PREDICTING PIH LEVELS AND IDENTIFYING FACTORS USING MACHINE LEARNING

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ACCEPTANCE

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Declaration

The under signed, here by certify that my work is included in the thesis. As per the globally recognized standards, I have credited and referenced all sources utilized in this research. I am aware that failure to uphold the standards of academic honesty and integrity, as well as the fabrication or misrepresentation of any idea, data, fact, or source, will be sufficient grounds for corrective action taken by the university. Failure to properly credit or acknowledge sources may also result in legal repercussions.

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Abstract

Pregnancy-induced hypertension is a significant health concern that affects approximately 5-8% of pregnancies worldwide, contributing to maternal mortality. In Ethiopia, PIH is a leading cause of maternal mortality, emphasizing the need for early detection and intervention. This research investigates the application of machine learning algorithms to predict the levels of PIH in pregnant women, aiming to enhance the accuracy and timeliness of diagnosis. The importance of research integrating machine learning technologies in healthcare, particularly in resource-limited settings like Ethiopia, to improve maternal and fetal health outcomes. Using supervised machine learning techniques we have to perform by extracting variables like BMI,sBP,dBP, urine in protein, blood in sugar, and other variables are training using the given dataset. For those features we have to select an algorithm such as Random Forest, SVM, Decision tree, Logistic Regression, and XGboost model the study develops a predictive model capable of classifying PIH levels into normal, low, moderate, and high categories. The model's performance is evaluated using metrics like accuracy, precision, recall, and F1-score. From this performance XGboost model has the highest Accuracy, Precision, Recall, and Fl-score are 98.56 %, 98.28 %, 98.93 %, and 98.58 % are measured respectively. Finally demonstrates its potential to assist healthcare providers in identifying factors and the level of hypertension from the predictive categories and implementing appropriate interventions. Future work can use ultrasound images can be used to detect structural abnormalities or blood flow issues that might correlate with PIH and Advanced image analysis techniques of algorithms, such as convolutional neural networks.

Keywords: *Machine learning, supervised machine learning, PIH level prediction, XGboost, random forest, logistic regression, SVM, decision tree*

Acronym and Abbreviation

ANC: ANTENATAL CARE

AUC: AREA UNDER THE ROC CURVE

BS: BLOOD IN SUGER

BSA: BODY SURFACE AREA

BT: BLOOD TEMPERATURE

CNN: CONVOLUTIONAL NEURAL NETWORKS

CPU: CENTRAL PROCESSING UNIT

DBP: DIASTOLIC BLOOD PRESSURE

DT: DECISION TREE

EDA: EXPLORATORY DATA ANALYSIS

EHRS: ELECTRONIC HEALTH RECORDS

FAR: FEDERAL ACQUISITION REGULATION

FN: FALSE NEGATIVE

FP: FALSE POSITIVE

GB: GIGABYTE

GHz: GIGA HERTZ

HP: HEWLETT-PACKARD

KNN: K-NEAREST NEIGHBOR

LDA: LINEAR DISCRIMINANT ANALYSIS

LR: LOGISTIC REGRESSION

ML: MACHINE LEARNING

mmHG: MILLIMETERS OF MERCURY

NGO: NON-GOVERNMENTAL ORGANIZATION

PE: PHYSICAL EDUCATION

PIH: PREGNANCY INDUCED HYPERTENSION

RAM: RANDOM-ACCESS MEMORY

RF: RANDOM FOREST

RQ: RESEARCH QUESTIONS

SBP: SYSTOLIC BLOOD PRESSURE

SMOTE: SYNTHETIC MINORITY OVER-SAMPLING TECHNIQUE

SVM: SUPPORT VECTOR MACHINE

TN: TRUE NEGATIVE

TP: TRUE POSITIVE

XGBOOST: EXTREME GRADIENT BOOSTING

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CHAPTER ONE

1. INTRODUCTION

1.1. Background of Study

Pregnancy-induced hypertension is a serious health issue that can affect both mother and child. It happens to about 5-8% of pregnant women worldwide is a serious condition that can have harmful effects on both the mother within child [1],[2]. Globally, pregnancy-induced hypertension and its factors are the leading cause of maternal mortality, contributing to around 14% of maternal deaths. It is responsible for 16% of maternal mortality in Sub-Saharan Africa and 16.9% of maternal mortality in Ethiopia [3]. Hypertension in pregnant is associated with hypertension and is known to poorly impact maternal and newborn mortality and illness. In our country, pregnancy-induced hypertension is a significant concern for maternal and fetal health, as it can lead to complications such as PIH, which are major causes of maternal and child mortality in the country. Access to quality antenatal care is essential for early detection and management of hypertension during the time of pregnancy [4]. Early detection and monitoring of pregnancy-induced hypertension are crucial to prevent complications and ensure the health of both the mother within the child. In recent years, machine learning algorithms have been increasingly used in healthcare settings to predict and monitor various medical conditions, including hypertension. By analyzing data from pregnant women within predictive factors, machine learning algorithms can help healthcare providers predict the likelihood of developing hypertension during pregnancy and take appropriate preventive measures [3]. By utilizing machine learning algorithms, healthcare providers can potentially improve the accuracy and efficiency of predicting PIH levels, allowing for early intervention and personalized care for pregnant women at risk. This can ultimately lead to better outcomes for both the mother within the child, reducing the risk of complications associated with hypertension during pregnancy. PIH is a major cause of disease and death in maternal, fetal, and newborn children. The most important parameters, SBP and DBP are used to predict the PIH levels (low PIH, moderate, and saver PIH) by applying machine learning algorithms. This technology to predict pregnancy-induced hypertension levels in Ethiopia has the potential to make a significant impact on reducing maternal and infant mortality rates and improving overall healthcare outcomes in the country Pregnancy-induced hypertension complicates about 6-10% of pregnancies [5]. It is defined as systolic blood pressure (SBP) >140 mmHg and diastolic blood pressure (DBP) >90 mmHg. It is classified as mild (SBP 140-149 and DBP 90-99 mmHg), moderate (SBP 150-159 and DBP (100-109 mmHg), and severe (SBP 160 and DBP 110 mmHg) [6]. Prevalence of hypertension among pregnant women, the prevalence of hypertension in pregnancy ranges from 10% to 20% or even higher in some areas which can lead to complications such as PIH. Machine learning algorithms can be utilized in healthcare to predict and control PIH levels among pregnant women. By analyzing data on health history and other relevant factors, machine learning models can help healthcare providers identify women at risk of developing hypertension during pregnancy and provide timely interventions to prevent complications. Implementing machine learning algorithms can improve the accuracy of predicting PIH levels, leading to better outcomes for both mother and child [7]. The role of developing PIH prediction levels is to reduce maternal and infant mortality rates and improve overall healthcare outcomes in this region of Ethiopia. Predicting PIH levels among ANC holds great improvement in maternal and fetal health outcomes and should be further explored and implemented in healthcare settings worldwide [8]. We have to use supervised machine learning stands from other researchers use real datasets from health centers, and record data up to 100, 1000 1,125 pregnant women we have to fill these critics according to sample size explanation 3479 data are used in the study in addition to the data collected from large and more diverse patient populations. The main predictor variables added to this study are urine in protein, use of contraceptive methods, gender, pregnant age, BMI, and blood sugar from those features additional variables are upgraded to get better output. For this study, we used the XGboost model is a better outcome from the comparison with other ensemble models. when we selected this model it is compatible with better quality datasets that have a suitable number of features, and instances, are appropriately cleaned and the model computes faster training and better tuning capabilities. Finally, some studies get like Accuracy of 94.36% but the study was generally about their hypertension using machine learning not a study in PIH. Our research using this model improves prediction accuracy and performance the accuracy is 98.56 with a better outcome of a confusion matrix. The full result is sit from the classification report for XGboost.

1.2. Statement of Problem

Pregnancy-induced hypertension is a serious health issue in Ethiopia. However, there is a lack of accurate methods for predicting and monitoring PIH levels among pregnant women, leading to delays in diagnosis and insufficient management. Existing healthcare is limited in terms of resources and capacity to address the growing burden of PIH among pregnant women effectively. Limited healthcare infrastructure and access to specialized providers exacerbate the issue [3]. Based on this integrated technology using machine learning we have to solve the problem of Ethiopian women being advised to adopt technology to improve the management of pregnancy-induced hypertension. Machine learning algorithms can predict and monitor PIH levels, providing real-time insights and personalized recommendations. Reducing maternal and newborn mortality rates, strengthening healthcare systems, and transforming maternal and fetal health outcomes in Ethiopia, particularly in areas heavily impacted by Pregnancy-Induced Hypertension [8]. PIH can restrict blood flow to the placenta, leading to reduced oxygen and nutrients reaching the child, which can result in poor fetal growth and low birth weight. Women who have had PIH are at an increased risk of developing hypertension, cardiovascular disease, and stroke later in life. PIH increases the risk of the placenta separating from the uterine wall before delivery, which can cause heavy bleeding and threaten the life of both the mother within child. It leads to so many problems related to pregnant women and also children. Pregnant women with PIH need to receive regular prenatal care and monitoring to detect and manage any complications early [9]. Moreover, existing PIH level prediction may not be fully enough because of the complexity of the underlying data. This leads to missed opportunities for early intervention and identification.

