis of Artificial Intelligence and Neural Network algorithm in case if maternal and fetal health risk level prediction, evaluating the actual and predicted value of the algorithms using new sample data and sensitivity analysis on the input parameters and target. In the sensitivity analysis section, which factors influence the risk most is evaluated.

4.1 INTRODUCTION

Families and communities are devastated when a mother or newborn dies during childbirth. The Sustainable Development Goals (SDGs) emphasize the significance of maternal and newborn health by making lowering the maternal mortality ratio and putting an end to unnecessary infant deaths their first targets under SDG 3: Good Health and Well-Being. The international community is working hard to realize these objectives and is urging the private sector to play a significant role in spreading technologies.

This chapter addresses the experiment and outcomes gained through Artificial Intelligence and Neural Network algorithms. The maternal and fetal health related dataset is used for prediciting the risk level. The whole dataset is divided into training and testing part. The training part is used for performance evaluation of the algorithms and the testing part is used to analyze how accurately the algorithms can predict the risk level of maternal and fetal health. 67% of the whole dataset is used for training and 33% is used for testing. The KNN , Decision tree, Random Forest and

Multilayer Perceptron algorithms gives the best accuracy. Other algorithms also give satisfactory results.

Several preprocessing techniques applied to the dataset like mapping categorical values to numerical value and replacing missing values by taking median for numerical values and mode for categorical values.

Furthermore, five performance metrics were observed to analyze the performance of implemented classifiers. The metrics are accuracy, precession, recall, f-1 score and ROC_AUC score. The algorithm with the highest accuracy and precision was K-Nearest Neighbors, Decision Tree, Random Forest and Multilayer perceptron neural network.

New samples of size 31 were used to evaluate how well the algorithms can predict the risk level. The accuracy of this prediction is also obtained to evaluate the performance of the algorithms and to see which algorithm performs better for this new samples. It is seen that the Decision Tree, Random Forest and Multilayer Perceptron algorithms gives best accuracy for these new samples also. Other algorithms performance were also satisfactory for the new samples.

Sensitivity analysis is performed to figure out how input and target factors interact. This study will use mean-based formula for calculating sensitivity analysis. Sensitivity is calculated while all parameters (input and output) are fixed in their reference condition.

4.2 IMPLEMENTATION OF MATERNAL AND FETAL HEALTH RISK PREDICTION MODEL

The whole prediction model is divided into two parts i.e. training the algorithms with maternal and fetal health risk dataset and testing the algorithms with new sample data.

4.2.1 Training

For all the techniques, the performance metrics were evaluated for original dataset and for dataset selected. For original dataset, missing values were replaced by the median for numeric value and by the mode for categorical values. In case of dataset selected, the attributes containing missing values were removed. By evaluating performance measures in both case, it is seen that original dataset gives the best result compared to the dataset selected.

For performance evaluation of the distinct techniques of the maternal and fetal health risk prediction model, python and matlab tools are used.

4.2.1.i Prediction Using Distinct Techniques and Python Tools

a) Multinomial Logistic Regression

For original dataset, the accuracy of multinomial logistic regression found that 89.58%. And for dataset selected, the accuracy is 84.04%. Also the solvers liblinear, newton-cg, sag, saga etc. was tried to find the best accuracy value. The detailed of Multinomial Logistic Regression evaluation is shown in Table 4.1:

Table 4.1: Multinomial Logistic Regression performance with different solver

Solver of MLR	liblinear	newton-cg	sag	saga
Accuracy for dataset	86.97%	89.58%	78.83%	79.48%
Accuracy for dataset selected	80.13%	84.04%	79.80%	82.08%

From the above table it is seen that highest accuracy found for solver newton-cg for both original dataset and for the dataset selected i.e. 89.58% and 84.04%.

The multinomial logistic regression confusion matrix for testing data is given in Figure 4.1:

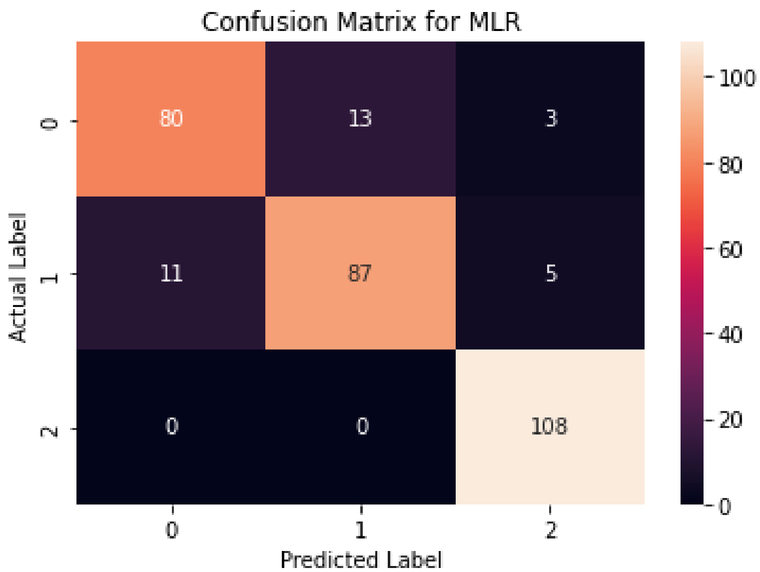


Figure 4.1: Confusion matrix for Multinomial Logistic Regression.

Out of 307 risk level, MLR correctly predicts 275 risk level. Here, the number of high risk level that were predicted accurately was 108. On the other hand , MLR also mispredicted 5 mid risk level and 3 low risk level as high risk level. It happens because there's some risk factors which actually indicate high risk but in case of whole scenarios perspective these class fallen to low or mid risk. Actually same things happen for mid risk and low risk prediction. MLR predicts 87 mid risk level and 80 low risk level accurately while it mispredicted 13 low risk level as mid risk level and 11 mid risk level as low risk.The performance of MLR is presented in Table 4.2:

Table 4.2: Performance matrices of Multinomial Logistic Regression

Performance Metrics	**Risk Levels**		
	Low risk	**Mid risk**	**High risk**
Precision	0.88	0.87	0.93
Recall	0.83	0.84	1.00
F1 score	0.86	0.86	0.96

Table 4.2 shows that MLR provides the highest precision, recall, and f1 scores for the low risk, mid risk, high risk class respectively. The comparison of precision values is shown in Figure 4.2:

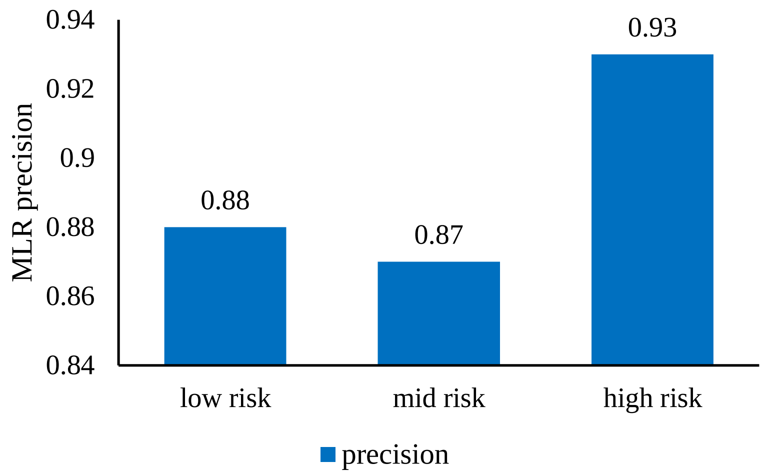


Figure 4.2: Precision values of Multinomial Logistic Regression algorithm.

The highest recall value of 1.00 was achieved for the high risk class and its precision and f1-score value was also high i.e. 0.93 and 0.96. On another side, for low risk and mid risk class it also gives satisfactory precision, recall and f1-score value. It is observable that MLR provides balanced precision, recall, and f1 score for low risk, mid risk and high risk classes.

The precision value indicates the proportion of correct classification of a specific class from cases that are predicted as this specific class. For instance, consider the 'High risk' class to calculate precision values. The high risk class's precision value is the ratio TP and the summation of TP and FP for this class. For high risk class, the formula of precision is:

$$Precision_{\,high\_risk} = \frac{TP_{high\_risk}}{TP_{high\_risk} + FP_{high\_risk}} = \frac{108}{108 + 8} = 0.931 \tag{4.1}$$

Similar to the "High risk" class, the precision value of additional classes can also be computed. The precision value for the 'low risk' and 'mid risk' classes was 88% and 87%.

The Area Under Curve (AUC) score is a measure of how separable something is. A model's ability to predict True Positives and True Negatives is improved by a greater AUC. The overall area beneath the ROC curve is quantified by the AUC score. Scale and threshold invariance are both characteristics of AUC. The likelihood that a classifier would rank a randomly selected positive instance higher than a randomly selected negative instance is the AUC score. The ROC_AUC score of MLR is : 98.09% that means MLR will correctly predict True positives and True negatives.

b) Naïve Bayes

For original dataset, the accuracy of multinomial NB found that 80.13%. And for dataset selected, the accuracy is 75.24%.

Table 4.3: Multinomial NB performance.

Data	**MNB**
Accuracy for dataset	80.13%
Accuracy for dataset selected	75.24%

The Multinomial NB confusion matrix, with alpha = 1, is shown in Figure 4.3.

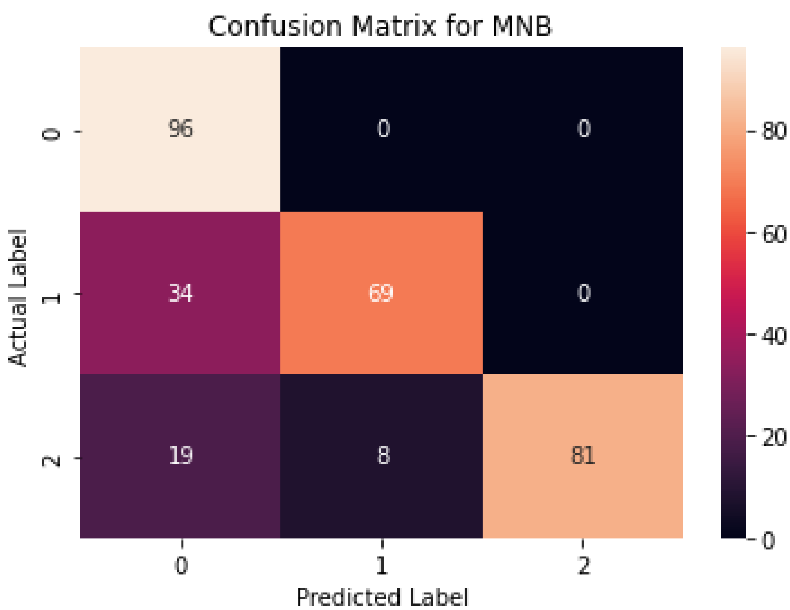


Figure 4.3: Confusion matrix for Multinomial Naïve Bayes.

Out of 307 risk level, MNB correctly predicts 246 risk level. Here, the number of high risk level that were predicted accurately was 81. MNB predicts 87 mid risk level and 80 low risk level accurately while it mispredicted 8 high risk level as mid risk level, 19 high risk level as low risk level and 34 mid risk level as low risk level. It happens because there's some risk factors which actually indicate high risk but in case of whole scenarios perspective these class fallen to low or mid risk and vice versa. The performance of MNB is presented in Table 4.4:

Table 4.4: Performance matrices of Multinomial Naïve Bayes.

Performance Metrics	**Risk Level**		
	Low risk	**Mid risk**	**High risk**
Precision	0.64	0.90	1.00
Recall	1.00	0.67	0.75
F1 score	0.78	0.77	0.86

Table 4.4 shows that MNB provides the highest precision and f1-score for high risk class and highest recall for the low risk class. The comparison of precision values is shown in Figure 4.4:

The highest recall value of 1.00 was achieved for the low risk class and its precision and f1-score value is 0.64 and 0.78. On another side, for high risk class it gives the highest precision value i.e. 1.00.and recall and f1-score value was also high i.e. 0.75 and 0.86. It is observable that MNB provides balanced precision, recall, and f1 score for low risk, mid risk and high risk classes.

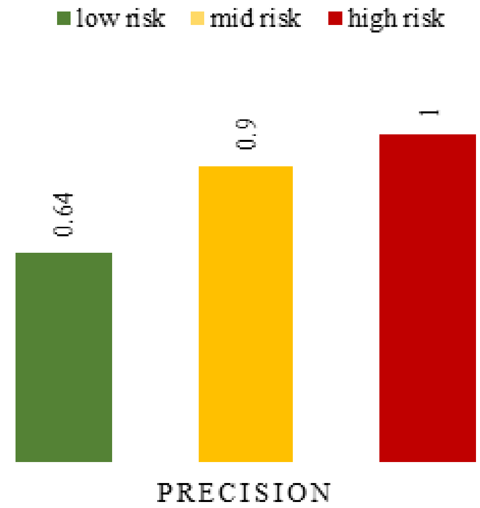


Figure 4.4: Precision values of Multinomial Naïve Bayes.

The precision value indicates the proportion of correct classification of a specific class from cases that are predicted as this specific class. For instance, consider the 'Mid risk' class to calculate precision values. The mid risk class's precision value is the ratio TP and the summation of TP and FP for this class. For mid risk class, the formula of precision is:

$$Precision_{\,mid\_risk} = \frac{TP_{mid\_risk}}{TP_{mid\_risk} + FP_{mid\_risk}} = \frac{69}{69+8} = 0.896 \quad (4.2)$$

Similar to the "Mid risk" class, the precision value of additional classes can also be computed. The precision value for the 'low risk' and 'high risk' classes was 64% and 100%.

The ROC_AUC score of MNB is : 94.78% that means MNB will correctly predict True positives and True negatives and AUC score is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

It is seen that the MNB algorithm doesn't provide better performance in terms of accuracy, precision, recall, f1-score and ROC_AUC score in comparison to the Multinomial logistic regression.

c) K-Nearest Neighbors

For the KNN algorithm, K=1 to K=4 was tried to find the best precision value. The highest accuracy of 100.0% for all the values of k was achieved. Same accuracy also found for the dataset selected. The detailed of KNNs evaluation are shown in Table 4.5:

Table 4.5:KNN algorithm performance with K=1 to 4.

Value of K	1	2	3	4
Accuracy	100.0%	100.0%	100.0%	100.0%

Figure 4.5 depicts the confusion matrix of the KNN model for testing data.

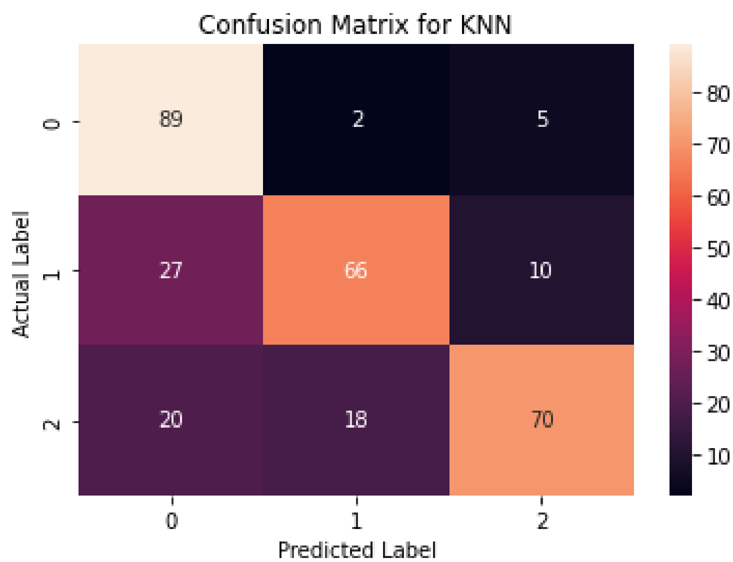


Figure 4.5: Confusion matrix for K-Nearest Neighbors.