Research question

a) What is the problem with the existing prediction model?
b) Which ML models were used to predict PIH?
c) What predictive factors of PIH are used to train the ML model?

1.3. Motivation

We have to be motivated to do this research because of existing prediction methods of PIH are manual in this case we have changed using PIH technology using supervised machine learning algorithms to improve pregnancy-related issues like hypertension, and pregnancy-induced hypertension by developing accurate prediction models using machine learning. This is to optimize resource allocation and clinical decision-making, leading to better maternal and fetal health outcomes. An accurate diagnosis is important to minimize the work pressure for the medical team and reduce the time of diagnosis. This research work depends on supervised machine learning because of am using level data.

1.4. Objective

1.4.1. General Objective

To develop a prediction model for identifying factor and pregnancy-induced hypertension levels of pregnant women using a machine learning algorithm.

1.4.2. Specific Objective

To achieve the general objective of this research, we have considered the following activity:

- To review literature related to predicting pregnancy-associated hypertension
- To select the quality of studies related to the prediction and screening of pregnancy-related medical studies.
- To design the system architecture
- To develop a predictive model using Machine learning algorithms
- To accurately predict PIH levels among pregnant women attending clinics.
- To identify and analyze relevant features from ANC data that can serve as predictive factors for PIH levels in pregnant women.
- To evaluate the performance of the developed model in terms of accuracy**,** Precision, Recall (Sensitivity), and F1 Score.
- To assess the clinical utility and practicality of the predictive model in assisting healthcare providers in identifying pregnant women at risk of developing PIH and guiding appropriate intervention strategies.

1.5. Scope and limitation

The scope of the study on predicting pregnancy-induced hypertension levels using machine learning algorithms includes predicting PIH levels in pregnant women, applying machine learning to healthcare, analyzing data, comparing algorithms, and enhancing predictive models. The limitations involve a focus on specific parameters, algorithm performance, and which is essential for assessing the generalizability of the predictive model. Another limitation the predictive model did not incorporate specific genetic dispositions or environmental factors like pollutants and toxins that could influence the development of PIH. Some features of the PIH level are not included because there is no instrument to check up on patient hypertension in this case some features aren't recorded. Some relevant features, such as history of infertility, physical activity levels, and life stress levels, not be recorded, leading to incomplete analysis.

1.6. Significance of the Research

The application of machine learning algorithms in predicting Pregnancy-Induced Hypertension levels aims to enhance the accuracy of predictive models for identifying and managing PIH in pregnant women. The study evaluates different algorithms such as decision trees, SVM, random forest, XGBoot, and logistic regression to improve the prediction of PIH levels and facilitate timely interventions for at-risk pregnant women [10]. The results of applying machine learning algorithms to predict Pregnancy-Induced Hypertension levels can benefit various stakeholders in the healthcare domain. These include pregnant women at risk of developing PIH who can receive timely interventions, and healthcare providers who can use predictive models for early detection and management, In the field of maternal health for further studies [11]. The communities where PIH operates are the main recipients of the organization's research. The research results help` address particular health issues related to technology, enhance how healthcare is delivered, and provide communities the power to take charge of their health.

The beneficiaries of this research should be diverse and include such as primary beneficiaries should be Patients and their families by early detection and intervention we can improve the PIH level of women. In addition to this we can recommend the concerned bodies to facilitate improved access to healthcare, better care, easier access to necessary services, and better health outcomes are the results for patients in a technological manner. Healthcare professionals including doctors, nurses, and community health workers are beneficiaries of this research to identify the factors and levels of PIH due to this by taking training programs and initiatives aimed to increase capacity for healthcare professionals. This guarantees front workers the know-how and abilities to deliver excellent care in environments with limited resources. In addition to this community, NGOs, academic and research communities are the beneficiaries of this research focus on community-driven solutions.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Introduction

Pregnancy is a critical period in a woman's life and monitoring maternal health is of dominant importance to ensure the well-being of both the mother and the unborn child. This study focuses on leveraging machine learning techniques to predict the hypertension level of pregnant women based on key health attributes. Finding hidden patterns in vast amounts of clinical data, analyzing the data to assist clinical practice, and providing current, reliable scientific information to healthcare practitioners to help lower diagnosis errors and enhance patient care [12].

The primary identification of PIH level factors, the formation of individualized care plans, and the use of automated alerts to monitor conditions and prompt action, machine learning plays a crucial role in diagnosing and treating pregnancy-induced hypertension. By utilizing influences including maternal age, newborn weight, blood pressure, and medical history, machine learning can enhance results and lower the probability of difficulties for both the mother and the child. The remarkable modifications made by the body to facilitate the growth and development of the fetus result in changes to the musculoskeletal, breathing, and circulatory systems. A variety of physical symptoms, such as tiredness, morning sickness, changes in appetite, and weight gain, can also be experienced by pregnant women [6].

Machine learning helps doctors figure out the best way to treat pregnant women with PIH by looking at how they respond to treatment and adjusting their drug accordingly. This helps identify risky pregnancies early on, create personalized care plans, and ultimately improve outcomes for both mother and child with targeted care. PIH affects pregnant women worldwide with PIH being a major cause of maternal and medical care for pregnant women's disease and mortality [13]. The aims of this research are to determine the prevalence of PIH level prediction and investigate pregnancy outcomes among women with this condition seeking motherhood services in machine learning by identifying factors for PIH level. Pregnancy is often associated with various symptoms and discomforts. These can include morning sickness, tiredness, mood swings, food cravings, weight gain, and changes in the breasts and skin. Throughout pregnancy, regular prenatal care and medical check-ups are important to monitor the health of both the mother and the child [7].

2.2. Pregnancy-Induced Hypertension

Elevated blood pressure that appears after 20 weeks of gestation in women who previously had normal blood pressure is known as pregnancy-induced hypertension. It includes illnesses like PIH and gestational hypertension. When high blood pressure suddenly appears without proteinuria or other systemic symptoms [14]. PIH is diagnosed when hypertension is accompanied by proteinuria or signs of end-organ damage. Significance for maternal health because of its link to maternal illness and mortality, PIH poses serious risks to the health of mothers. Pregnant women who have this condition may experience complications like heart failure, renal failure, and other cardiovascular events [6]. PIH raises the possibility of unfavorable outcomes, such as placental insufficiency, fetal growth restriction, preterm delivery, placental abruption, stillbirth, and newborn death, for both the mother and the fetus. To sum up, pregnancy-induced hypertension is a dangerous illness that can harm the health of the mother and the fetus. This makes it crucial to identify the condition early on and to take proper care of it during pregnancy.

2.2.1. Factors of Pregnancy-Induced Hypertension

Pregnancy-induced hypertension is a medical condition marked by elevated blood pressure that appears during pregnancy. Women who become pregnant for the first time are more likely to experience gestational hypertension. Several risk factors can arise. There is a higher chance of pregnancy-induced hypertension in women who are older than 40. Having a high body mass index or being overweight before becoming pregnant can increase the chance of high blood pressure during pregnancy. Hypertension is more likely to occur in women who are expecting twins, triplets, or more. Women who have autoimmune (immune system) diseases like lupus, diabetes, or kidney disease are more likely to develop pregnancy-induced hypertension. Pregnancy-induced hypertension is a condition that can increase the PIH level of developing during pregnancy if there is a family history of these disorders [15].

1.1.1. Complications Associated with Pregnancy-Induced Hypertension

Pregnancy-induced hypertension, a dangerous condition resulting from gestational hypertension, can cause high blood pressure, organ damage, and seizure control electrical activity in the brain. Before the birth of the child, a severe condition can lead to seizures (uncontrolled electrical activity) and serious risks for both mother and child. Placental insufficiency, preterm delivery, and low birth weight can also occur. Understanding factors of pregnancy features and treating pregnancy-induced hypertension is crucial [16].

2.2.3. Importance of Predicting Pregnancy-Induced Hypertension Levels

Early detection of high-risk pregnancies depends on the ability to predict PE levels using machine learning techniques. Early detection lowers the chance of complications for both the mother and the unborn child by enabling medical professionals to closely monitor and manage the condition. To reduce the negative effects of hypertension maternal, healthcare professionals can apply preventive interventions like close monitoring or low-dose aspirin therapy by accurately predicting hypertension levels [17]. Permitting prompt medical interventions, such as suitable management techniques and possible early delivery if necessary, early prediction of hypertasion levels can improve outcomes for both mother and child. by analyzing a variety of clinical and laboratory data machine learning models can customize predictions based on specific factors for hypertension during pregnancy [18]. This makes it possible to create more successful personalized care plans for pregnant. By using machine learning techniques to predict hypertension levels, researchers can better understand the underlying mechanisms of the condition and develop treatment options that improve outcomes for both mothers and fetuses [19]. It can be predicted by machine learning algorithms through analysis of variables such as depression, use of contraceptives, prior use of contraceptives, Weight (kg), Height (cm), BMI(kg/m2), sBP, dBP, and other parameters. To improve condition management, they can also monitor vital signs, develop individualized care plans, and maximize treatment responses pregnant women can have better results [20].

Machine learning models aid in early intervention, personalized care, and better outcomes for mothers and infants by identifying high-risk pregnancies, delivering personalized care plans, and enhancing proactive and focused care. Pregnancy-induced hypertension detection and management using machine learning integration presents exciting new prospects to improve outcomes, reduce risks, and improve care delivery. To make accurate predictions and well-informed decisions, data quality, interpretability, and ethical use are essential. Maternal healthcare practices could be further advanced by additional study and development [21].

2.3. Machine Learning in Healthcare

Machine learning plays a crucial role in healthcare by analyzing vast amounts of data to identify patterns, trends, and correlations that human analysts might miss. This capability allows healthcare proffasion to predict various aspects of patient care, disease progression, treatment efficacy, and overall health outcomes with greater accuracy. Machine learning algorithms can evaluate patient data, such as electronic health records, medical imaging findings, and genetic data, to forecast the probability of developing specific medical diseases or the possible consequences of particular treatments. It can also assist in disease diagnosis and identification by examining medical pictures to identify differences or early warning indicators of diseases [11]. Personalized medicine is another area where machine learning plays a key role. By customizing treatment regimens for each patient, machine learning models can make personalized treatment recommendations that are more likely to be successful. This revolutionized medical research by speeding up the discovery of new drugs, finding disease biomarkers, understanding intricate biological processes, and forecasting disease trajectories [22].

Current studies have focused on exploring changes in static parameters at a specific time during pregnancy, and prospectively assessing the risk of Pregnancy-Induced Hypertension. A few prediction models demonstrated comparatively high rates of early-onset pregnancy-induced hypertension detection [6]. Machine learning models can be trained on data to predict the likelihood or level of PIH based on various features and input variables. Machine learning, the term "PIH level" refers to predicting or classifying the risk or severity of Pregnancy-Induced Hypertension using machine learning algorithms. Models can be trained on data to predict the likelihood or level of PIH based on various features and input variables [23].

2.4. Overview of Binary Classification and PIH Detection

Binary classification for the identification of PIH. The objective of a binary classification scenario is to predict if a patient has PIH (a normal or healthy pregnancy) or not. The data preparation compiles a dataset of expectant pregnancy with the binary target label (PIH or normal pregnancy) and features (e.g. age, blood pressure, BMI, medical history) [24]. Divide the dataset into testing and training sets so that the performance of the model can be assessed. After data preparation, model selection is performed for good binary classification algorithms, like Decision Trees, SVMs, or Logistic Regression. These models can be trained to predict a patient's probability of having PIH and are well-suited for binary classification tasks. Finally, Evaluate the trained model's performance on the testing data using the confusion matrix and related metrics [25]. Permit more frequent monitoring of patients who are at risk and less frequent monitoring of those who are not as likely to develop pregnancy-induced hypertension. Few studies have shown clinically sufficient properties, even though prior research has examined biomarkers and examined clinical features for effective prediction [2].

2.4.1. Machine Learning in Predictive Modeling for Disease Diagnosis and Prognosis

Machine learning algorithms can detect early stages of disease through the analysis of patient data, which facilitates timely treatment and improved outcomes. It can be used to develop individualized treatment regimens that consider each pregnant woman's particular traits and medical history to achieve more favorable outcomes. By using predictive analytics based on PIH historical data, healthcare providers can make educated decisions about treatment outcomes, possible consequences, and disease progression. Machine learning optimizes resource allocation and lowers costs by forecasting patient admissions, detecting high-risk patients, and speeding up administrative procedures [20]. Healthcare doctors can benefit from machine learning algorithms by identifying potential issues or dangers, recommending treatments, and analyzing complex medical data. To assist, machine learning predicts medication interactions, finds potential novel treatments, and examines molecular structures.

2.4.1. Overview of PIH and the use of ML in healthcare

Gestational hypertension, another name for pregnancy-induced hypertension, is a condition in which elevated blood pressure develops during pregnancy. It can cause serious complications for the mother and the child if it is not managed appropriately. Artificial intelligence's machine learning field has seen a rise in the use of AI in healthcare to forecast, identify, and treat a wide range of illnesses, including PIH. High blood pressure, proteinuria, edema, and headaches are the hallmarks of PIH [26]. If left untreated, it can worsen and put the mother and child in danger by developing conditions like pregnancy-induced hypertension and eclampsia. Machine learning, which examines variables like age, weight, blood pressure readings, and medical history, is essential for the early prediction and risk assessment of PIH [20]. Moreover, machine learning enhances treatment responses for improved PIH management. Improved outcomes for both mother and child, early intervention, and individualized care are some of the advantages of implementing machine learning in PIH management [27]. However, issues like interpretability, ethical use, and data quality need to be considered. All things considered, the application of machine learning to PIH detection and management may improve the quality of care provided and the progress of maternal healthcare procedures [28].

2.5. Approach of Pregnancy-Induced Hypertension

Hypertensive diseases that occur during pregnancy, analysis of the blood pressure measurements, and the machine learning algorithms for determining the occurrence of hypertension. the approach to predict PIH levels in pregnant women to predict accurately the levels of PIH as normal, low, moderate, and high using supervised machine learning algorithms to predict the levels of PIH and prevent related complications. This prediction should be used for providing timely treatment to pregnant women and prevent complications associated with PIH. The methodology of the research work included data collection, feature selection, data analysis, selection of algorithms, and evaluation of their performance. Finally evaluate the model using parameters like accuracy, confusion matrix, precision, recall, and F1-score [10].

2.6. Machine Learning Algorithm In Pregnancy-Induced Hypertension

Supervised machine learning algorithms are used for both regression and classification. Algorithms like logistic regression used for regression tasks and other algorithms like LR, SVM, RF, DT, and XGboost algorithms are used for classification tasks are used to evaluate hypertension. Test subsets are generated through the train test split method in the CSV. The criteria include primary sampling units like weight, BMI, height, mean systolic and diastolic blood pressure in mm Hg, heart rate, blood temperature, urine in protein, and other measurement factors included in this study [29].

An adequate set of objectives is given to a training set in supervised learning. In classification, the trained system divides inputs into classifications using classification techniques. Regression uses continuous sources as opposed to discrete ones. Regression predictions are assessed using root-mean-squared error, whereas classification predictions are assessed using accuracy. Supervised learning aims to use a shared dataset to anticipate a known outcome. Most of the time, a taught individual can also complete tasks carried out by supervised learning. The main goals of supervised learning are prediction, which involves estimating an unknown, and classification within the level dataset, which includes selecting which subgroups best fit a given data instance [11].

2.6.1. Logistic Regression Algorithm for PIH Detection

It is supervised machine learning used primarily for binary classification tasks, Before making predictions, it computes using the logistic function, learns the logistic regression model's coefficients, and then applies the logistic regression model. The linear component and link function make up the two sections of this generalized linear model. The link function is in charge of conveying the results of the computation, while the linear component is in charge of performing the classification model's calculations. LR is an algorithm for supervised machine learning that requires a cost function and a hypothesis. It should be mentioned that cost function optimization is crucial [30]. It is an regression showed good standardization ability compared to machine learning methods for predicting unfavorable outcomes for mothers and newborns. Machine learning methods provide a more data-driven approach to binary predictive modeling, handling complex interactions and identifying complex patterns, while it is a standard statistical method. Regarding discrimination power, machine learning techniques such as support vector machines, multi-layer perceptrons, and random forest classifiers performed better than logistic regression. Depending on the particulars of the prediction task, machine learning or logistic regression may be used [11].

Using machine learning to predict PIH levels via logistic regression logistic regression is a useful approach for utilizing machine learning to predict Pregnancy-Induced Hypertension levels. A popular statistical technique for binary classification problems, logistic regression can be used to predict categorical outcomes such as the presence or absence of PIH [31]. Logistic regression can be utilized to examine different characteristics and their influence on the probability of acquiring before born the child infection when incorporated into a machine-learning framework. Prenatal laboratory data, ultrasound findings, maternal characteristics, medical history, and other features can be used by machine learning algorithms, such as logistic regression, to predict the likelihood or severity of prenatal infection in expectant mothers. Through training on past data including these characteristics and matching PIH [32]. Model of logistic regression with the training set of data. The correlation between the input features and the likelihood of a specific result. The binary classification tasks such as PIH detection, logistic regression, and efficient yet straight forward algorithms. To increase prediction accuracy you might think about utilizing ensemble methods or more sophisticated machine-learning techniques for scenarios that are more complicated or involve high-dimensional data. Furthermore, it is imperative to engage in consultations with healthcare professionals and domain experts during the model development process to guarantee the clinical relevance and accuracy of the model[31].