Here, the number of high risk class that were predicted accurately was 70. There was a conflict between low risk and mid risk level. 5 low risk level and 10 mid risk level was predicted as high risk by the KNN model. Probably the reason behind this was the similarity between the risk level's parameters. On the other side, the KNN model mispredicted 18 high risk levels as mid risk levels and also 2 low risk class as mid risk. KNN correctly predicted 66 mid risk and 89 low risk class. The precision, recall, and f1 score of the KNN model to predict the risk level of the maternal and fetal health is shown in Table 4.6:

Table 4.6: Performance matrices of K-Nearest Neighbors.

Performance Metrics	Risk Level		
	Low risk	**Mid risk**	**High risk**
Precision	0.65	0.77	0.82
Recall	0.93	0.64	0.65
F1 score	0.77	0.70	0.73

Table 4.6 shows that KNN provides the highest precision for high risk class i.e. 0.82, highest recall and f1-score for the low risk class i.e. 0.93 and 0.77. The comparison of precision values is shown in Figure 4.6:

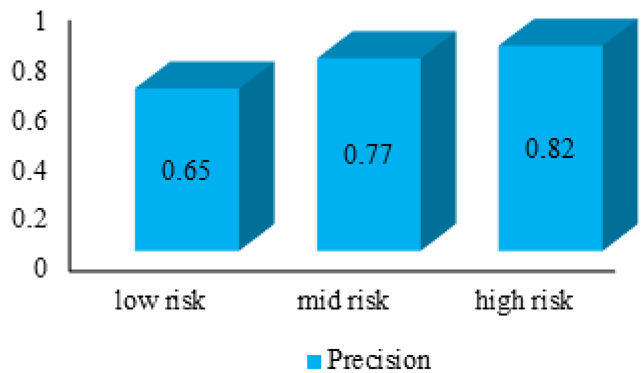


Figure 4.6: Precision values of K-Nearest Neighbor.

The highest precision value of 0.82 was achieved for the high risk level. 0.93 and 0.77 were the highest recall and f1 score values for low risk levels.

The accuracy of KNN algorithm 100% which is the best accuracy achieved in comparison to the MLR and MNB, but it’s precision, recall and f1-score are not so much better in comparison to the previous algorithms.

d) Support Vector Machine

For the SVM classifier, four kernels were examined for original dataset and dataset selected. The kernels were RBF, Sigmoid, Polynomial, and Linear. The Liner kernels' performance is higher than the Polynomial, RBF and Sigmoid kernels for original and selected dataset. The accuracy for both dataset are 90.23% and 89.25%.The SVM's performance of the original dataset for these four kernels is presented in Table 4.7.

Table 4.7: Performance of SVM classifier for different kernels.

Kernel Type	Metrics	Risk Level		
		Low risk	Mid risk	High risk
Linear	precision	0.83	0.87	1.00
	recall	0.86	0.83	1.00
	f1-score	0.85	0.85	1.00
	Accuracy	90.23%		
	ROC_AUC score	98.05%		
Polynomial	precision	0.62	0.82	0.89
	recall	0.92	0.60	0.72
	f1-score	0.74	0.69	0.80
	Accuracy	74.27%		
	ROC_AUC score	90.34%		

Kernel Type	Metrics	Risk Level		
		Low risk	Mid risk	High risk
Sigmoid	**precision**	0.29	0.19	0.56
	recall	0.75	0.10	0.05
	f1-score	0.42	0.13	0.09
	Accuracy	28.34%		
	ROC_AUC score	66.75%		
RBF	**precision**	0.61	0.75	0.94
RBF	**recall**	0.92	0.66	0.63
	f1-score	0.73	0.70	0.76
	Accuracy	72.96%		
	ROC_AUC score	88.21%		

Among the four, the SVM classifier with Linear kernel performed best, and the sigmoid kernel performed worse concerning accuracy. 90.23% accuracy was achieved with Linear kernel. In comparison, 28.34% accuracy was for SVM with the sigmoid kernel. On the other side, polynomial kernel and RBF kernel achieve 74.27% and 72.96% accuracy. The highest precision, recall, f1-score,ROC_AUC score also achieved for linear kernel and for high risk class. The confusion matrix for SVM linear kernel for testing data is depicted in Figure 4.7:

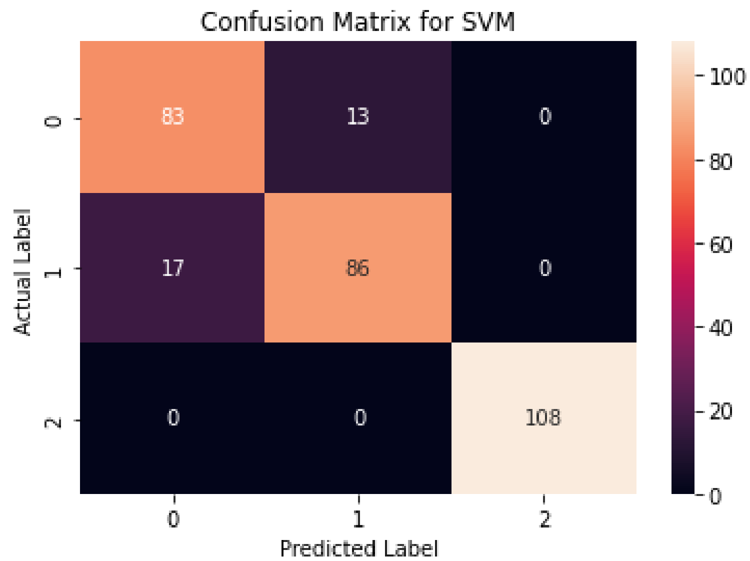


Figure 4.7: Confusion matrix for Support Vector Machine.

Among 307 test risk class linear SVM predict 293 risk level correctly. The confusion matrix of linear SVM is shown in figure 4.27. If consider the high risk class then TP for this class was 108, FN was 0, FP was 0 and TN was 199.

That means that 108 risk level of 'high risk' class were predicted correctly and 199 risk levels were predicted as accurate but for the other class. Since FP and FN for high risk class is zero that means high risk class didn't conflict with other class. Similarly, TP, FP, TN, and FN can be calculated for other classes. The 'Low risk' class had the highest FP of 17, and the 'High risk' class had the maximum TP of 108 and the lowest FP. The low risk class had the lowest TP. It can summarize that Linear SVM classifier performance can be considered to predict the risk level for maternal and fetal health.

e) Decision Tree

The main goal of decision trees is to identify the descriptive features that provide the most "information" about the target feature. Once these features are identified, the dataset is divided along their values so that the target feature values for the resulting sub-datasets are as pure as possible. This search for the "most informative" feature continues until a halting criterion is met, at which point we arrive at what are known as leaf nodes. The maximum depth for decision tree is considered 2 for this algorithm and found 100.0% accuracy for both the original and selected dataset. The confusion matrix for the decision tree algorithm is given in Figure 4.8:

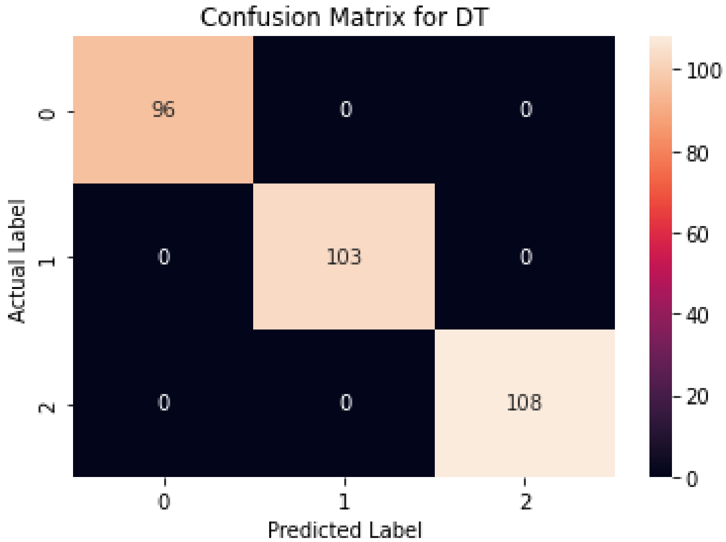


Figure 4.8: Confusion matrix for Decision Tree.

The ‘High risk’ class's DT model TP value was 108, FP value was 0, FN value was 0 and TN was 199. The 'Mid risk' class had the TP value 103 and the 'Low risk' class had the 96 . The FP and FN value for all the class is 0 since the accuracy of the DT classifier is 100.0%. This means the algorithm correctly predict all the risk levels of maternal and fetal health. The precision, recall and f1-score can be calculated from TP, TN, FP and FN value. The depiction of precision, recall and f1-score is given in Figure 4.9 :

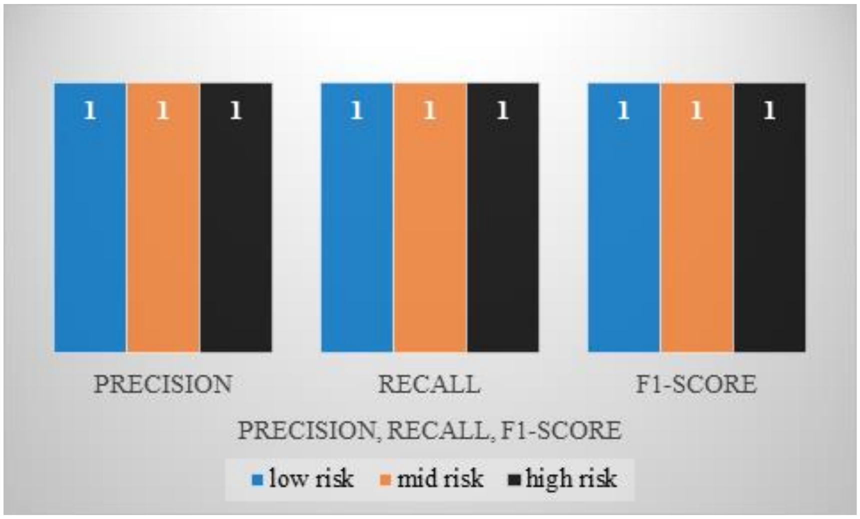
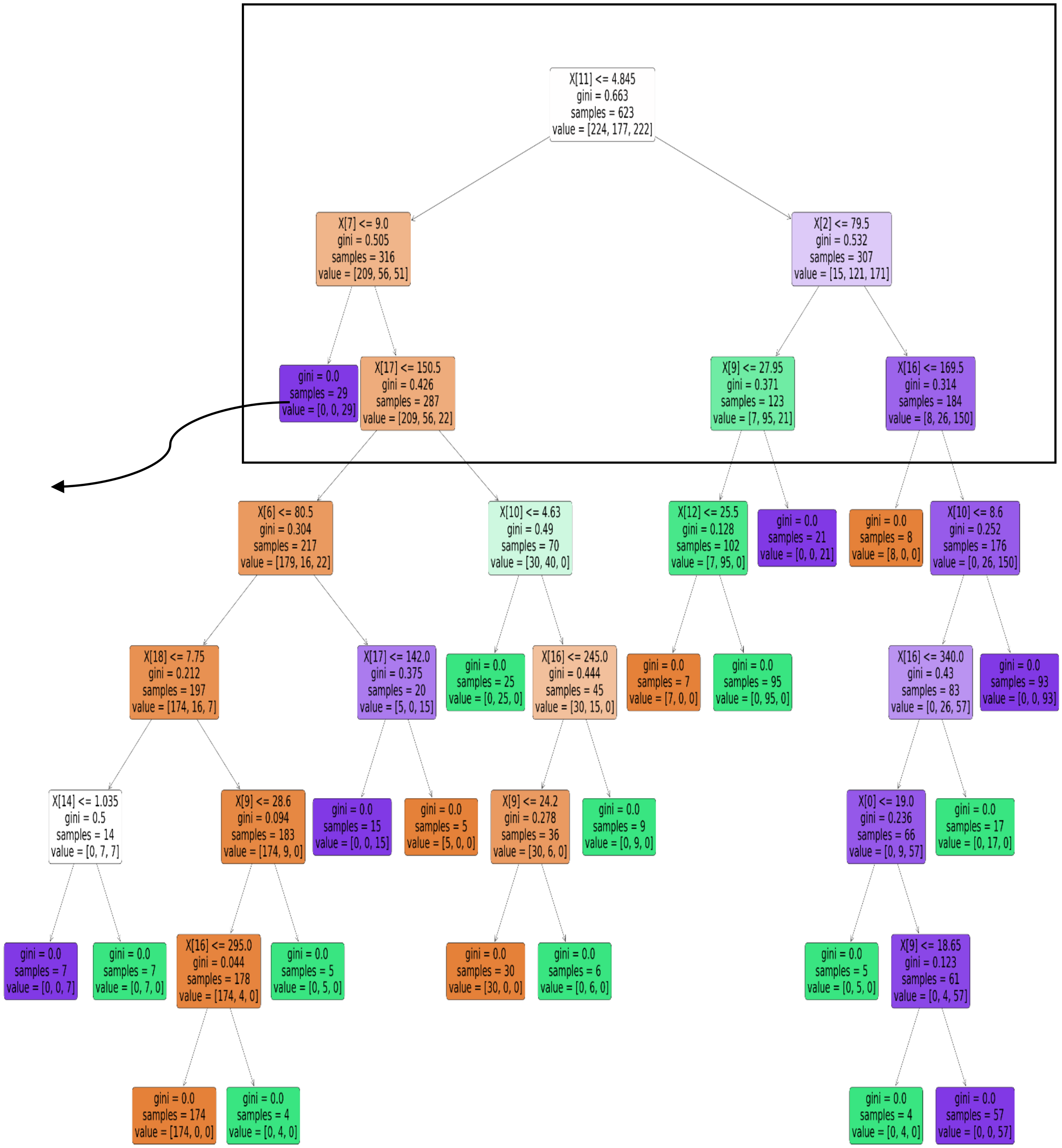


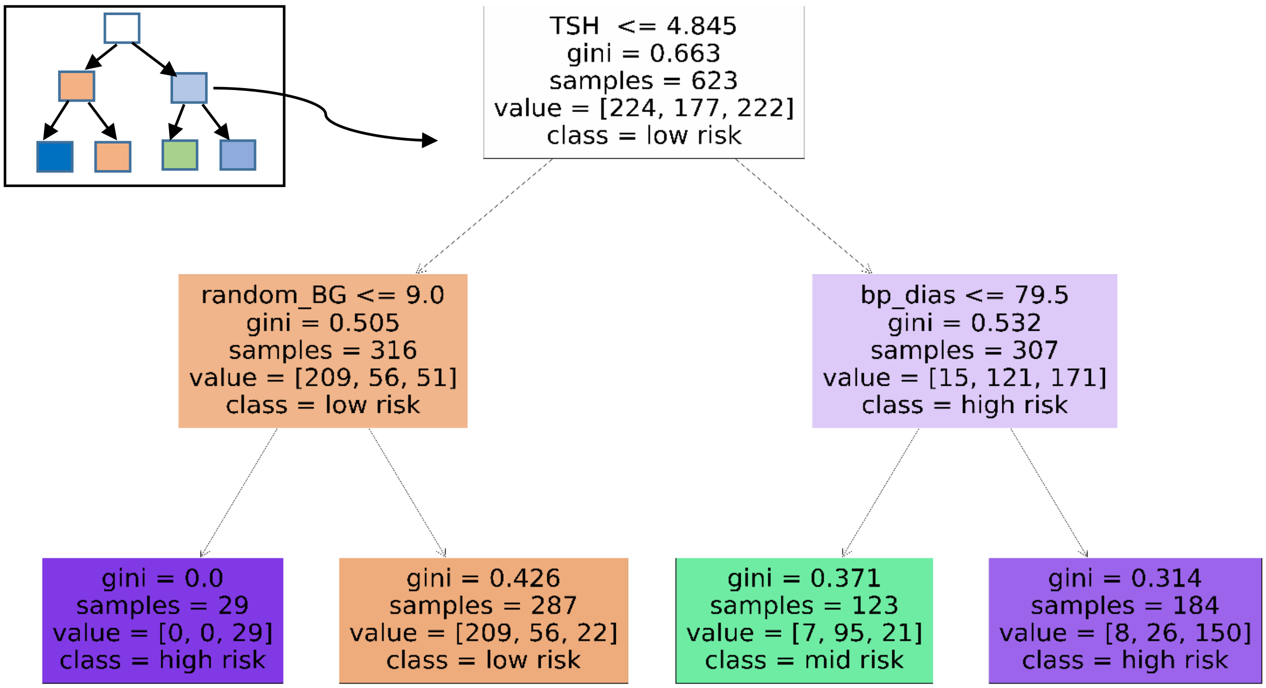
Figure 4.9: Precision, recall and f1-score values of Decision Tree.

A good precision, recall and f1-score means the algorithm performs well for the positive prediction and the number instances predicted are more accurate. The DT classifier predict the risk level more accurately and the results obtained from it are satisfactory.The ROC_AUC score of the algorithm is also 100.0%. It means that the algorthm had a good measure of separability for the maternal and fetal health risk factors.

The depiction of the Decision Tree for the maternal and fetal health data are given below:


X[11] <= 4.845 gini = 0.663 samples = 623 value = [224, 177, 222]
X[7] <= 9.0 gini = 0.505 samples = 316 value = [209, 56, 51]
X[2] <= 79.5 gini = 0.532 samples = 307 value = [15, 121, 171]
gini = 0.0 samples = 29 value = [0, 0, 29]
X[17] <= 150.5 gini = 0.426 samples = 287 value = [209, 56, 22]
X[9] <= 27.95 gini = 0.371 samples = 123 value = [7, 95, 21]
X[16] <= 169.5 gini = 0.314 samples = 184 value = [8, 26, 150]
X[6] <= 80.5 gini = 0.304 samples = 217 value = [179, 16, 22]
X[10] <= 4.63 gini = 0.49 samples = 70 value = [30, 40, 0]
X[12] <= 25.5 gini = 0.128 samples = 102 value = [7, 95, 0]
gini = 0.0 samples = 21 value = [0, 0, 21]
gini = 0.0 samples = 8 value = [8, 0, 0]
X[10] <= 8.6 gini = 0.252 samples = 176 value = [0, 26, 150]
X[18] <= 7.75 gini = 0.212 samples = 197 value = [174, 16, 7]
X[17] <= 142.0 gini = 0.375 samples = 20 value = [5, 0, 15]
gini = 0.0 samples = 25 value = [0, 25, 0]
X[16] <= 245.0 gini = 0.444 samples = 45 value = [30, 15, 0]
gini = 0.0 samples = 7 value = [7, 0, 0]
gini = 0.0 samples = 95 value = [0, 95, 0]
X[16] <= 340.0 gini = 0.43 samples = 83 value = [0, 26, 57]
gini = 0.0 samples = 93 value = [0, 0, 93]
X[14] <= 1.035 gini = 0.5 samples = 14 value = [0, 7, 7]
X[9] <= 28.6 gini = 0.094 samples = 183 value = [174, 9, 0]
gini = 0.0 samples = 15 value = [0, 0, 15]
gini = 0.0 samples = 5 value = [5, 0, 0]
X[9] <= 24.2 gini = 0.278 samples = 36 value = [30, 6, 0]
gini = 0.0 samples = 9 value = [0, 9, 0]
X[0] <= 19.0 gini = 0.236 samples = 66 value = [0, 9, 57]
gini = 0.0 samples = 17 value = [0, 17, 0]
gini = 0.0 samples = 7 value = [0, 0, 7]
gini = 0.0 samples = 7 value = [0, 7, 0]
X[16] <= 295.0 gini = 0.044 samples = 178 value = [174, 4, 0]
gini = 0.0 samples = 5 value = [0, 5, 0]
gini = 0.0 samples = 30 value = [30, 0, 0]
gini = 0.0 samples = 6 value = [0, 6, 0]
gini = 0.0 samples = 5 value = [0, 5, 0]
X[9] <= 18.65 gini = 0.123 samples = 61 value = [0, 4, 57]
gini = 0.0 samples = 174 value = [174, 0, 0]
gini = 0.0 samples = 4 value = [0, 4, 0]
gini = 0.0 samples = 4 value = [0, 4, 0]
gini = 0.0 samples = 57 value = [0, 0, 57]

(a)



(b)

Figure 4.10: Decision Tree for the maternal and fetal health data.

(a) The whole Decision Tree.

(b) A portion of the whole Decision Tree with the name of risk level.

From the above description and depending on the performance metrics i.e accuracy, precision, recall and f1-scores results it can be said that the DT classifier performs well for the prediction of the risk level of maternal and fetal health. It also performs better in comparison to the MLR, MNB, SVM and also KNN in terms of all accuracy, precision, recall, f1-score and ROC_AUC score.

f) Random Forest

The RF method employs a collection of decision trees, with the output from each tree combined to yield a more precise conclusion. Combining the results is known as the "bagging" procedure. The quantity of trees is variable. The RF model does not overfit, therefore one can run as many trees as desired. It is advised to train the model using a lot of trees, though. To accommodate the RF model, the study's initial 100 trees were achieved satisfactory accuracy and it was 100.0%.Same accuracy also achieved for dataset selected.

The confusion matrix for the RF model is shown in Figure 4.11.The ‘High risk’ class's RF model TP value was 108, FP value was 0, FN value was 0 and TN was 199. The 'Mid risk' class had the TP value 103 and the 'Low risk' class had the 96 .

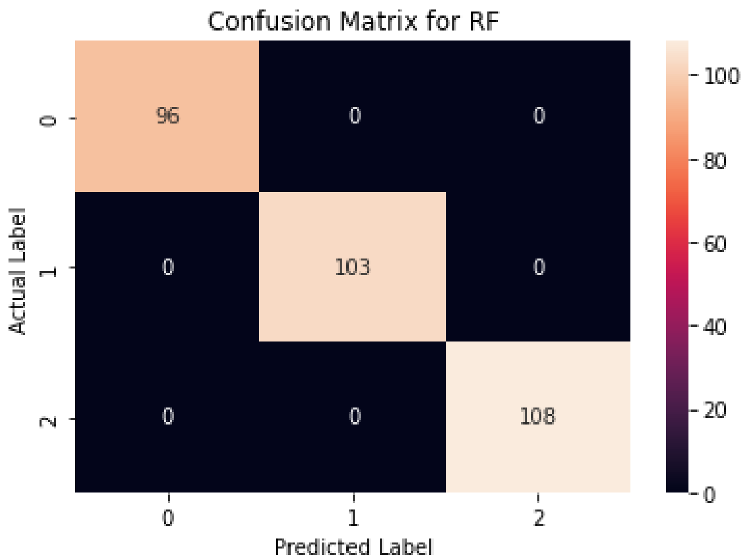


Figure 4.11: Confusion matrix for Random Forest.

Since the RF models detects the risk levels accurately, FP and FN value for all the classes are 0. From the value of FP, FN, TP, and TN, the precision, recall, and f1 score can be calculated for each class. The precision, recall and f1- score for all the classes is given in the Figure 4.12 :

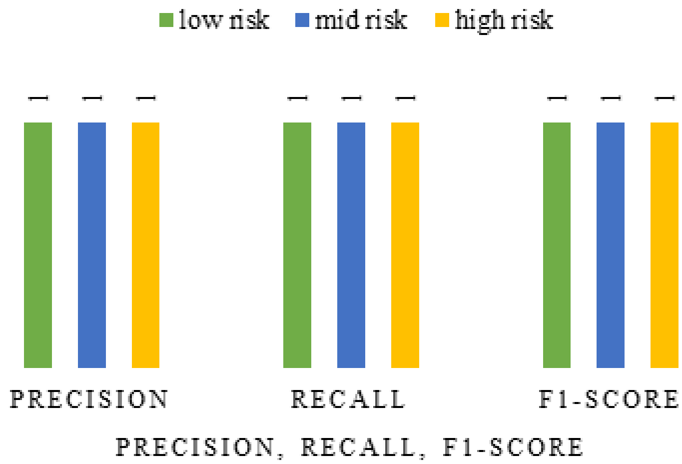


Figure 4.12: Precision, recall and f1-score values of Random Forest.

In conclusion, it can be said that the RF model performs well for the detection of the risk level of maternal and fetal heath as like the KNN and Decision Tree algorithms. In terms of precision, recall and f1-score, RF algorithm also performs well.

g) Multilayer Perceptron

A multilayer perceptron (MLP) is a fully connected class of feedforward artificial neural network (ANN). An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear regularization function alpha. The MLP algorithm is tested for different number of hidden layers with regularization function (alpha = 1e-5) and max iteration 5000. The highest accuracy achieved for 13 hidden layer i.e. 100.0% for both the original and selected dataset. The initial number of hidden layer started from 10.The accuracy for different number of hidden layer is given in the following Table 4.8 :

Table 4.8: Accuracy achieved for Multilayer Perceptron with the number of hidden layers

Number of hidden layer	Accuracy achieved for MLP
10	72.62%
11	61.56%
12	94.79%
13	100.00%
14	94.46%
15	100.00%
16	100.00%

Accuracy fluctuated with the number of hidden layers, sometimes rising and sometimes falling. The lowest accuracy was for 11 number of hidden layers and the highest was for 13,15 and 16 number of hidden layers. Considering the medium label of hidden layers numbers of 15, the other performance metrics were analyzed for this number of hidden layers. The confusion matrix for the MLP model is shown in Figure 4.13:

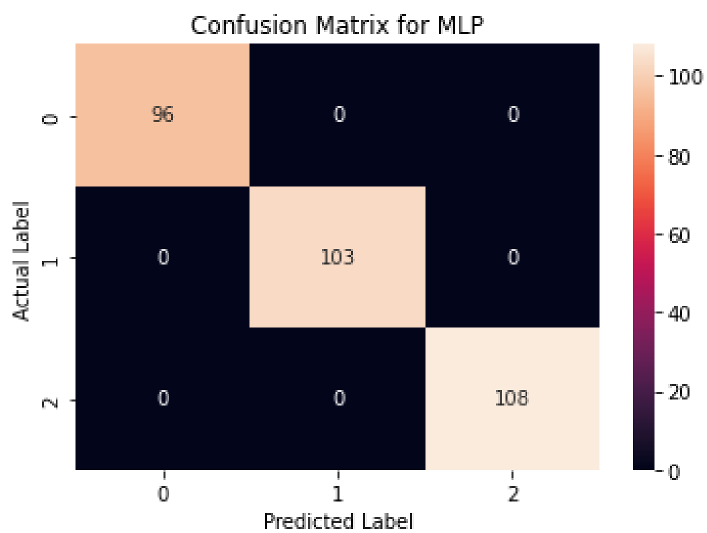


Figure 4.13: Confusion matrix for Multilayer Perceptron.

The "High risk" class's MLP model's TP value was 108, FP value was 0, and FN value was 0. The TP value for 'Low risk' and 'High risk' class are 96 and 103 which means the MLP algorithm accurately detect the 'Low risk' and 'High risk' class.The TP, TN, FP, FN values of the risk level obtained by the MLP model is shown in Table 4.9.

Table 4.9: The TP, FP, FN and TN value for Multilayer Perceptron algorithm

Risk level	**Value**			
	TP	**FP**	**FN**	**TN**
Low risk	96	0	0	211
Mid risk	103	0	0	204
High risk	108	0	0	199

From the value of FP, FN, TP, and TN, the precision, recall, and f1 score can be calculated for each class. . The precision, recall, and f1 score for the RF model is shown in Figure 4.14. If we consider the 'Mid risk' class, precision indicates 100% correct was the identification of the

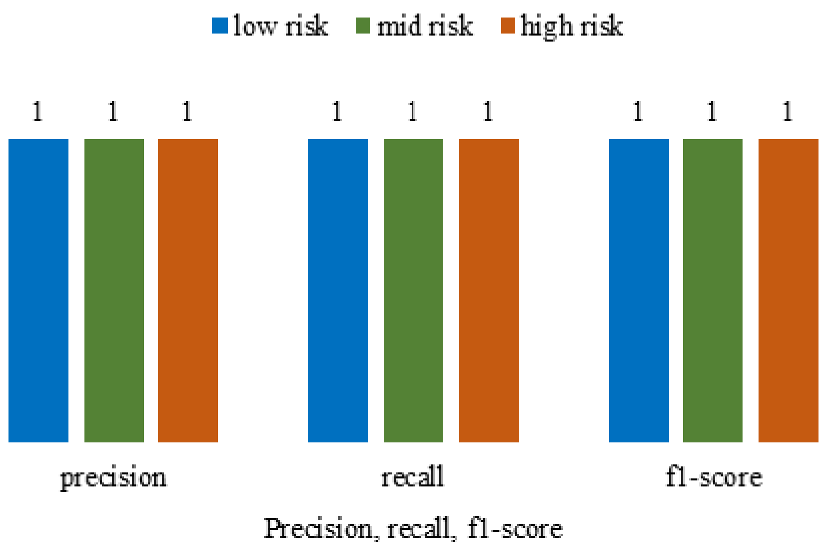


Figure 4.14: Precision, recall and f1-score values of Multilayer Perceptron.

'Mid risk' level. 100% of actual 'Mid risk' level was identified correctly. The MLP model with 15 hidden layer perfectly classifies 100% of observations into the correct 'Mid risk' class.

The precision, recall, f1-score for the low risk , mid risk and high risk class were the highest that means the MLP algorithm with 15 hidden layers correctly detect the risk levels.

In conclusion, it can be said that the MLP model's performance was better than the MLR, KNN, SVM and Naïve Bayes model as it was able to anticipate all types of risk levels. Also, the accuracy of the MLP model was 10.42% , 19.87% and 9.77% higher than the MLP, MNB and SVM models. However, the performance was also good as like as the DT and RF model in terms of precision, recall and f1-score value.