2.6.2. Random Forest Algorithm for PIH Detection

It is a popular machine-learning method that is used for both classification and regression tasks. This algorithm uses supervised learning and relies on recursion as its foundation. This technique uses the bagging approach for training while creating a set of decision trees [11]. This algorithm is used for predicting the women who are at risk of pregnancy-induced hypertension. The model was evaluated by using evaluation metrics that are an area under the curve (AUC), accuracy, precision, f1-score, and recall that varied predictive machine learning models for pregnancy-induced hypertension one strong algorithm that is particularly good at analyzing a variety of factors, including maternal features, and medical history [33].

2.6.3. Support Vector Machine for PIH Level Prediction

It is a supervised machine learning technique that is mostly used to solve classification problems, while it can also be applied to solve regression problems. The data items are then plotted as points in n-dimensional space using this approach, with the feature value serving as the specific coordinate. The hyperplane that divides the data points into two classes is identified [34]. This maximizes the marginal distance between instances between the border and the decision hyperplane. The fundamental functions of SVM allow it to map points to other dimensions through the use of nonlinear relationships, which sets it apart from other algorithms. SVM is also referred to as the no probabilistic binary classifier since it splits the data points into two classes. SVM is more accurate than numerous others [11].

The SVM model relies on proper feature selection, hyperparameter tuning, and high-quality data. To guarantee the model's accuracy and dependability in predicting PIH, speaking with subject matter experts and medical professionals is essential when doing machine learning. A classification is carried out to identify the plane that divides a pair of chosen classes [22].

2.6.4. Decision Tree

Machine learning prediction in the context of pregnancy-induced hypertension, decision trees are a type of machine learning technique that can be used to predict the level of PIH. Because of their interpretability, ease of visualization, and ability to handle both category and numerical input, decision trees are frequently employed in machine learning [20]. Decision trees have a tree-like structure, with each leaf node signifying the outcome or prediction, each interior node denoting a trait or characteristic, and each branch expressing a decision rule. by dividing the data recursively according to characteristics. Decision trees can look at a variety of factors for predicting PIH levels in expectant mothers, such as maternal characteristics and professionals with expertise in pregnancy-related hypertension and medicine [35].

Decision trees is a supervised algorithm that takes decisions, their consequences, and their results into account using a tree-like model. A question is carried out by each node, and an outcome is represented by each branch. Class labels are leaf nodes. The label of the related node assigned to the sample when a leaf node is reached by the sample data. This method works best when the dataset is small and the problem is straightforward. Despite being simple to understand, the technique has some drawbacks, such as the overfitting problem and biased results when using imbalanced datasets. However, DT can map relationships that are both linear and nonlinear [11].

Utilise decision trees' predictive potential to estimate the degree of pregnancy-induced hypertension, offering insightful information and aiding in clinical judgment when it comes to maternal health. Models generated by decision trees are very easily interpreted and visualized. What's useful for stakeholders and domain specialists is that the tree structure makes it easy to comprehend how the model produces predictions. Decision trees don't require a lot of data preprocessing to handle a wide range of data types, including text, numerical, and categorical data [36]. When choosing characteristics and comprehending the underlying relationships in the data, decision trees can offer insights into which features are most crucial for generating predictions. In machine learning, the volume of data required to produce a trustworthy analysis rises sharply with the dimensionality of the data. Feature subset selections function by removing features that are unnecessary or redundant. By learning to generate predictions based on the information at hand, decision trees can accommodate missing values in the input data. Frequently utilized as the foundational estimator in ensemble techniques like Random Forests [37].

2.6.5. XGboost Algorithm

A highly successful and scalable version of the Boosting technique is XGboost, and it can be used to predict pregnancy-induced hypertension levels in some studies like "Gradient Boosting with Feature Engineering for early prediction of pregnancy-induced hypertension" and "Interpretable Gradient Boosting for Pregnancy-Induced Hypertension Risk Assessment" In terms of accuracy, F1-score, and area under the ROC curve, the study compared the performance of XGboost with other machine learning algorithms for PIH prediction and discovered that XGboost tired the alternatives [38]. Using the held-out test set(It is used to provide an unbiased estimate of the model's performance to split the training and testing dataset.), assess the trained XGboost model using suitable regression assessment metrics such as R-squared, mean squared error, evaluate the model's performance and determine how well it can forecast PIH levels. Analyze the XGboost model's feature significance scores to determine which input features have the greatest bearing on PIH level prediction. This data can help build more useful risk assessment models for pregnancy-induced hypertension and offer insightful information to the medical Profession [39].

Assess the model's performance using methods like cross-validation or a validation set to prevent overfitting. Analyze the XGboosting model's feature importance scores to determine which input features have the greatest behavior on PIH-level prediction. This data can help build more useful risk assessment models for pregnancy-induced hypertension and offer insightful information to medical experts [20]. Create a reliable and understandable model to forecast the levels of hypertension brought on by pregnancy. Iterative model refining, feature engineering, and domain-specific information can all be used to further enhance the model's performance [40].

2.7. Related Work

Using machine learning involves several steps that are similar to any classification task but with specific considerations tailored to the healthcare context. Enhancing early identification and intervention strategies in prenatal care is the goal of an emerging field of study that uses machine learning to predict the likelihood of pregnancy-induced hypertension. An overview of related work in this field, surrounding several models, techniques, and procedures, is given below.

The study was conducted on High blood pressure prediction based on AAA++ using machine-learning algorithms like the J48 algorithm a decision tree-based classifier that classifies the input instances by passing it through the tree starting at the top and getting down to the leaf node [41]. However, it was studied in only high blood pressure prediction it does not relate to pregnancy in somehow there are some variables to predict pregnancy-induced hypertension level. It achieved a result in a random forest algorithm accuracy of 87.5% in predicting high blood pressure including 1000 patients. It mainly focuses on the factors like SBP and DPB. However, future work considers other attributes such as gender, smoking, alcohol consumption, job satisfaction, and marital status to improve the prediction performance of the classifiers. he was recommended for future researchers to further investigate the impact of these factors on blood pressure, expand the dataset, evaluate the approach on a larger and more diverse patient population, and investigate methods to manage psychological factors like anger and anxiety to control high blood pressure.

Another study was conducted entitled 'Prediction of Pregnancy-Induced Hypertension Levels using machine learning algorithms using supervised machine learning algorithm within three comparison algorithms (DT, SVM, LR) was used from this he was getting better results of accuracy in percentage in DT, SVM, and LR are 90, 86.667 and 83.334 respectively [41]. Estimation was classified into three levels (severe, moderate, and mild) based on this blood pressure level is classified. The accuracy using the decision tree algorithm (90%) is better than that of SVM (86.667%) and LR (83.334%), DT (precision, R-call, F1-score,91,90, and 90),%SVM (precision, R-call, F1-score,86,87, and 86) % precision, R-call, F1-score, 93, 93, and 93%. It recommends that a more diverse sample size may be needed to further validate the performance of the machine learning models, Absence of proteinuria data amount of protein in the urine. The number of sample datasets is 100 and adding more data can get better model performance.

A machine learning approach for predicting hypertension and its associated factors using population-level data from three South Asian countries by using a diverse dataset of around 818,603 participants from population-based surveys. The algorithm used Random Forest (RF) and Decision Tree (DT) achieved accuracy scores of 89% and 83%, respectively Precision Decision Tree (DT) achieved a precision value of 91%. LR, precision values of 90%. LR, and recall LR, and LDA achieved a recall value of 100%. Random Forest (RF) scored a recall value of 99%. Decision Tree (DT) achieved a recall value of 90%. LR, F1-scores of 95%. Random Forest (RF) scored an F1-score of 94%. Decision Tree (DT) achieved an F1-score of 90%. Future studies incorporating biochemical markers are needed to improve the ML algorithms and evaluate them in real life to further improve the performance of the machine learning models for predicting hypertension.