4.2.1.ii Prediction Using Distinct Techniques and Matlab Tools

Here, we also did maternal and fetal health risk prediction using Decision Tree and Multilayer Perceptron network. MATLAB tools was used here for performance of evaluation of these two techniques.

a) Decision Tree Algorithm

Decision trees, also known as classification and regression trees, forecast data responses. Follow the decisions in the tree from the root (starting) node all the way down to a leaf node to forecast a response. The answer is in the leaf node. Nominal answers like "true" or "false" are provided by classification trees. Regression trees respond with numbers.

Each step in a prediction involves checking the value of one predictor (variable). The Decision tree based on the maternal and fetal health data that is evaluated using MATLAB platform is given in Figure 4.15 :

This tree predicts classifications based on 19 predictors. To predict, start at the top node, represented by a triangle (Δ). The first decision is whether Random blood sugar(Ran_BG) is smaller than 5.915. If so, follow the left branch i.e. node 2.

If, however, Ran_BG exceeds 5.915, then follow the right branch to the node 3 else the tree classifies the data as High risk. Same procedures repeated to all other predictiors.

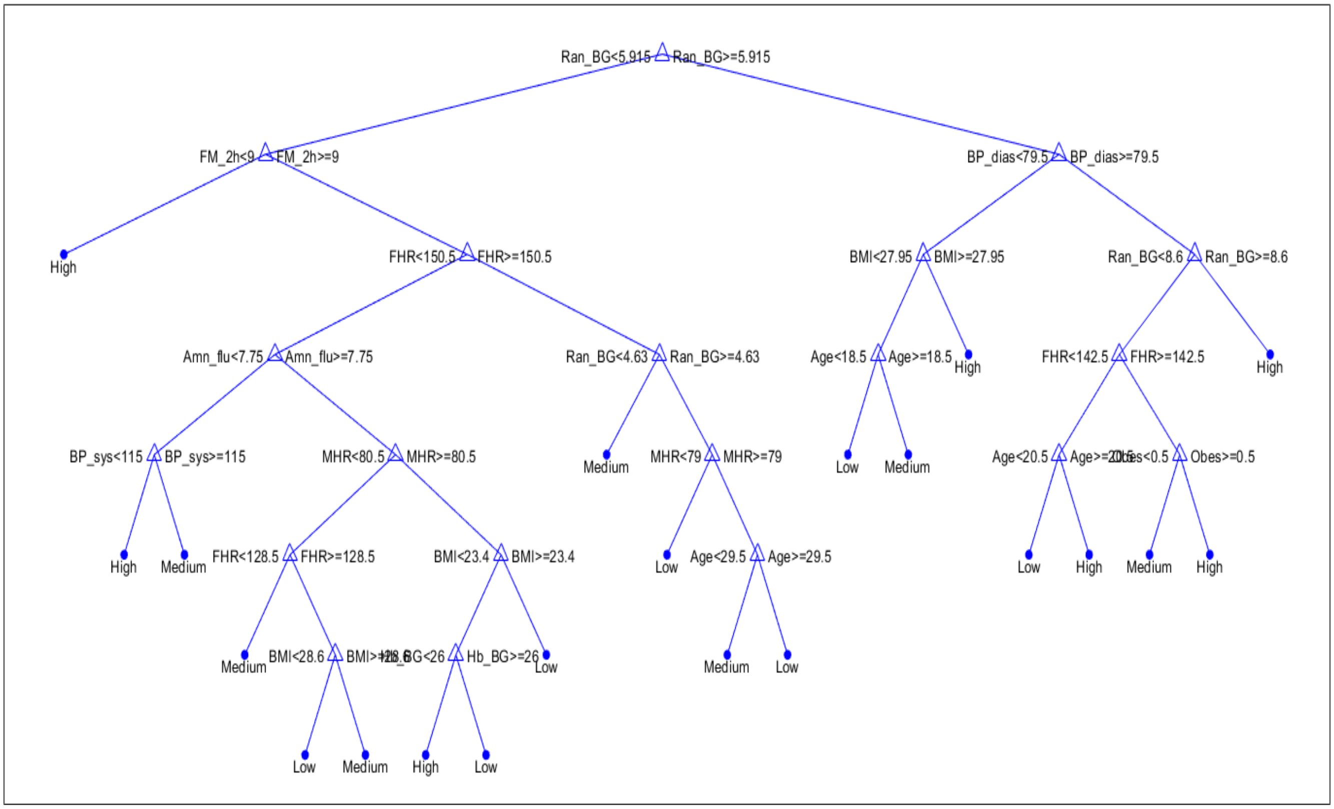


Figure 4.15: Decision Tree for the maternal and fetal health data.

The description of the Decision tree for classification is given below:

1 if Ran_BG<5.915 then node 2 elseif Ran_BG>=5.915 then node 3 else High

2 if FM_2h<9 then node 4 elseif FM_2h>=9 then node 5 else Low

3 if BP_dias<79.5 then node 6 elseif BP_dias>=79.5 then node 7 else High

4 class = High

5 if FHR<150.5 then node 8 elseif FHR>=150.5 then node 9 else Low

6 if BMI<27.95 then node 10 elseif BMI>=27.95 then node 11 else Medium

7 if Ran_BG<8.6 then node 12 elseif Ran_BG>=8.6 then node 13 else High

8 if Amn_flu<7.75 then node 14 elseif Amn_flu>=7.75 then node 15 else Low

9 if Ran_BG<4.63 then node 16 elseif Ran_BG>=4.63 then node 17 else Medium

10 if Age<18.5 then node 18 elseif Age>=18.5 then node 19 else Medium

11 class = High

12 if FHR<142.5 then node 20 elseif FHR>=142.5 then node 21 else High

13 class = High

14 if BP_sys<115 then node 22 elseif BP_sys>=115 then node 23 else Medium

15 if MHR<80.5 then node 24 elseif MHR>=80.5 then node 25 else Low

16 class = Medium

17 if MHR<79 then node 26 elseif MHR>=79 then node 27 else Low

18 class = Low

19 class = Medium

20 if Age<20.5 then node 28 elseif Age>=20.5 then node 29 else High

21 if Obes<0.5 then node 30 elseif Obes>=0.5 then node 31 else Medium

22 class = High

23 class = Medium

24 if FHR<128.5 then node 32 elseif FHR>=128.5 then node 33 else Low

25 if BMI<23.4 then node 34 elseif BMI>=23.4 then node 35 else High

26 class = Low

27 if Age<29.5 then node 36 elseif Age>=29.5 then node 37 else Medium

28 class = Low

29 class = High

30 class = Medium

31 class = High

32 class = Medium

33 if BMI<28.6 then node 38 elseif BMI>=28.6 then node 39 else Low

34 if Hb_BG<26 then node 40 elseif Hb_BG>=26 then node 41 else High

35 class = Low

36 class = Medium

37 class = Low

38 class = Low

39 class = Medium

40 class = High

41 class = Low

It is seen that the DT classifier performs well in both platforms i.e. Jupyter Notebook and Matlab. So it can be said that the DT classifier model can be used for the proposed model of maternal and fetal health risk prediction.

b) Multilayer Perceptron

For train dataset with Multilayer Perceptron Algorithm; load dataset, initialize input parameter and target value. There are 19 parameters are used as an input in input layer, one hidden layer with 15 neurons which is shown in Figure 4.16.

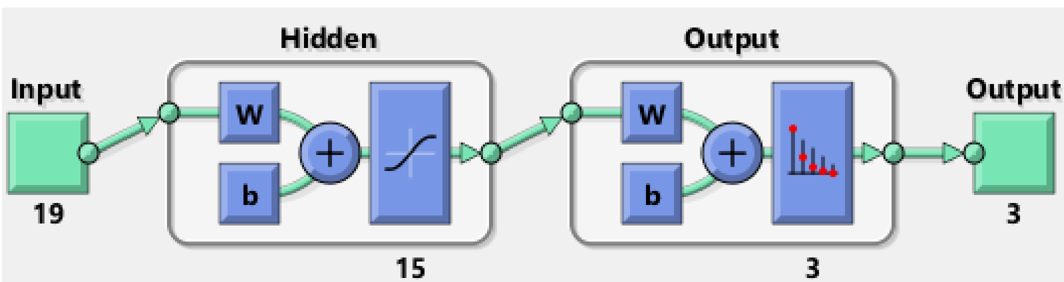
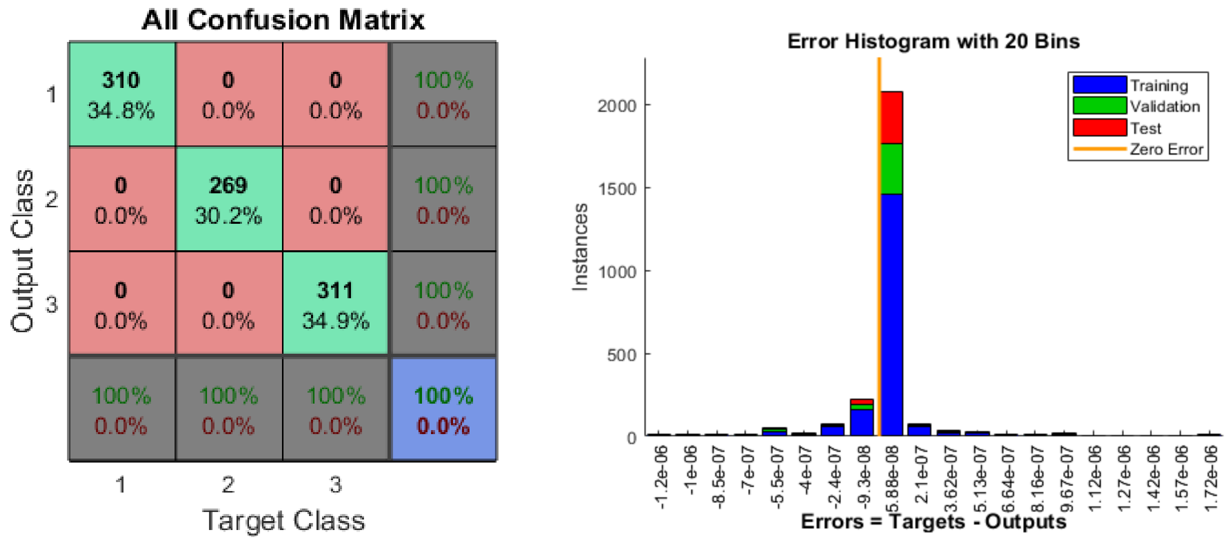


Figure 4.16: Architecture of Multilayer Perceptron algorithm

The figure 4.17(a) is stand for confusion matrix by multilayer perceptron algorithm where the green cell is shown where the output class is matched with the target class. And the red cell is shown where the output class is not matched with the target class.

The figure 4.17(b) shows the error histogram for MLP algorithm. X axis represents errors (Targets-Outputs) and Y axis represents instances.



(a) (b)

Figure 4.17: (a) Confusion matrix for Multilayer Perceptron algorithm.

(b) Error histogram for Multilayer Perceptron algorithm.

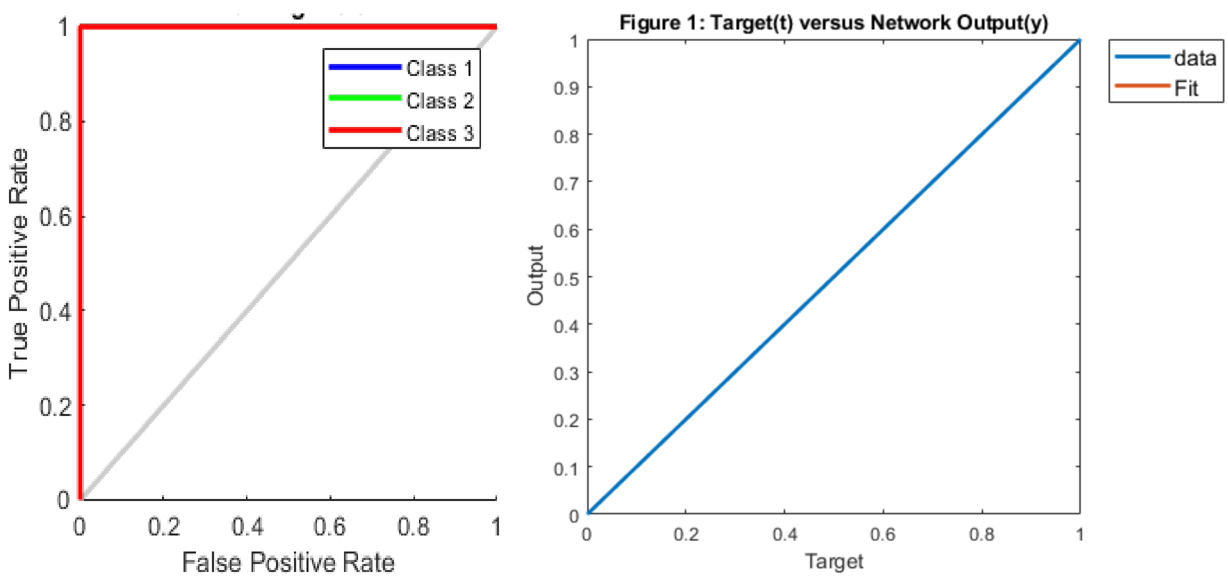
The model in figure 4.17(a) employs a dataset relevant to maternal and fetal health risks; all row classes represent the output class. The target classes are displayed in columns. In the first column below, 100% of the class 1 are true positives, representing the true positive rate, while false negatives are 0%, representing the false negative rate. The following columns also show the same results that 100% of class 2 and class 3 are correctly classified and representing the false negative rate 0%.In figure 4.17(b) zero error point falls under the bin with center 5.88e-08, which is the closest value to zero.

The confusion matrix is generated from the ―trainmlp‖ function by using MLP ANN algorithm and the results value is shown in Table 4.10:

Table 4.10: Accuracy result of Multilayer Perceptron algorithm (MATLAB)

Class	No. of Instances	Correctly predicted instances	Incorrectly classified instances	Error (%)	Accuracy (%)
Class _1	310	310	0	0	100%
Class _2	269	269	0	0	100%
Class_3	311	311	0	0	100%
Total	890	890	0	0	100%

In the table 4.10, correctly classified instances are 890 which means 100% accurately classified. In figure 4.18(a) is for ROC curve for measuring performance. The Y axis is stand for true positive rate and X axis is for false positive rate. Area under ROC for Class 1, Class 2 and Class 3 is 1.0.



(a) (b)

Figure 4.18: (a) ROC Curve for measuring performance of Multilayer Perceptron

(b) Regression graph of Multilayer Perceptron algorithm

Figure 4.18(b) displays the MLP algorithm's regression graph. Each plot's dashed line depicts the ideal outcome, which is when outputs equal targets. The best-fitting linear regression line between the outputs and the targets is represented by the solid line. The link between the outputs and the targets is shown by the R value. If R = 1, then the relationship between the outputs and the targets is exactly linear. In this case, R = 1, indicating a precise linear relationship between the outputs and the targets.

Figure 4.19 displays the performance graph for the MLP algorithm's training, validation, and testing of the maternal and fetal health dataset. Cross-Entropy, a loss function, is represented on the X axis, and epochs are represented on the Y axis. At 198 epochs, the best validation performance was found to be 5.1695Ee-08.

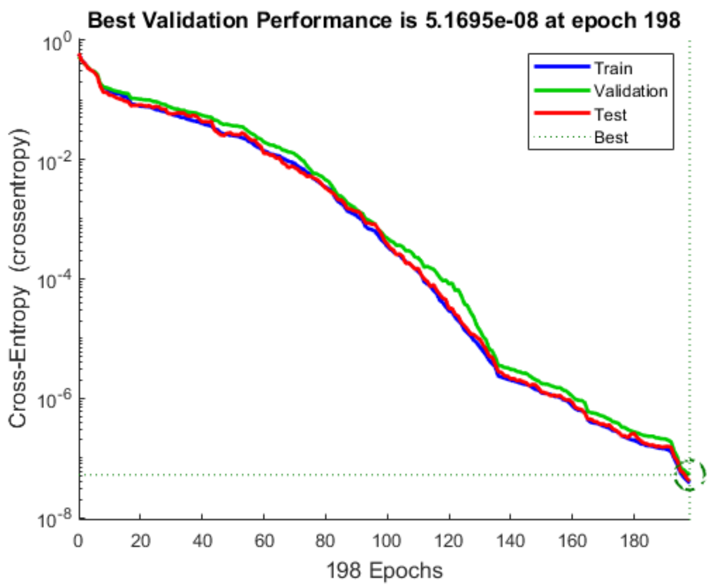
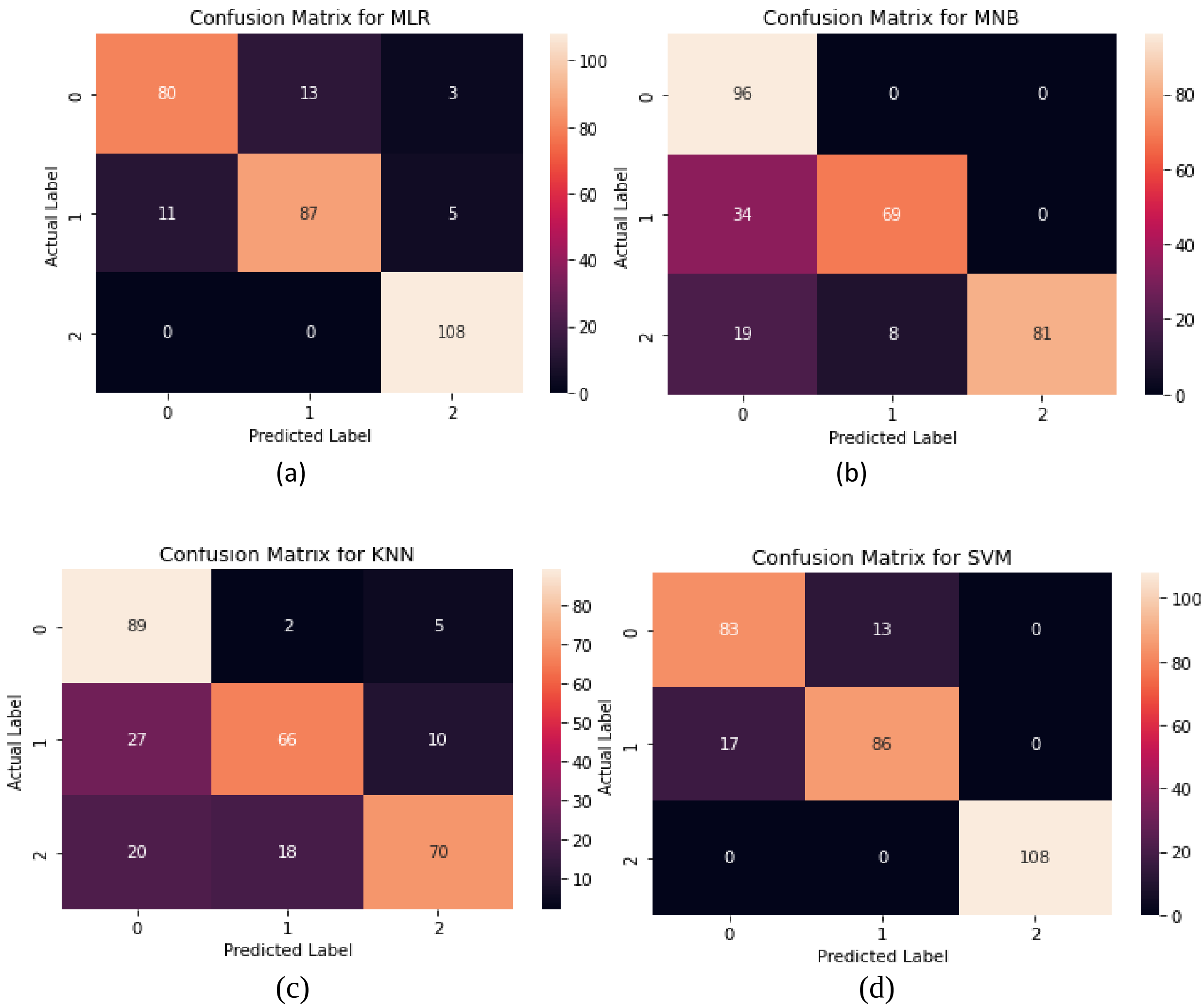


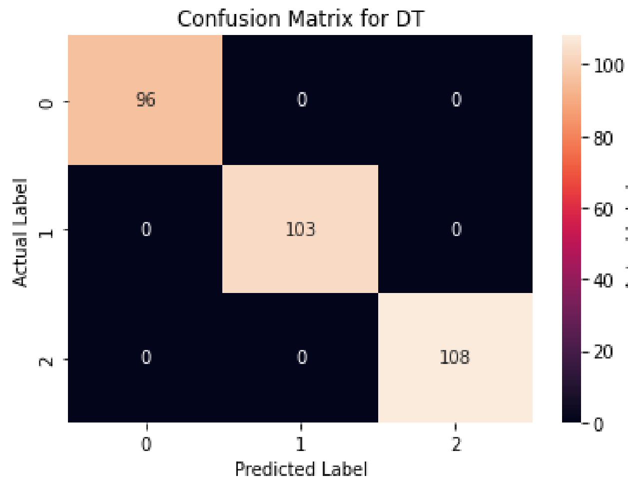
Figure 4.19: Performance graph of train, validation and test for Multilayer Perceptron algorithm.

4.2.1.iii COMPARATIVE ANALYSIS OF DIFFERENT TECHNIQUES

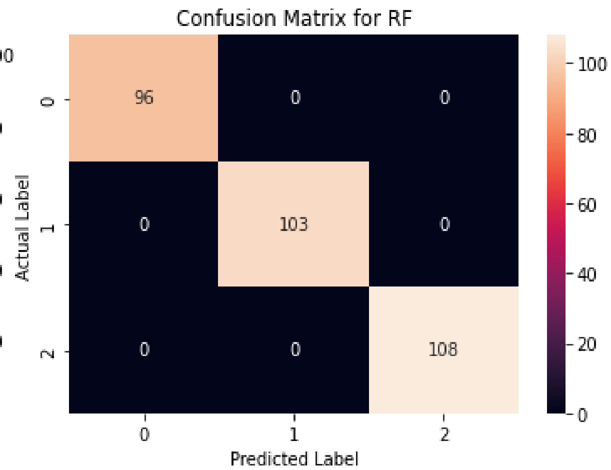
Comparison of different performance terminologies like confusion matrix, accuracy, precision, recall, f1-score and ROC_AUC score etc. of different Artificial Intelligence and neural network algorithms used in this work is shown below :

Comparison of confusion matrix between different AI and NN algorithms is shown in figure 4.20. In this figure 4.20(a) represents confusion matrix of MLR algorithm, 4.20(b) represents confusion matrix of MNB algorithm , 4.20(c) represents confusion matrix of KNN algorithm, 4.20(d) represents confusion matrix of SVM algorithm, 4.20(e) represents confusion matrix of DT algorithm, 4.20(f) represents confusion matrix of RF algorithm and 4.20(g) represents confusion matrix of MLP algorithm.

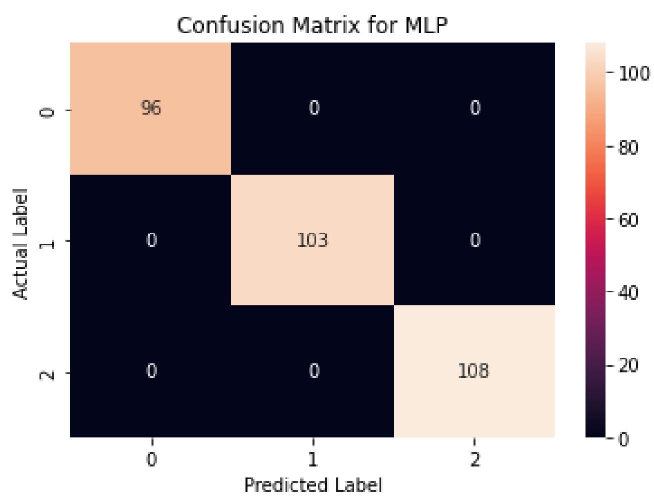




(e)



(f)



(g)

Figure 4.20: Comparison of confusion matrix between different Artificial Intelligence and neural network techniques.

(a) Multinomial Logistic Regression, (b) Multinomial Naïve Bayes,

(c) K-Nearest Neighbors, (d)Support Vector Machine

(e)Decision Tree, (f)Random Forest and (g)Multilayer Perceptron.

Comparison table of prediction accuracy, precision, recall, f1-score and ROC_AUC score between MLR, MNB, KNN, SVM, DT, RF and MLP algorithms is shown Table 4.11.

From the Table 4.11, it is seen that DT, RF and MLP achieved the highest accuracy, precision, recall, f1-score and ROC_AUC score i.e. 100%. To justify the performance, the DT and MLP algorithm also evaluated using MATLAB. Same satisfactory results also achieved from the MATLAB.

Though accuracy of KNN algorithm is high i.e. 100%, it's precision, recall, f1-score and ROC_AUC score is not so much satisfactory. Again MLR, MNB and SVM achieved good result but not so much satisfactory as KNN, DT, RF and MLP algorithms.

According to the performance result i.e. accuracy, precision, recall, f1-score and ROC_AUC score, it is seen that the DT, RF and MLP algorithms gives the best result for the maternal and fetal health dataset. So it can be said that these three model can be used for the further analysis and upgradation of the work in future.

Table 4.11: Comparison of performance between different algorithms

Performance Metrics	Algorithms								
	Multinomial LR	**Naïve Bayes**	**KNN**	**SVM**	**Decision Tree**	**Random Forest**	**Multilayer Perceptron Network**	**Decision Tree (MATLAB)**	**Multilayer Perceptron (MATLAB)**
Precision	89.33%	80.25%	74.85%	89.96%	100.0%	100.0%	100.0%	-	-
Recall	89.26%	80.66%	73.87%	89.98%	100.0%	100.0%	100.0%	-	-
F1 score	89.23%	84.68%	73.03%	89.95%	100.0%	100.0%	100.0%	-	-
Accurary	89.58%	80.13%	100.0%	90.23%	100.0%	100.0%	100.0%	100.0%	100.0%
ROC_AUC Score	98.09%	94.78%	91.3%	98.05%	100.0%	100.0%	100.0%	-	-

Comparison of the performance results of MLR, MNB, KNN, SVM, DT, RF and MLP algorithms is depicted in the following Figure 4.21:

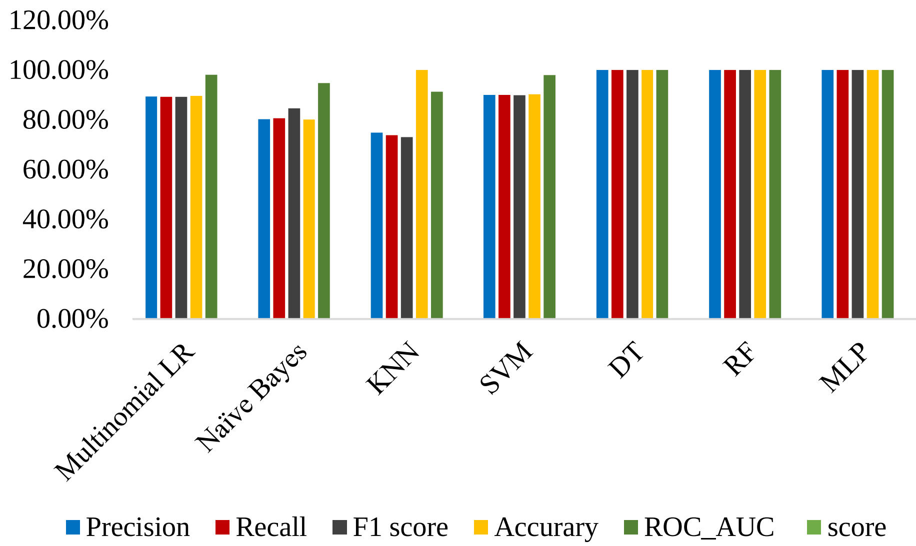


Figure 4.21: Comparison chart of different performance metrics of the Artificial Intelligence and neural network techniques.

4.2.2 Testing The Techniques With New Samples

Now the algorithms will be used for testing with new samples which are unused before. The steps of the prediction process of the algorithm are given bellow:

1. Test the dataset with new 31 instances. The new instance data set is in the main dataset. The last 31 samples of total samples are used for prediction accuracy.
2. Initialize the inputs and targets data.
3. Train the algorithms.
4. Then using the new instances of the maternal and fetal health dataset, the actual and predicted output is achieved from the trained algortithms
5. Accuracy of the algorithms based on the new instances is also determined.

The Table 4.12, shows the comparison of the actual and predicted output of the algorithms based on the new instances of maternal and fetal health data. The accuracy achieved from these algorithms is also shown in the Table 4.12:

Table 4.12: Actual and Predicted value of new samples of AI and NN algorithms

Actual value	predicted value						
	MLR	NB	KNN	SVM	DT	RF	MLP
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
high risk	high risk	high risk	mid risk	high risk	high risk	high risk	high risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
high risk	low risk	low risk	low risk	low risk	high risk	high risk	low risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
high risk	mid risk	mid risk	mid risk	mid risk	high risk	high risk	mid risk
high risk	mid risk	mid risk	mid risk	mid risk	high risk	mid risk	high risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
high risk	high risk	high risk	high risk	high risk	high risk	high risk	high risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
high risk	high risk	high risk	high risk	high risk	high risk	high risk	high risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
high risk	high risk	high risk	high risk	high risk	high risk	high risk	high risk
high risk	high risk	high risk	high risk	high risk	high risk	high risk	high risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
high risk	low risk	low risk	low risk	low risk	high risk	high risk	low risk
high risk	high risk	high risk	high risk	high risk	high risk	high risk	high risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
high risk	high risk	high risk	high risk	high risk	high risk	high risk	high risk
mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk	mid risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
low risk	low risk	low risk	low risk	low risk	low risk	low risk	low risk
Accuracy	70.96%	87.09%	83.87%	87.09%	100.00%	96.77%	90.32%

One of the main tasks of the research is to show the prediction with new samples. From the Table 4.12, it is seen that DT, RF and MLP algorithms also given better accuracy for the new sample data. The accuracy of MLR, MNB, KNN and SVM algorithms also satisfactory but less than the DT, RF and MLP algorithms.