Table 2. 1: Related work from different researchers

Title	**Author**	**Used algorithm**	**Result**	**Critics**
"A Machine-Learning-Based Prediction Method for Hypertension Outcomes Based on Medical Data"	Wenbing Chang Yinglai Liu et al. 2019	SVM C4.5 Decision Tree RF XGboost	**XGboost classifier** Accuracy: 94.36% F1-score: 0.875 Area Under Curve (AUC): 0.927	There was a need for a more robust and reliable prediction method to help clinicians intervene and prevent serious adverse outcomes in hypertension patients.
"Machine-learning predictive model of pregnancy-induced hypertension in the first trimester"	Yequn Chen1, Xiru Huang1 et al. 2023.	LASSO LR, RF Backpropagation neural network SVM	LASSO logistic regression model showed good discrimination, with an AUC of 0.847 (95% CI: 0.805-0.889) in the training set and 0.753 (95% CI: 0.653-0.853) in the validation set.	The paper did not discuss how the developed nomogram could be practically integrated into clinical workflows and decision-making processes. The clinical utility and impact of using the predictive model on patient outcomes are not evaluated.
"Prediction of Pregnancy-Induced Hypertension Levels Using Machine Learning Algorithms"	Anuja Hiwale Pratvina Talele et al.	Decision tree Support vector machine (SVM) Logistic regression	Decision tree 90% SVM model accuracy of 86.667% Logistic regression model accuracy of 83.334%	It uses 100 samples and it was very small, it needed to further validate the performance and absence of main predictors like the amount of protein in urine and others
"Predictive models of hypertensive disorders in pregnancy based on support vector machine algorithm"	Lin Yang Ge Sun et al.	Support Vector Machine (SVM) Algorithm	High-accuracy pregnancy (over 92% in weeks 28-34 and ≥35)	Use of a multi-risk factor approach combined with dynamic gestational week prediction using machine learning. Continuous monitoring from early to late pregnancy.

"Identification of Risk Factors and Prediction of Sepsis in Pregnancy Using Machine Learning Methods"	Georgy Kopanitsa*, Oleg Metsker, David Paskoshev, and Sofia Greschischeva	Gradient Boosting regression, Random forest regression, Linear regression, and Voting regression	The gradient boosting model on the test data set is 95% AUC	Uncovered novel clinical and patient-level predictors of sepsis in pregnancy that can inform better risk assessment and management strategies.
“Prediction of Preeclampsia from Clinical and Genetic Risk Factors in Early and Late Pregnancy Using Machine Learning and Polygenic Risk Scores”	Vesela P Kovacheva1 et al.	1,125 pregnant women used in in dataset XGboost (XGboost) Linear regression	XGboost using clinical variables was AUC of 0.91 and linear regression model from AUC 0.70 to 0.71	Explore the integration of additional data sources like lifestyle factors Not provide details on model interpretability or feature importance like understanding the key drivers of preeclampsia risk.
"Predicting hypertension using machine learning: Findings from Qatar Biobank Study"	Latifa A. AlKaabi, Lina S. Ahmed, Maryam F. Al Attiyah, Manar E. Abdel-Rahman	987 records dataset Decision tree, Random forest, and Logistic regression	Random forest: Accuracy = 82.1%, Logistic regression: Accuracy = 81.1%, Decision tree: Accuracy = 82.1%	Exploring a wider range of machine learning algorithms beyond the three evaluated in this study to identify more accurate predictive models. Additional important predictors of hypertension into the models to further enhance their performance.
"Predicting hypertension using machine learning: Findings from Qatar Biobank Study."	Latifa A. AlKaabi Lina S. Ahmed et al.	987 records Decision Tree Random Forest Logistic Regression	Accuracy: 82.1%, 82.1%, and 81.1% Respectively	Assessing other predictors and using different prediction algorithms like support vector machine, , and XGboosting machines.

CHAPTER THREE

3. SYSTEM DESIGN

3.1. Introduction

The research methodology in the context of machine learning refers to the systematic approach and processes used to conduct research and experiments in the field of machine learning. It encompasses the techniques, strategies, and tools employed to design, implement, evaluate, and validate machine learning models and algorithms. The goal of this research is to create a predictive model that can precisely determine a pregnant woman's risk utilizing machine learning techniques. The following issues are the focus of our study. Those are determining the risk level of PIH in pregnant women with data collected in real life from records in health centers by adding main predictor variables. After identifying the main predictor variables using the compatible model getting a high degree of prediction accuracy is the main goal [6]. The thesis attempts to create a model that can efficiently classify pregnant women into distinct risk categories based on their relevant health factors by utilizing machine learning techniques and data analysis. Enabling early PIH identification is another goal, as this may result in prompt interventions and suitable medical care. Through precise PIH level prediction, healthcare [42]. The thesis attempts to fill any research gaps in the field of machine learning-based PIH prediction, thereby adding to the body of current literature. This entails assessing how well various machine learning algorithms work, investigating the effects of different characteristics, and determining the elements that have a major impact on the accuracy of PIH predictions [43].

Within the thesis, machine learning is heavily reliant on the PIH level of prediction. It acts as the primary goal of the study, directing the approach, gathering of data, feature engineering, choice of algorithms, and assessment of the model [19]. The machine learning study employed a mix of clinical and laboratory data collected during early pregnancy prenatal screening to predict the degrees of pregnancy-induced hypertension (PE). These data sources included a variety of variables, including maternal features, medical history, prenatal test findings, and ultrasound results. They were gathered by retrospective evaluation of medical records [2]. The study created prediction models for PE risk assessment using a total of eighteen variables including the target variable. These factors were essential for teaching the machine learning algorithms to correctly forecast PE levels. LR, SVM, DT, XGBoot, and RF were among the models used in the investigation [2].

3.2. Research Design

To accomplish this research, we have to consider data gathering and also prepare the data with its class, selection of appropriate development models and approach, and test methodology for evaluating the proposed approach fit with the model. We have to discuss each methodology as follows:

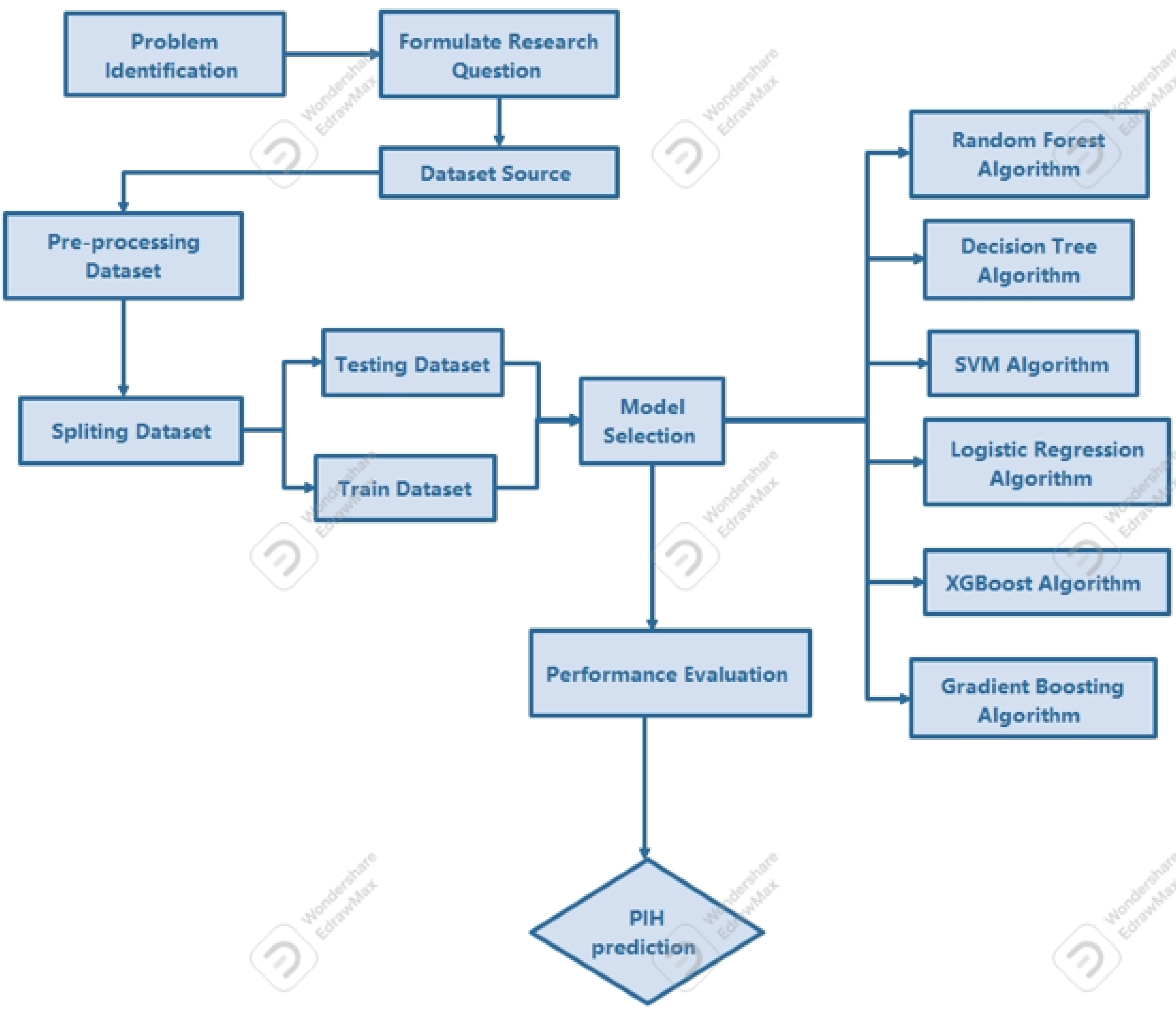

Figure 3. 1: Architecher of PIH research flow

3.2.1. Data Collection

when designing a model, the sources of data play a crucial role in ensuring the model's accuracy and relevance. Due to this, we have obtained the data from Bahir Dar Tibeb Giwon Specialized Hospital. In Bahir Dar Specialized Hospital we collected 4130 medical records with 19 features before preprocessing and their target variables whether low-level PIH, moderate-level PIH, normal-level PIH, and high-level PIH pregnant. To design the prediction model it is better to know the main predictor variables like pregnancy age, heart rate, blood temperature, urine in protein, sleep (in hours), blood in sugar, family history of hypertension, how many times pregnant, number of abortion, pregnant related complication, ANC visit in the current pregnancy, platelet, prior use of contraceptive, weight, height, BMI, sBP, and dBP. These factors were essential for teaching the machine learning algorithms to predict PIH levels correctly. LR, SVM, DT, XGboost, and RF were among the models used in the investigation. Developed prediction models employing machine learning approaches for estimating PIH risk levels from early pregnancy information by utilizing various clinical and laboratory data sources acquired during prenatal screening.

3.3. Specific Features Selected for the Prediction Model

The specific features selected for the prediction model for the title of Pregnancy-induced hypertension level prediction in machine learning depend on various factors such as the dataset used, the machine learning algorithm employed, and the clinical context. However, some common features have been identified in the literature for predicting PIH levels [21].

The selection of features for a PIH prediction model may vary depending on the specific dataset and machine learning algorithm used. Some algorithms are more sensitive to certain features than others. Additionally, some features may be highly correlated, leading to multicollinearity issues that can impact model performance. Therefore, it is important to carefully consider the selection of features and perform feature selection techniques such as correlation analysis and principal component analysis to optimize model performance [44].

3.4. Feature Engineering Techniques to The Predictive Power of the Selected Features

A key component in increasing the predictive capability of machine learning models is feature engineering. Predicting pregnancy-induced hypertension levels can be done more accurately and effectively by using a variety of feature engineering techniques [45]. A few of the crucial methods consist.

Features of Polynomials is possible to capture non-linear correlations between the input features and the target variable by introducing polynomial features. The model can more effectively match complex patterns in the data about PIH levels by generating new characteristics that are powers or interactions of pre-existing variables. Using polynomial features can aid in identifying non-linear correlations between the target variable and the input features [46]. The model can more effectively match complex patterns in the data about PIH levels by generating new characteristics that are powers or interactions of pre-existing variables. Interaction features merging two or more preexisting features, interaction features can be created that give the model new data. For instance, calculating the product of blood pressure and pregnant age may provide information not readily apparent when examining these characteristics separately. During model training, some features may not predominate over others if the features are scaled to a similar range using normalization or standards. This guarantees that each feature makes an equal contribution to the PIH-level forecast [47]. Feature selection prevent overfitting and enhance model interpretability, finding and choosing the most relevant characteristics for PIH-level prediction is crucial. The most informative features can be chosen with the use of methods like Recursive Feature Elimination (RFE) or feature significance from tree-based models [48]. Feature aggregation combining related features into a single representative feature can simplify the model while retaining important information. For example, aggregating daily blood pressure readings into weekly averages can help make the distribution of skewed features more Gaussian-like, which is often preferred by many machine learning algorithms [49]. Dealing with missing values in a meaningful way is crucial for accurate predictions. Techniques like imputation (mean, median, mode), deletion of rows/columns with missing values [50]. features include to predict PIHLevel such as:

RQ3. **What predictive factors of PIH are used to train the ML model?**

Table 3. 1: Pregnant variables within each description

Variables	**Type**	**Description**
Pregnancy Age(year)	Numeric	Age in years when a woman is pregnant.
Heart rate (bpm)	Numeric	Increased blood volume and demands during pregnancy, and an elevated resting heart rate are typical and usual.
Body temperature	Numeric	The measure of the amount of heat in the human body.
Urine protein	Numeric	Also called proteinuria, refers to the presence of proteins in the urine during pregnancy.
Sleep (hours)	Numeric	The natural state of rest for the body and mind
Blood in sugar	Numeric	Refers to the concentration of glucose in the blood
Family History of Hypertension	Binary	One or more close blood relatives, such as parents, siblings, or grandparents, have been diagnosed with hypertension.
Number of abortion	Numeric	A person having undergone one or more voluntary terminations of pregnancy in the past.
History of pregnancy-related complications	Binary	A person having experienced one or more adverse health conditions or events during a previous pregnancy.
How many times pregnant	Numeric	How many children were born before the current one?
Number of ANC visits in current pregnant	Numeric	How many times are cheeks up from the current pregnant?
Platelet	Numeric	Platelets are tiny, disc-shaped blood cell fragments that are essential to the body's capacity to halt bleeding. These are important details regarding platelets.
Prior use of contraceptives	Binary	Utilization of various methods or devices to prevent pregnancy. Contraceptives are used to control fertility and plan or space out pregnancies.
Weight	Numeric	Measurement of a person's total body mass, typically expressed in units such as pounds (lbs) or kilograms (kg).

Height	Numeric	Refers to the vertical measurement of a person's stature or the distance from the base of their feet to the top of their head.
BMI(body mass index)	Numeric	Refers to the measure of a pregnant woman's body composition based on her weight and height.
Systolic BP	Numeric	The upper value of Blood Pressure in mmHg is another significant attribute during pregnancy.
Diastolic BP	Numeric	Lower value of Blood Pressure in mmHg, is another significant attribute during pregnancy.
PIHLevel	string	Which is target variable for pregenancy induced hypertasion predicted

3.4.1. Data Processing

Display data Before being used for model training, the original medical data must be processed, which usually entails three steps: data screening, outlier deletion, and filling in missing values.

Figure 3. 2: Data processing Flow chart

Preprocessing the data involves several steps to clean and prepare the datasets. In this stage, the datasets handle the missing values, encoding the categorical values by using numerical features, normalizing the numerical feature, and splitting the data into training, validation, and test sets. From a total of 4130 medical record observations after preprocessing we have used 3479 with 18 independent variables should be used. One cannot directly feed lists of integers, numbers, texts, or categorical values from the acquired raw data into a machine-learning model. All the dataset numerical and ecoding features are present raw dataset collected in CSV format. The features that are provided above are inappropriate input for any learning system. These factors led to the application of data preparation techniques, such as data cleansing, standardization, balancing, and numericalization the mapping of symbolic-valued and non-numerical data to numeric data.

Data preprocessing is the process of cleaning and preparing data so that it may be used with machine learning models. This improves the machine learning model's accuracy and efficiency. The raw dataset properties contain both numeric and non-numeric values, as was previously described. As a result, encoding and numericalization techniques were used to convert non-numeric properties to numerical values. Next, data balancing was used to address the issue of an imbalanced dataset that causes biases in machine learning, whereas data normalization was limited to numerical properties. Python libraries are required to process data. To conduct experiments, import Numpy, pandas, matplotlib, Sklearn, and a few Python functions and classes using the Python code that follows. Use the read_csv() Python function to import the patient data in Comma Separated Value (CSV) file format after importing Python libraries.

3.4.1.1. Data Cleaning

```
# Load the data
data1 = pd.read_csv(r"E:\MCS\pih_level.csv", low_memory=False)
print(data1.head())
  Pregnancy Age(year)  HeartRate  BT (°C)  ...  sBP  dBP  PIH_level2
0                  25         86     37.2  ...  130   80    moderate
1                  35         70     37.8  ...  140   90        high
2                  29         80     36.9  ...   90   70         low
3                  30         70     38.1  ...  140   85    moderate
4                  35         76     37.0  ...  120   60      normal

[5 rows x 19 columns]
```

The most crucial step in data preprocessing is data cleaning, which involves deleting or changing any data

```
# Drop rows with any missing values
data1.dropna(inplace=True)

# Drop rows with missing values in a specific column
data1.dropna(subset=['column_name'], inplace=True)
```

that is inaccurate, missing, unnecessary, duplicated, or formatted incorrectly to prepare the data for analysis. Numerous methods exist for filling in missing values, including imputation, average, mode, and median filling in the missing value, as well as removing the missing data from both rows and columns. The 651 missing data points from the dataset were eliminated utilizing the deleting rows with missing data technique rather than filling in the missing data values on the characteristics that were previously indicated in After deleting 651 missing data rows, the dataset's initial total of 4130 data rows was reduced to 3479 data rows. For additional data processing, the remaining data rows were utilized.

3.4.1.2. Data Encoding

It is well known that just numerical values are required for machine learning algorithms to function properly. To change the unified format of non-numeric features, we used feature conversion. The dataset has three non-numeric features and 16 numerical features. A numerical matrix is what machine learning algorithms should get as input. As a result, non-numeric features like "family history of hypertension", "prior use of contraceptives", and "PIH Level" are transformed into numerical form. The target variables classified as normal-level PIH, low-level PIH, moderate-level PIH, and high-level PIH classes labeled.

3.4.1.3. Data Balancing

Machine learning experiences biases due to the issue of imbalanced datasets. It is imperative to balance the dataset due to the frequently unequal distribution of PIH values. Applying SMOTE to balance PIH data is necessary in order to make sure your machine learning model is capable of accurately predicting severe PIH. SMOTE or any of its variations can be used to balance the dataset. SMOTE's goal is to create synthetic cases by interpolating between existing instances for the minority PIH classes (such as normal PIH level, low PIH level, moderate PIH level, and high PIH level). This makes these under represented classes better represented, which improves the model's capacity for learning. Utilization use SMOTE to generate a balanced dataset with an equal or more balanced number of samples for each PIH category to forecast PIH values. The dataset is considered imbalanced if one class is substantially underrepresented in comparison to the others. Before training a classifier, the data must be balanced. The dataset's imbalance may indicate an incorrect class distribution or the presence of errors [51]. The Challenge of Imbalanced PIH Data In the context of predicting PIH levels, the dataset typically includes multiple classes, like Normal PIH level, Low PIH level, Moderat PIH level, and High PIH level.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Age	HeartRate	BT (Â°C)	U Pro (mg	Sleep (ho	BS	Family His	How many	Number o	history of	Number o	platelet	prior use (	Weight (k	Height (cn	BMI(kg/m	sBP	dBP	PIHLevel
2	25	86	37.2	106	8	15	No	0	0	0	2	269	yes	70	165	21.58504	130	80	moderate
3	35	70	37.8	480	6	13	Yes	0	1	0	2	356	no	85	165	18.8659	140	90	high
4	29	80	36.9	150	9	8	No	0	1	0	2	259	yes	58	160	29.62262	90	70	low
5	30	70	38.1	560	5	7	Yes	1	0	0	2	241	yes	75	160	33.20507	140	85	moderate
6	35	76	37	280	7	6.1	No	1	1	0	2	197	yes	65	163	20.01552	120	60	normal
7	23	70	37.5	400	6	7.01	No	5	2	0	2	284	yes	80	164	18.52638	140	80	moderate
8	23	78	37.1	305	10	7.01	No	1	1	0	2	307	no	68	163	20.04408	130	70	moderate
9	35	86	37.9	495	5	11	Yes	1	1	0	2	296	yes	87	166	21.44763	85	60	low
10	32	70	36.8	140	7	6.9	Yes	0	1	0	2	337	no	54	158	30.60614	120	90	high
11	42	70	38.2	575	7	18	No	0	1	0	2	206	yes	77	162	20.17388	130	80	moderate
12	23	76	36.9	270	9	7.01	No	0	0	0	2	216	yes	62	161	24.62005	90	60	low

Figure 3.3: Sample CSV file

High cases are typically far less common in real-world data than normal, low, and moderate PIH-level cases. A machine learning model that is biased towards forecasting the majority class may be created by this class imbalance, which could impair the diagnosis of high PIH, which is crucial for patient management. The model becomes more sensitive to the minority classes by balancing the dataset, particularly with methods like Borderline-SMOTE. This is important for identifying high PIH early on. Well-balanced datasets improve generalization, which is important in a clinical environment because it means the model works well not only on training data but also on fresh untested instances. Generally, developing strong machine learning models for PIH-level prediction requires balancing the dataset using SMOTE or its equivalents. The model's ability to correctly identify and forecast the severity of PIH is enhanced when each level of PIH is fairly represented. This eventually improves clinical decision-making and improves outcomes for expectant mothers.

3.4.2. Model Design

In this research, we have to follow an experimental research procedure. The goal of this research is to develop a classification model as an experimental research design approach has been conducted. An experimental research method has been employed to solve the problem wisely. Machine learning works by developing algorithms and models that can learn from data and make predictions or decisions based on that data. Machines learn from data, improve performance from experiences, and predict things without being explicitly programmed. Supervised machine learning is under this machine learning in pregnancy-induced hypertension using label data. For those variables we have to use ensemble models in this case we use those comparison algorithms logistic regression, decision tree, SVM, random forest, and XGbooting algorithm.

3.5. Model to Predict PIH

When the first prenatal visit, and late, before delivery admission. To reduce data leakage, any data collected after the time point was omitted if a patient was diagnosed with pregnancy-induced hypertension delivered before that point. We created supervised machine learning models since there may be nonlinear connections between predictors [2]. Next, the predictive power of each model using only clinical, only genetic, or both genetic and clinical factors, respectively, to see if the addition of SBP and DBP increased the predictive power of the corresponding model. Patients who have established clinical risk factors are evaluated for pregnancy-induced hypertension early in pregnancy[52]. These PIH variables served as the basis for our predictive models.

Based on the selected variables pregnancy blood pressure urine in protein, blood in sugar, heart rate, SBP DBP, and another variable the history of pregnancy-induced hypertension during a previous pregnancy are the most predictive variables in the model. Scheduled outpatient prenatal visits provide more clinical information by the time of delivery and become more frequent. The clinical data that was available before (but not after) the admission linked to the diagnosis of pregnancy-induced hypertension was used to create the late pregnancy models.

Pregnancy-induced hypertension has been predicted using machine learning algorithms, which has improved PIH's early detection and treatment. Several machine learning algorithms that take advantage of pattern recognition and data analysis have been used in studies to predict PIH. Several machine learning algorithms are frequently employed for PIH prediction [21]. Based on a variety of input features, logistic regression is a statistical model that is frequently applied to binary classification tasks, which makes it appropriate for determining whether or not a pregnant woman. To increase prediction accuracy, Random Forest is an ensemble learning technique that combines several decision trees. It works well for managing big datasets using machine learning techniques [53], such as based on a variety of input features, and logistic regression is a statistical model. It works well for managing big datasets using substantial data sets. Among other things, these machine learning algorithms have been crucial in creating predictive models for preterm infants PIH, which allow medical professionals to detect high-risk pregnancies early and start the right treatments to reduce the negative effects of PIH [12].

Ensemble method that combines multiple decision trees, reducing overfitting. Can handle large datasets with high dimensionality. Sometimes it has a limited black-box model, making it harder to interpret compared to individual decision trees. Sequentially builds trees, improving accuracy by fixing mistakes made by earlier trees. able to effectively handle missing data without imputation. Prone to overfitting in cases where the tree count is excessively high. more complicated than random forests, requiring careful hyperparameter adjustment [53].

The decision tree is a machine learning algorithm that is composed of a highly stochastic tree classifier. When splitting a tree node, it substantially randomizes the choice of cut-point as well as the attribute. As criteria, we have chosen the random split at each node split criteria, the requirement for at least one sample to be at a leaf node, two minimum amounts of samples to split an internal node, and impurity (the chance of misclassifying an observation) to quantify the quality of a split [12].

A Logistic regression algorithm is a straightforward but effective statistical technique for binary and multi-class classification issues. There are many benefits to using, two of which are its interpretability and simplicity of use. Because it is simple to use and understand, logistic regression is perfect for applications in healthcare where it is important to understand the association between risk variables and outcomes. Probability estimates for each class are provided via logistic regression, which helps determine the various levels of PIH risk. In a Logistic Regression model, the coefficients help identify important factors linked with PIH by directly indicating the intensity and direction of the association between each feature and the outcome.

SVM is an effective high-dimensional space, making it suitable for datasets with many features. Versatile as different kernel functions can be used to model complex relationships. Sometimes it happens to overfitting, especially with complex trees. Decision trees can be unstable, as small variations in the data can result in a completely different tree structure [36].

XGboost is a strong machine-learning technique that is frequently applied to regression and classification problems, particularly those involving structured or tabular data. Because of its robustness to different data difficulties, feature importance ranking, and capacity to handle complex interactions, XGboost can provide several advantages. Scale_pos_weight is one of the XGboost options that helps manage class imbalance, a significant problem in PIH datasets where severe instances are frequently underrepresented. A feature importance rating offered by XGboost can be utilized to locate the main causes of PIH [54]. Knowing which clinical, demographic or lifestyle characteristics are most indicative of PIH levels is especially helpful from this perspective. Because of its resilience against overfitting and capacity to handle complicated, high-dimensional data, XGboost is a solid contender for PIH-level prediction. Through the proper utilization of XGboost, healthcare providers can acquire valuable insights into the primary components that contribute to pressure injury PIH and develop precise models that anticipate the severity of the illness, ultimately improving patient outcomes [6].