Since the main goal of the research is to find out the best algorithm which will give better accuracy than the early prediction system of maternal and fetal health risk. So from this analysis it can be said that the DT, RF and MLP algorithms can be selected for further extension of the maternal and fetal health risk prediction and prevention system. The depiction of the algorithms accuracy on the new sample data is given in the Figure 4.22 :

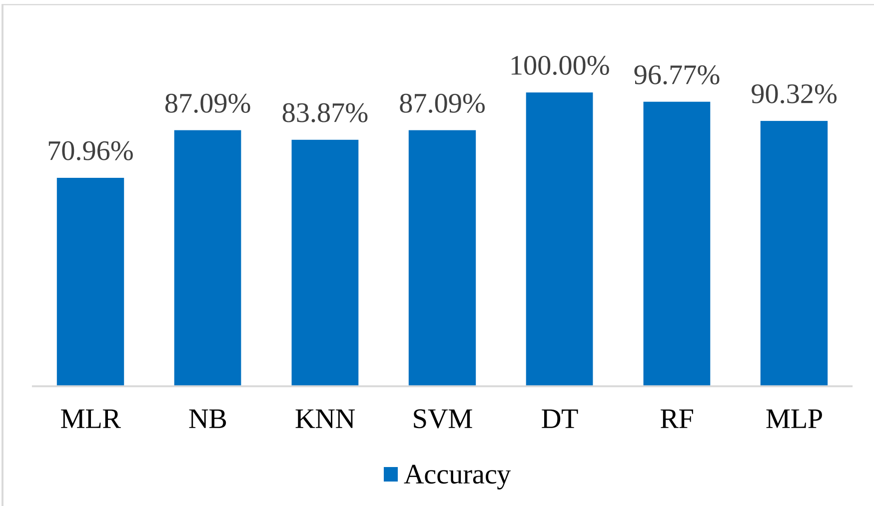


Figure 4.22: Accuracy of the algorithms on new sampled maternal and fetal health data.

4.3 SENSITIVITY ANALYSIS

Sensitivity analysis is a strategy for modifying model input in a controlled manner and evaluating the impact of these changes on the model output. This method reveals the model's sensitivity to these changes, as well as the impact of particular features on the model's performance. The objective of sensitivity analysis is to figure out how input and target factors interact.

Table 4.13 shows that, input parameters like blood pressure(systolic), blood pressure(diastolic), fetal movement in 2 hour, fetal heart rate, amount of amniotic fluid influences the risk level most compare to the other input parameters. After those parameters BMI, fasting blood glucose, Hb1Ac blood glucose, maternal heart rate also influences the risk level significantly. From this analysis, it can be said that the imbalance range of these parameters will increase the risk and the consequences will become serious for both the mother and the child.

Table 4.13: Sensitivity analysis values for maternal and fetal health risk level.

Name of input parameters	Sensitivity
Age	64.83
bp_systolic	97.21
bp_diastolyc	97.72
fever_cough_cold	45.36
body_temp_fahreheit	60.20
body_temp_celcius	65.99
maternal_heart_rate	78.50
fetal_movement_in_2_hour	92.62
obesity	59.74
BMI	80.27
random_blood_glucose	75.67
fasting_blood_glucose	85.99
HbA1C_blood_glucose	81.46
HBsAg	53.62
TSH	51.06
serum_sgpt	63.52
serum_uric_acid	51.25
fetal_heart_rate	91.69
amount_of_amniotic_fluid	93.47

It is crucial to comprehend the relative significance of the numerous components leading to maternal and fetal health risk occurrences in order to determine the optimal strategy for lowering the number of positive cases. According to the study's sensitivity analysis indices, the prevalence of maternal and fetal health risks depends significantly on each parameter. The most important factors in the sensitivity analysis technique, as shown by Figure 4.23, are bp_diastolic, bp_systolic, fetal movement, fetal heart rate, and the amount of amniotic fluid.

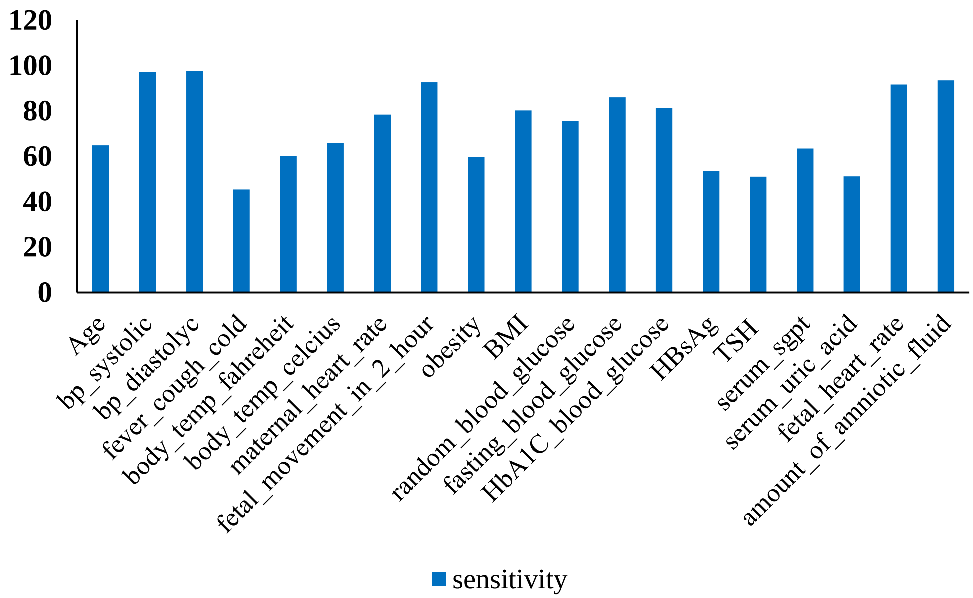
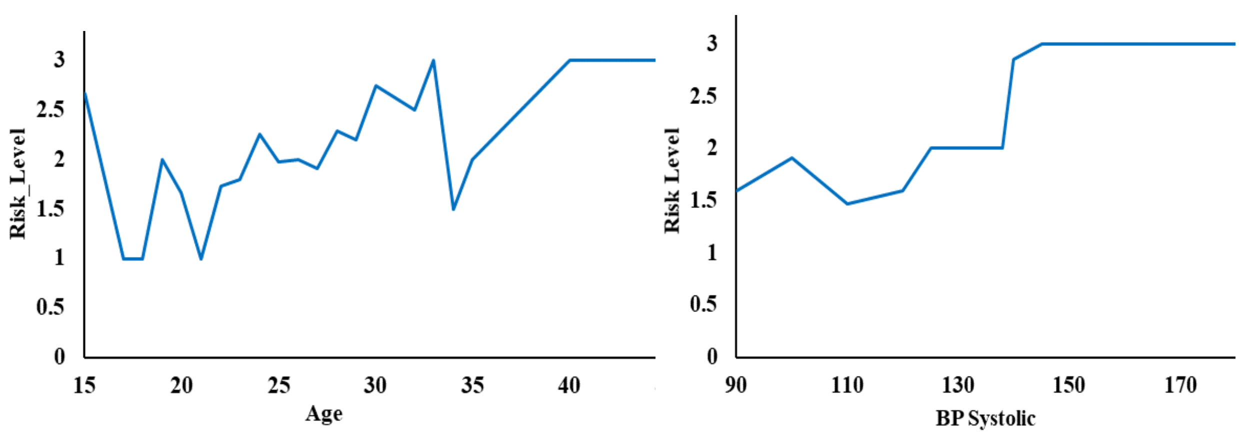


Figure 4.23: Sensitivity analysis of the maternal and fetal health related dataset.

How specific input parameters influence the risk and how the risk level changes with the specific risk factors is depicted in the Figure 4.24:

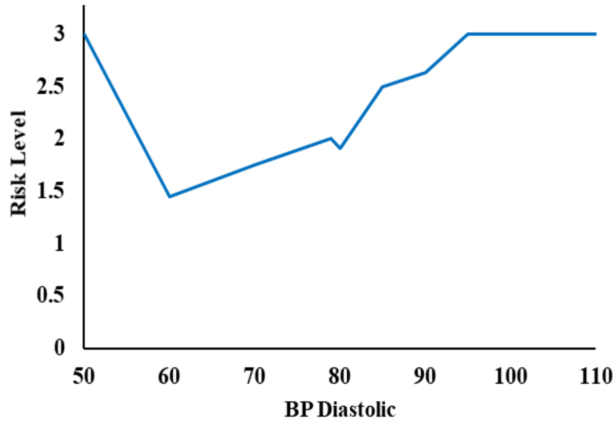
- **Effect of age on the maternal and fetal health risk:**

  Here, the effect of age on the maternal and fetal health risk is depicted in the Figure 4.24(a):

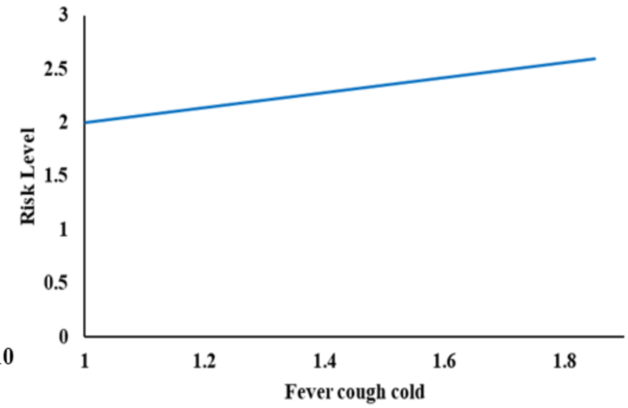


(a) (b)

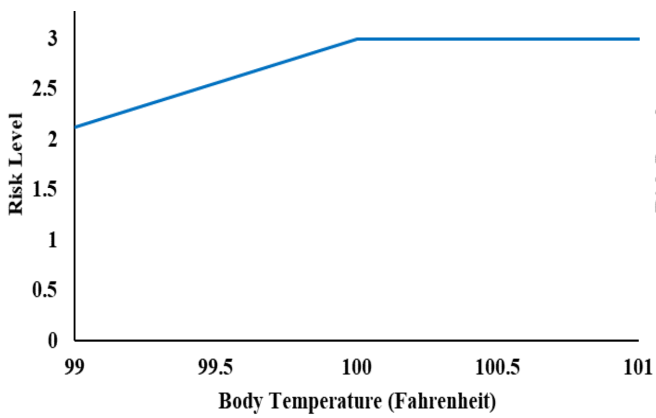
Age influences the maternal and fetal health risk level significantly when the age of a mother is less than 15 or greater than 35 years as seen from Figure 4.24(a). Between this range of age, risky situations can be created depending on the other maternal and fetal health risk parameters.



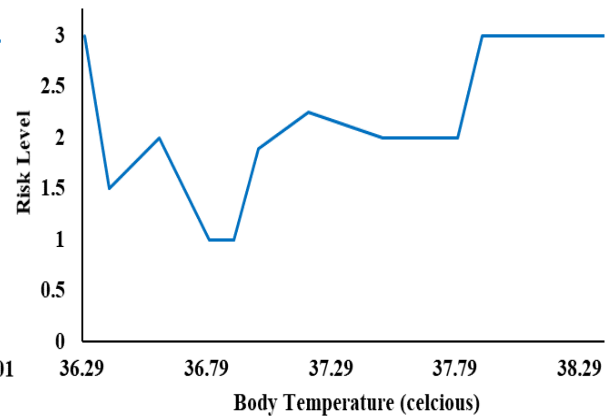
(c)



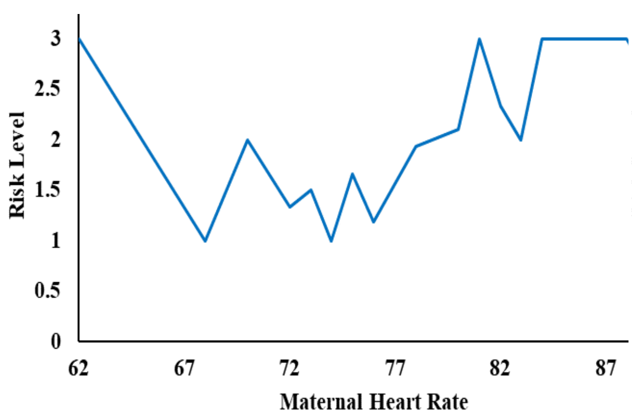
(d)



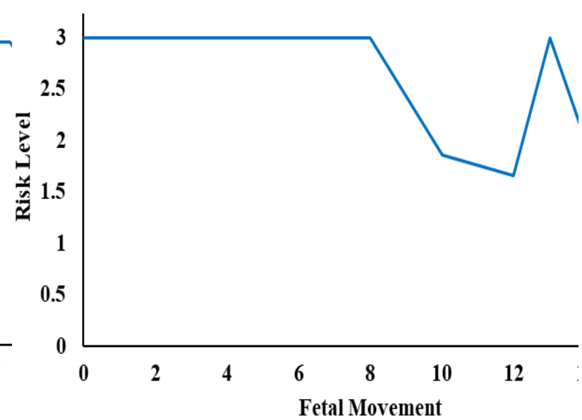
(e)



(f)



(g)

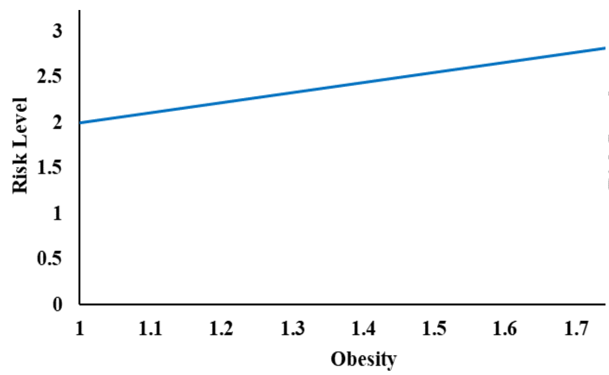


(h)

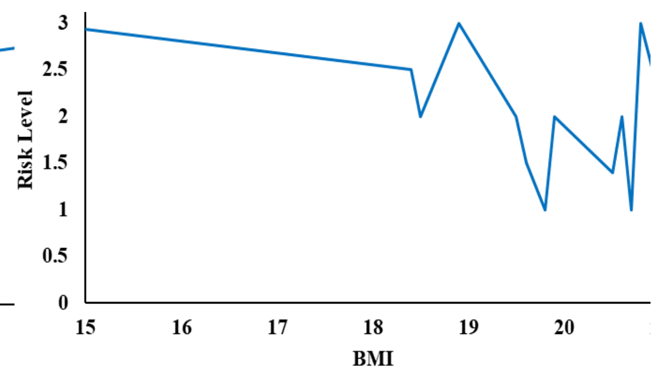
- **Effect of BP systolic on the maternal and fetal health risk:**

Here, the effect of BP Systolic on the maternal and fetal health risk is depicted in the Figure 4.24(b). Blood pressure systolic is the second most significant parameter in the sensitivity analysis of maternal and fetal health risk. High range of BP systolic i.e. greater than or equal to 100 mm

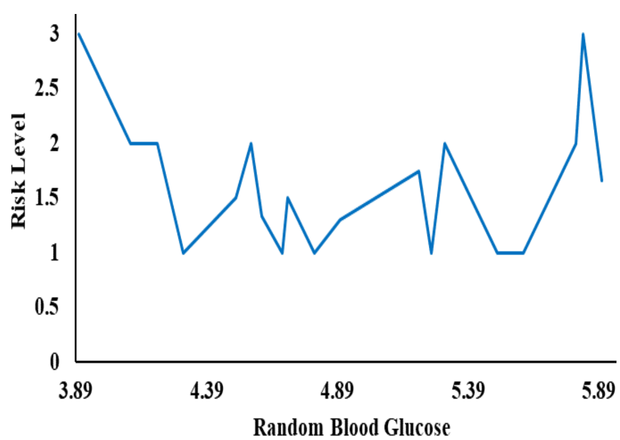
Hg can cause the risky situation like pre-eclampsia. Preeclampsia, pronounced pre-e-CLAMP-si-a, is a chronic high blood pressure condition that can appear during pregnancy or after giving birth. It is frequently linked to high protein levels in the urine, the recent onset of decreasing blood platelets, kidney or liver problems, fluid buildup in the lungs, or symptoms of brain problems such seizures and/or visual difficulties. It is specific to human pregnancy and is detected by the rise in the expecting mother's blood pressure, usually after the 20th week of pregnancy.



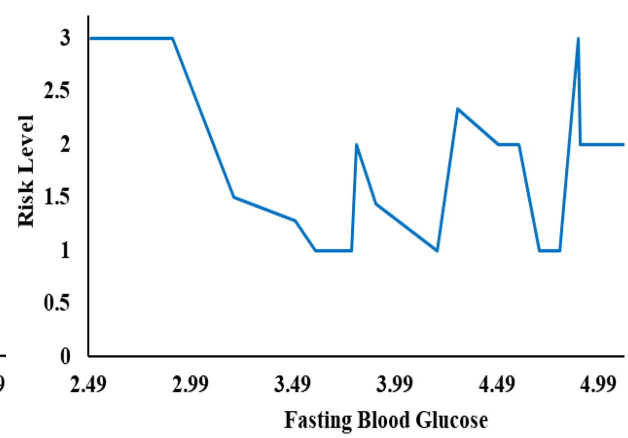
(i)



(j)



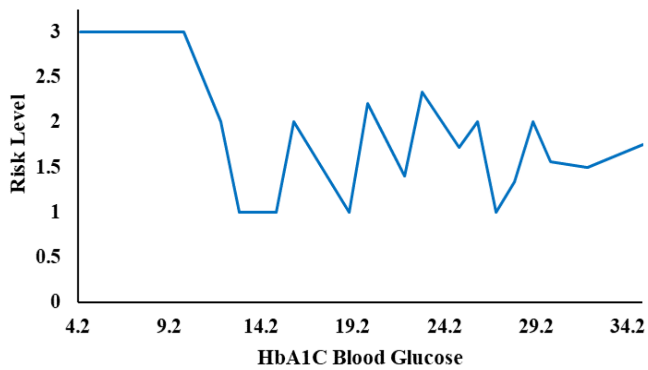
(k)



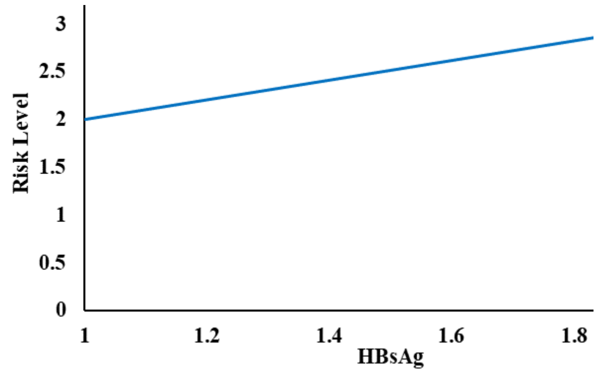
(l)

- **Effect of BP diastolic on the maternal and fetal health risk:**

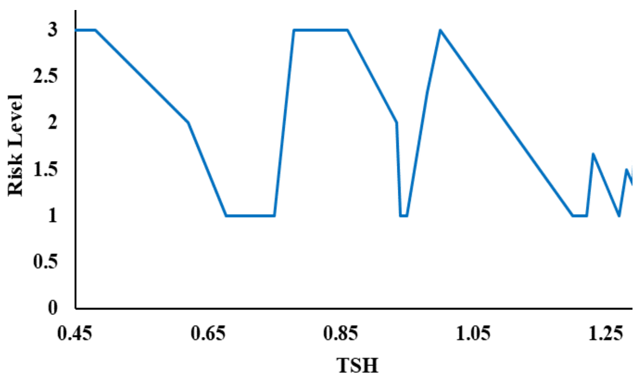
  BP diastolic is the most significant parameter in the sensitivity analysis of maternal and fetal health risk. Here, the effect of BP Diastolic on the maternal and fetal health risk is depicted in the Figure 4.24(c).High range of BP diastolic also causes risky situation like pre-eclampsia, hence lead to death of mother and the child in most cases.



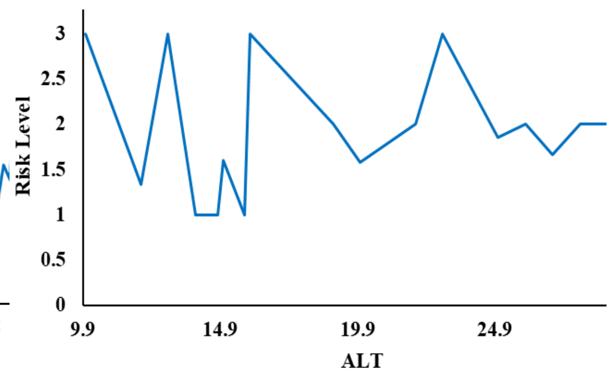
(m)



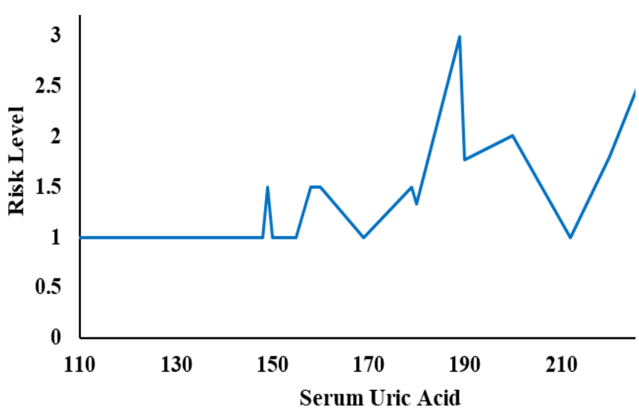
(n)



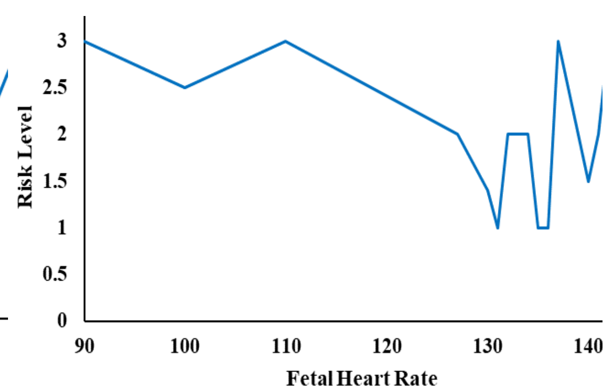
(o)



(p)



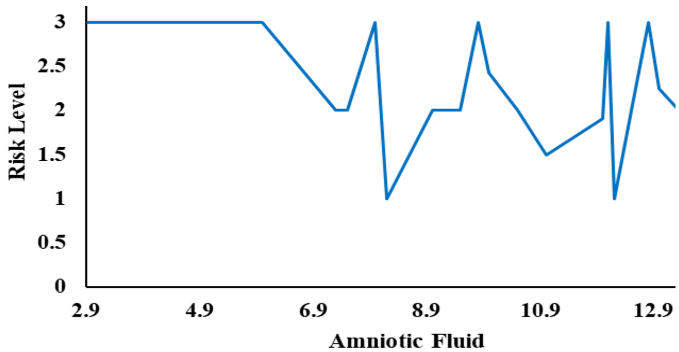
(q)



(r)

- **Effect of Fever cough cold on the maternal and fetal health risk:**

Fever cough cold maintains a linear relationship with risk level as seen from Figure 4.24(d). A pregnant woman's immune system may change during the pregnancy, making her more prone to the flu and the common cold. Numerous viral kinds, rhinoviruses being the most prevalent, can cause a cold. A viral or bacterial infection in the respiratory tract, which can be brought on by a cold, is what causes a cough. Even after a cold has passed, one's respiratory airways may continue to be swollen, painful, and inflamed, which can result in a chronic cough. Having fever cough cold during pregnancy is also risky for the mother and the child.



(s)

Figure 4.24: Effect of distinct variables on maternal and fetal health risk. (a)Age, (b) BP Systolic, (c) BP Diastolic, (d) Fever cough cold, (e) Body Temperature (Fahrenheit), (f) Body Temperature (celsius), (g) Maternal Heart Rate, (h) Fetal Movement, (i) Obesity, (j) BMI, (k) Random Blood Glucose,(l)Fasting Blood Glucose, (m) HbA1C Blood Glucose, (n) HBsAg, (o) TSH, (p) Serum SGPT/ALT, (q) Serum Uric Acid, (r) Fetal Heart Rate(FHR) and (s) Amniotic Fluid.

- **Effect of Body Temperature (Fahrenheit) on the maternal and fetal health risk:**

Here, the effect of Body Temperature (Fahrenheit) on the maternal and fetal health risk is depicted in the Figure 4.24(e). Although 98.6 degrees Fahrenheit is thought to be a typical body temperature, pregnant women often experience somewhat higher body temperatures, especially in the first trimester, which is completely acceptable. The increasing levels of progesterone in a woman's body during the first trimester are mostly responsible for this rise in body temperature. During a woman's ovulation cycle, progesterone is also responsible for increasing the basal body temperature. A first-trimester pregnancy with low body temperature may also have low progesterone levels, which raises the possibility of a miscarriage.

- **Effect of Body Temperature (celsius) on the maternal and fetal health risk:**

Here, the effect of Body Temperature (celsius) on the maternal and fetal health risk is depicted in the Figure 4.24(f). One is said to have a high temperature if their body temperature is greater than 37.5 degrees Celsius. A miscarriage may occur if a temperature exceeds 39.5 degrees, especially if it happens in the first trimester. Birth abnormalities, notably neural tube anomalies, have been linked to high temperatures during the first trimester. Spinal cord and brain function are impacted by neural tube abnormalities. Because the brain and neurological system fully develop during the first trimester, high fevers raise the chance of congenital abnormalities. Preterm labor can happen when an infection, particularly a kidney or uterine infection, causes a fever. These infections may cause the mother's body to attempt an early delivery of the child.

- **Effect of Maternal Heart Rate on the maternal and fetal health risk:**

Here, the effect of Maternal Heart Rate on the maternal and fetal health risk is depicted in the Figure 4.24(g). The typical mother heart rate usually rises by 10 to 20 beats per minute during pregnancy. Therefore, a rate of at least 100 beats per minute while at rest is considered tachycardia [61]. In general, if a pregnant woman's heart rate is under 60 beats per minute, her doctor should perform a comprehensive examination to rule out any underlying cardiovascular or other medical conditions. Some medications, congenital heart defects, high blood pressure, heart infections, scarring from heart surgery, disorders that cause an excess of iron in the body, hypothyroidism, or low thyroid, sleep apnea, a breathing disorder, and an imbalance of certain chemicals called electrolytes in the blood are just a few of the many potential causes of slow heart rate that doctors can identify. Bradycardia deprives both the pregnant person and fetus of oxygen.

- **Effect of Fetal Movement on the maternal and fetal health risk:**

Here, the effect of Fetal Movement on the maternal and fetal health risk is depicted in the Figure 4.24(h). As early as 13 to 16 weeks after the start of their last period, some mothers report feeling their baby move. These initial fetal movements, known as quickening, are frequently referred to as flutters. A pregnant lady may decide to quicken and count the quantity and variety of movements she feels the fetus making. A kick count is the colloquial name for this total. According to the American Pregnancy Association, the benefits of performing kick counts range from allowing a pregnant woman to bond with her unborn child to lowering the incidence of stillbirth; kick counts are particularly advised in high risk pregnancies. However, it's possible that telling women to watch for fetal movements will make them more anxious. When there has just been one episode of decreased fetal movements, 70% of pregnancies are straightforward. If a woman is above 28 weeks pregnant and believes her baby has stopped moving or is moving less, she should call her midwife, according to the UK's Royal College of Obstetricians and Gynecologists.

- **Effect of Obesity on the maternal and fetal health risk:**

Here, the effect of Obesity on the maternal and fetal health risk is depicted in the Figure 4.24(i). When a person's BMI is 30 or greater, obesity is declared. The most prevalent medical condition among women of reproductive age is obesity. Pregnancy-related obesity has negative short- and long-term effects on the mother and the unborn child. In early gestation, obesity promotes spontaneous pregnancy loss, infertility issues, and congenital abnormalities. Metabolically, obese women have higher insulin resistance in the first trimester of pregnancy, which clinically manifests as glucose intolerance and fetal enlargement in the second and third trimesters. The likelihood of a cesarean delivery and wound complications rises as gestation progresses. Obese postpartum women are more likely to experience depression, venous thromboembolism, and breastfeeding challenges.

- **Effect of BMI on the maternal and fetal health risk:**

Here, the effect of BMI on the maternal and fetal health risk is depicted in the Figure 4.24(j).Higher BMI leads to obesity, hence after many risky situation appears from it.

- **Effect of Random Blood Glucose on the maternal and fetal health risk:**

Here, the effect of Random Blood Glucose on the maternal and fetal health risk is depicted in the Figure 4.24(k). One of the most significant elements during pregnancy is blood glucose control. There is a slight increase in the risk of infant mortality or birth defects in babies of mothers with diabetes compared to those without. When a pregnant woman has an abnormally high level of blood glucose, the baby will naturally store excess glucose as body fat. It has been reported that on average 2% to 4% of women develop temporary diabetes, also known as gestational diabetes. As a result, when the baby is born at the gestational age, it will be bigger than usual. The medical term for this is fetal macrosomia.

- **Effect of Fasting Blood Glucose on the maternal and fetal health risk:**

Here, the effect of Fasting Blood Glucose on the maternal and fetal health risk is depicted in the Figure 4.24(l). Fasting plasma glucose (FPG) is now frequently assessed in the first trimester of pregnancy to look for diabetes (FPG 7 mmol/L). Early intermediate hyperglycemia, defined as FPG in the range of 5.1 to 6.9 mmol/L, and early gestational diabetes mellitus have both been discovered as a result of this screening (eGDM). Although early FPG has been linked to bad pregnancy outcomes, the IADPSG's recommendation that women with eGDM be referred for prompt care is more practical than evidence-based [62].

- **Effect of HbA1C Blood Glucose on the maternal and fetal health risk:**

Here, the effect of HbA1C Blood Glucose on the maternal and fetal health risk is depicted in the Figure 4.24(m). A mother and her unborn child are less likely to experience difficulties thanks to good blood glucose management. Prior to and during pregnancy, mothers should maintain a HbA1c of 6.1% (or 43 mmol/mol). In the beginning, diet and exercise will be used to treat pregnant women who acquire gestational diabetes; but, if blood sugar levels continue to rise, they may also be prescribed oral hypoglycemics (tablets) or insulin injections.

- **Effect of HBsAg on the maternal and fetal health risk:**

Here, the effect of HBsAg on the maternal and fetal health risk is depicted in the Figure 4.24(n). In poorer nations, HBsAg positive during pregnancy, a symptom of hepatitis B virus infection, is a well-recognized problem. However, it is unclear if this condition is linked to poor maternal outcomes. GDM, PPH, intrahepatic cholestasis, and Caesarean section were all more common in pregnant women who tested positive for HBsAg. HBsAg positivity during pregnancy was also linked to a higher risk of numerous poor maternal outcomes.

- **Effect of TSH on the maternal and fetal health risk:**

Here, the effect of TSH on the maternal and fetal health risk is depicted in the Figure 4.24(o). Thyroid Stimulating Hormone (TSH) must be present in a healthy range for effective operation. The thyroid gland is not producing enough thyroxine hormone if the level of TSH is high. Hypothyroidism is the name given to this condition. TSH levels may fluctuate while a woman is pregnant. The trimester may have an impact on TSH levels. TSH levels should be between 0.6 and 3.4 mIU/L in the first trimester and between 0.37 and 3.6 mIU/L in the second trimester. The typical TSH range for the third trimester is 0.38 mIU/L to 4.04 mIU/L. Iodine deficiency may cause low thyroxine levels, which in turn may cause an elevated TSH level. It is an autoimmune condition called Hashimoto's disease. In this illness, the body creates antibodies that harm the thyroid gland as well as other bodily tissues. It's unclear what caused this specifically.

- **Effect of Serum SGPT/ALT on the maternal and fetal health risk:**

Here, the effect of ALT on the maternal and fetal health risk is depicted in the Figure 4.24(p). When the liver is healthy, ALT enzymes are generally retained within the liver cells; however, when the liver cells are harmed or damaged in any way, ALT enzymes are released into the bloodstream, which raises levels. Therefore, we can assess the severity of liver damage by evaluating the level of ALT enzymes in the blood. A higher ALT value denotes more serious liver injury. Hepatitis A, B, or C, chronic viral hepatitis, cirrhosis of the liver (liver fibrosis caused by prolonged liver inflammation), alcohol-induced liver damage, hemochromatosis (a genetic condition caused by long-term liver damage), and decreased blood flow to the liver (from shock or heart disease) are the most common diseases that cause abnormally high SGOT and SGPT levels.

- **Effect of Serum uric acid on the maternal and fetal health risk:**

Here, the effect of serum uric acid on the maternal and fetal health risk is depicted in the Figure 4.24(q). Preeclampsia can result from having high uric acid levels during the first trimester of pregnancy. Women who have higher uric acid levels during pregnancy may also be more likely to develop gestational diabetes. This syndrome may appear in about 4% of pregnant women. If a woman has this problem, her body won't be able to make or utilise the hormone insulin, which controls blood sugar levels. Having high uric acid levels while pregnant can have an impact on the baby's health. A pregnant woman's baby's weight may be impaired if she has high levels of uric acid, which could result in fetal harm or even death. Diabetes, heart disease, and hypertension are a few of the long-term repercussions of this disorder.

- **Effect of Fetal heart rate on the maternal and fetal health risk:**

Here, the effect of fetal heart rate on the maternal and fetal health risk is depicted in the Figure 4.24(r). Fetal heart rate is one of the most significant parameter in the sensitivity analysis of maternal and fetal health risk. Fetal cardiac monitoring may be performed by a woman's healthcare professional during labor and late pregnancy. Fetal heart rates typically range from 110 to 160 beats per minute. 5 to 25 beats per minute can be different. As the unborn child reacts to circumstances in her uterus, the fetal heart rate may fluctuate. The baby may not be getting enough oxygen or may be experiencing other issues if the fetal heart rate is irregular.

- **Effect of amniotic fluid on the maternal and fetal health risk:**

Here, the effect of amniotic fluid on the maternal and fetal health risk is depicted in the Figure 4.24(s). The amount of amniotic fluid is also one of the most significant parameter in the sensitivity analysis of maternal and fetal health risk. A fetus is cushioned by amniotic fluid, a clear to slightly yellowish liquid, inside the amniotic sac. Throughout a pregnancy, the unborn child floats in amniotic fluid. The fetus "inhales" or consumes the amniotic fluid before expelling it by urinating, causing the amniotic fluid to circulate continuously. A pregnant woman with oligohydramnios, also known as low amniotic fluid, has insufficient amniotic fluid. At around 32–36 weeks of gestation, oligohydramnios is suspected if the AFI reveals a fluid volume of less than 500 ml, a fluid thickness of less than 5 centimeters, or the lack of a fluid pocket that is 2-3 cm deep. Some factors that contribute to low amniotic fluid levels include congenital disorders, membrane leakage or rupture, issues with the placenta, etc. Additionally, many people develop polyhydramnios, which is defined as an amniotic fluid volume of up to 2,000 ml, or an amniotic index of at least 20 cm. The main causes of polyhydramnios are many pregnancies or nervous system disorders in the fetus. Polyhydramnios is readily caused by pregnant women with diabetes, big fetuses, and faulty placentas. Due to the longer labor and delivery process caused by polyhydramnios, fetal discomfort and postpartum hemorrhage are frequently encountered.

The chance of a rapid rupture of the membranes, which can result in an early birth, increases when the amount of amniotic fluid is above the recommended limit.

4.4 SUMMARY

The ultimate model among the neural networks and Artificial Intelligence algorithm that are taken into consideration for this work is chosen in this chapter after analyzing the parameters and thoroughly discussing the results of all algorithms. To determine which parameter affects risk the most, sensitivity analysis was also done on the dataset for maternal and fetal health risks.

CHAPTER 5

CONCLUSION

5.1 INTRODUCTION

This chapter discusses the thesis' conclusion and its potential for further research. In the conclusion part, the overall summary of this thesis work is first offered. The future research scope section then offers prospective directions for future research.

5.2 CONCLUSION

Maternal Mortality Ratio (MMR), which is defined as deaths per 100,000 live births per time period, has fallen globally, with South-East Asia and Africa both experiencing declines of at least 59%. By 2015, the Millennium Development Goal of reducing maternal mortality by 75% has not yet been achieved in any regions. Maternal mortality in Bangladesh is 245 deaths for every 100,000 live births. Every year, Bangladesh loses 7,660 women to preventable conditions associated to pregnancy and childbirth.

In order to improve early risk detection for maternal and fetal health, this study focuses on the application of multiple supervised classification and neural network methodologies. High-risk pregnancies can frequently result in multiple physical and mental losses for the mother and the kid, which ultimately causes death. Here, a real-time dataset of pregnant women from hospitals and clinics was employed. A sensitivity analysis was also conducted to determine which parameters in this study most significantly increase the danger to the health of the mother and the fetus. All of the experiments in the proposed scheme are based on the real dataset and PYTHON and MATLAB tools are employed.

The Multinomial Logistic Regression, Multinomial Naive Bayes, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, and Multilayer Perceptron neural network methods were employed in this research. The Multilayer Perceptron training approach uses a hidden layer with 15 neurons and an input layer with 19 parameters. The results of each algorithm are used to choose which classifiers are the most accurate. The performance factors are used to compare these particular algorithms.

MLR (Multinomial Logistic Regression) provides 89.58% accuracy, 89.33% precision, 89.26% recall, 89.23% f1-score, and 98.09% ROC AUC score in the training state. 80.13% accuracy, 80.25% precision, 80.66% recall, 84.68% f1-score, and 94.78% ROC AUC score are provided by Multinomial Naive Bayes(MNB). K-Nearest Neighbors (KNN) provides 100.00% accuracy, 74.85% precision, 73.87% recall, 73.03% f1-score, and 91.3% ROC AUC score. Support Vector Machine (SVM) yields 90.23% accuracy, 89.96% precision, 89.98% recall, 89.95% f1-score, and 98.05% ROC AUC score. 100% accuracy, 100% precision, 100% recall, 100% f1-score, and 100% ROC AUC score are all provided by the decision tree (DT). Accuracy, precision, recall, f1-score, and ROC AUC are all 100% for Random Forest (RF). In terms of accuracy, precision, recall, f1-score, and ROC AUC score, multilayer perceptron provides a perfect score of 100.

This article concludes that Decision Tree (DT), Random Forest (RF), and Multilayer Perceptron (MLP) algorithms can be regarded as the best algorithms due to their greatest prediction accuracy of 100% after evaluating the experimental results of all algorithms. These algorithms can be utilized for early maternal and fetal health risk prediction since DT, RF, and MLP provide more accuracy.

The purpose of this study is to offer better performance and prediction. Use the f1-score, accuracy, precision, recall, and ROC AUC scores to determine performance.

5.3 FUTURE RESEARCH SCOPE

Here are some examples of future scope to consider:

I. This type of work can be implemented also for other region of Bangladesh by collecting maternal and fetal health related data from these regions.
II. The algorithms used here can be used with the extensions of the system like developing a remote maternal and fetal health care system.
III. Data collection process can be automated and more realistic by collaborating Internet of Things(IOT) to this work.
IV. Cloud based facility can also be provided to achieve more realistic scenario in this kind of health system.

Maternal and child morbidity becomes a curse for the generation of 2022. When each corner of the world updating day by day and all the people of the world becoming educated then this type of scenario like maternal and child morbidity during pregnancy due to unavailability proper medication is not acceptable at all. By collaborating our medical sector with the advanced technology we can overcome this type of situation. In this case, this research will contribute more.

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APPENDICES

A. DATASET

A-1 Raw Dataset

Here, bp_sys (Blood Pressure Systolic), bp_dias(Blood Pressure Diastolic), temp_fah(Temperature Fahrenheit), temp_cel(Temperature Celcious), FM_2h(Fetal Movement in 2 hour), random_BG(Random Blood Glucose), TSH (Thyroid Stimulating Hormone), ALT(Alanine Aminotransferase) etc. 20 parameters used in this work are shown below:

Age	bp_sys	bp_dias	fever	temp_fah	temp_cel	MHR	FM_2h	obesity	BMI	random_BG	fasting_BG	HbA1C_BG	HBsAg	TSH	ALT	uric_acid	FHR	amniotic_fluid	risk_level
18	100	80	no	98	37	75	10	No	22.5	7	5.6	35	negative	2.5	25	3	130	17	low risk
22	120	80	no		37	80	12	No	22.4	4.9	3.5	30	negative	1.29	20	3.5	144	8.2	low risk
27	110	80	no	98	37	80	12	No	20.5	5.5	4.5	30	negative	2.733	25	148	135	15	low risk
20	110	80	no	98	37	76	10	No	19.5	4.8	3.7	30	negative	1.89	20	200	148	14.5	low risk
23	90	70	no	98	37	76	10	No	22.5	4.9	3.7	30	negative	1.9	20		140	15	low risk
21	110	80	no	98	37	76	12	No	21.3	4.9	3.7	30	negative	1.78	20	212	130	12	low risk
26	100	80	no	98	37	78	10	No	18.4	7		40	negative	2.7	28	270	169	12.5	mid risk
25	100	60	no	98	37	75	10	No	20.5	6.4	5.7	29	negative	0.935	20	180	159	12	mid risk
18	100	60	no	98	37	73	10	No	20.7	4.9	3.9	25	negative	1.29	20	150	140	12	low risk
26	120	70	no	98	37		10	No	22.9	4.9	3.6	35	negative	1.5	25	250	130	14	low risk
30	110	80	no	98	37	78	8	yes	26.9	6.9	5.3	35	negative	0.86	25	220	160	12.1	high risk
22	110	80	no	98	37	78	12	No	22.8	5.25	4.7	28	negative	1.75	20		154	14	low risk
27	100	60	no	98	37	80	12	No	27.9	4.68	3.9	25	negative	1.89	20	190	148	14	low risk
26	90	60	no		37	78	10	No	18.5	4.5	3.9	35	negative	1.89	20	180	130	12	low risk
21	110	80	no	98	37	78	10	No	20.5	5.8	4.9	35	negative	1.5	20	149	140	15	low risk
26	100	80	no	98	37	80	10	No	26	4.56	3.9	30	negative	0.98	20	200	152	14	mid risk
27	140	110	no	98	37	85	8	No	28.9	5.83	4.9	35	negative	0.98	20	290	150	14.9	high risk
26	110	80	no	98	37	80	10	No	26.9	4.9	3.9	30	negative	0.78	15	200	143	6	high risk
22	110	70	no	98	37	78	10	No	28.9	4.7	3.9	25	negative	1.46	20	190	132	30	mid risk

A-2 Preprocessed Data

Here, bp_sys (Blood Pressure Systolic), bp_dias(Blood Pressure Diastolic), temp_fah(Temperature Fahrenheit), temp_cel(Temperature Celcious), FM_2h(Fetal Movement in 2 hour), random_BG(Random Blood Glucose), TSH (Thyroid Stimulating Hormone), ALT(Alanine Aminotransferase) etc. 20 parameters used in this work are shown below:

Age	bp_sys	bp_dias	fever	temp_fah	temp_cel	MHR	FM_2h	obesity	BMI	random_BG	fasting_BG	HbA1C_BG	HBsAg	TSH	ALT	uric_acid	FHR	amniotic_fluid	risk_level
18	100	80	0	98	37	75	10	0	22.5	7	5.6	35	0	2.5	25	3	130	17	0
22	120	80	0	98	37	80	12	0	22.4	4.9	3.5	30	0	1.29	20	3.5	144	8.2	0
27	110	80	0	98	37	80	12	0	20.5	5.5	4.5	30	0	2.733	25	148	135	15	0
20	110	80	0	98	37	76	10	0	19.5	4.8	3.7	30	0	1.89	20	200	148	14.5	0
23	90	70	0	98	37	76	10	0	22.5	4.9	3.7	30	0	1.9	20	200	140	15	0
21	110	80	0	98	37	76	12	0	21.3	4.9	3.7	30	0	1.78	20	212	130	12	0
26	100	80	0	98	37	78	10	0	18.4	7	3.9	40	0	2.7	28	270	169	12.5	1
25	100	60	0	98	37	75	10	0	20.5	6.4	5.7	29	0	0.935	20	180	159	12	1
18	100	60	0	98	37	73	10	0	20.7	4.9	3.9	25	0	1.29	20	150	140	12	0
26	120	70	0	98	37	78	10	0	22.9	4.9	3.6	35	0	1.5	25	250	130	14	0
30	110	80	0	98	37	78	8	1	26.9	6.9	5.3	35	0	0.86	25	220	160	12.1	2
22	110	80	0	98	37	78	12	0	22.8	5.25	4.7	28	0	1.75	20	200	154	14	0
27	100	60	0	98	37	80	12	0	27.9	4.68	3.9	25	0	1.89	20	190	148	14	0
26	90	60	0	98	37	78	10	0	18.5	4.5	3.9	35	0	1.89	20	180	130	12	0
21	110	80	0	98	37	78	10	0	20.5	5.8	4.9	35	0	1.5	20	149	140	15	0
26	100	80	0	98	37	80	10	0	26	4.56	3.9	30	0	0.98	20	200	152	14	1
27	140	110	0	98	37	85	8	0	28.9	5.83	4.9	35	0	0.98	20	290	150	14.9	2
26	110	80	0	98	37	80	10	0	26.9	4.9	3.9	30	0	0.78	15	200	143	6	2
22	110	70	0	98	37	78	10	0	28.9	4.7	3.9	25	0	1.46	20	190	132	30	1