3.6. Performance Evaluation During Hypertension in Pregnancy

PIH is working in an actual manner and also gives some trust to the prediction model. We have followed four phases. In the first phase, prepare and analyze the raw and Split the data into training and testing sets. In the second phase, we select appropriate machine learning algorithms for the task and train the chosen machine learning models on the training dataset. In the third phase, Evaluate the trained models on the testing dataset using performance metrics Finally, we have to use supervised machine learning techniques for pregnancy-induced hypertension prediction using PIH factors at the end of this prediction Interpret the results from the comparison of the algorithm and select the better performance of the evaluation to understand the strengths and weaknesses of the model.

3.6.1. Data Slicing

The data set is divided into training and testing sets for this technique. Training sets are used to train models. The test and training data sets should differ when developing a model. The test set then uses the trained model for assessment. A random sample of the data should be taken before separating the set. In the work that has been submitted [22].

3.6.2. Confusion Matrix

Confusion matrix classification tasks, a performance measuring tool used for PIH level prediction is the confusion matrix. It offers a thorough analysis of how effectively your model has predicted the various PIH levels or classifications [41].

Table 3. 2: Confusion matrix actual and prediction class

Actual class		Prediction class	
		P	**N**
	P	True positive(TP)	False negative **(FN)**
	N	False positive(FP)	True negative (**TN**)

For a classification task, it is a matrix of the actual class and expected class outcomes. The true positive predicted value is indeed positive. When the model accurately predicts a patient as being at risk of developing PIH, that would be a true positive. The percentage of real positive cases that the model correctly detects is the true positive rate, which is sometimes referred to as sensitivity or recall. The true negative predicted value is negative and it is true. A specific result when the model correctly classifies a negative instance as negative is known as a TN. Stated differently, this is an instance where the model correctly forecasts the lack of a specific condition or result. is a metric that quantifies the percentage of real negative examples that the model accurately detects. A false positive is The predicted value is positive and it is false. It is a particular result that occurs when a negative occurrence is mistakenly identified as positive by the model. Put otherwise, this refers to a situation in which the model predicts the existence of a specific condition or event, but the condition or outcome that occurs is negative. False negative is The predicted value is negative and it is false. is a particular result that occurs when a positive occurrence is mistakenly classified as negative by the model. Stated otherwise, this refers to an instance in which the model forecasts a specific condition or result to be absent, but the condition or result that occurs is positive.

Accuracy

One metric to assess the trained model is accuracy. Accuracy is the ratio of the actual dependent variable to the expected output dependent variable. A more accurate model has been trained. Random forest, Decision trees, SVM, LR, and XGboosting are used to assess the trained model's accuracy [55].

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} * 100\%$$

Precision

A machine learning performance measurement problem called a confusion matrix allows for the output of two or more classes. The number of samples for which the true and predicted samples are equal is represented by the diagonal elements of the confusion matrix, whereas the classifier has incorrectly categorized other elements [56]. $\mathbf{p} = \frac{\mathbf{TP}}{\mathbf{TP+FP}}$

The ratio of relevant samples that are categorized as positive to the retrieved samples that are classed as positive is known as precision (p).

Recall

It measures how many of the actual positive samples in the dataset were correctly identified by the model. Recall (r) is the ratio of relevant samples classified as positive to the relevant positive samples in the test set. $Recall = \frac{\text{TP}}{\text{TP} + \text{FN}}$

F1-score

Machine Learning Models' F1 Score: When evaluating a system for binary or multi-class classification problems, use the F1 score. By modifying the decision threshold or hyperparameters, you can optimize your model and increase the F1 score. These instructions help you use the F1 score in machine learning to assess and enhance the performance of your models [5]. F1-score is the weighted average of precision and recall. $\text{f1} - \text{score} = \frac{2\text{pr}}{\text{p} + \text{r}}$

CHAPTER FOUR

4. EXPERIMENTAL RESULT AND SIMULATION SETUP

4.1. Overview

This chapter covers the creation of models and the execution of experiments using the suggested framework. Furthermore, this experiment and evaluation illustrate the chosen machine learning models and demonstrate the reality of the architecture described. The experiment, the explanation of the findings, and an assessment of each model's performance using Python software are included in this chapter.

This chapter presents the preprocessing actions that were carried out on the dataset, along with a summary of some of the most significant tasks that were completed. This part outlines the framework architecture's implementation and provides an overview of the key experiments conducted to determine the best model for achieving the goal in Chapter One. Some experiments are carried out to determine which algorithms provide prediction models with different sizes, recall, precision, and accuracy. This also includes several development-related tasks, such as assessing the models constructed, choosing the best model, and offering a justification for the chosen model.

4.2. Implementation Tool

4.2.1. Hardware Tools

Hardware components can enhance, accelerate, and enable machine learning processes on the hardware tools. It is crucial for optimizing performance, efficiency, and real-time capabilities in deploying machine learning solutions. Due to this Microsoft Windows 10 64-bit is the operating system in use. Hardware tools are used to conduct the experiment and analysis on an HP Elitebook 840 G8 laptop with an Intel(R) Core(TM) i5-8265U processor, 1.60 GHz CPU, 8GB RAM, and a 1TB hard drive.

4.2.2. Software Tool

Software frameworks, libraries, and platforms can facilitate the development, training, and deployment of machine learning models. To improve the effectiveness of your machine learning projects. Each tool serves a specific purpose and can be chosen based on the needs of the research, the complexity of the tasks, and the desired outcomes. when talking about Python software tools it covers some packages that are the main package to predict the target variabls in research. the main function of import package describes under the table within each expression. Numpy as np is used in Python to import the NumPy library, which is a powerful library for numerical computing. By using np there are some functions in the dataset. N-dimensional arrays multi-dimensional arrays, or arrays, are supported by NumPy and are a more effective numerical operations tool than Python lists. Array manipulation NumPy facilitates the manipulation of arrays by making it simple to reshape, slice, and index them. pandas as pd is used in Python to import the Pandas library, a powerful tool for data manipulation and analysis. using as pd, create an identify for the library, allowing pd as a shorthand reference to Pandas throughout the code. Some importance of this package. Data manipulation filtering, grouping, combining, and altering datasets are just a few of the many capabilities it provides. Handling missing data Pandas makes it simpler to clean datasets by including built-in techniques for finding, eliminating, and filling missing data. Matplotlib. pyplot as plt is an important exploratory Data Analysis (EDA) before building machine learning models, pyplot is often used to visualize the dataset to understand the distributions, relationships, and differences in data. Some Common visualizations are histograms to check distributions, scatter plots to assess relationships between features, and box plots to identify outliers. Visualizing Model Performance Learning Curves Plots of training vs. validation loss or accuracy over epochs to indicate how well the model is learning. Confusion matrices Visualizing performance metrics for classification problems to understand where the model is making errors (TP, FP, TN, FN). ROC curves Receiver Operating Characteristic curves help evaluate the trade-off between sensitivity and specificity for classification models. Precision-recall curves are useful for evaluating performance on imbalanced datasets. seaborn as sns is an important library developed on top of Matplotlib, Seaborn is a Python data visualization library. It serves several purposes in the machine-learning setting and is frequently utilized. The task of making visually appealing and educational statistics visualizations is made easier by Seaborn. It facilitates the visualization of complicated information, making data distributions, linkages, and structures easier for machine learning professionals to comprehend. Machine learning relies heavily on the visualization of variable correlations. connection matrices are frequently displayed using Seaborn's heatmap tool, which aids in locating features that have a strong connection with the target variable. The pre-installed themes and color schemes in Seaborn enhance the visuals' visual appeal and make them simpler to understand and interpret. Imports XGboost library, which is a powerful and efficient implementation of the gradient boosting framework. This allows you to access all the functionalities provided by XGboost for machine-learning tasks. which are widely used for classification and regression tasks. It includes various algorithms.

4.4. Design Predictive Model

The process of creating a mathematical instrument or model that produces an accurate prediction is predictive modeling [58]. Data analysis was done by humans, but because of the volume of data, they were unable to make sense of it, so they automated systems that could learn from the data. and the adjustments made to the data to adjust to the changing data environment. By examining both recent and historical data, predictive modeling creates a model that may be used to forecast future events or behaviors. Predictive modeling involves gathering and preprocessing data, developing a model, making predictions, and validating (or revising) the model when new data becomes available [59]. General essential to incorporate the target variable PIH level and relevant attributes into the dataset. Such as creating training and testing sets from the data, Constructing the given algorithm classifier and adjusting the hyperparameters, Make use of the training data to train the model, Analyze the model's precision using the test data.

4.2.1. Random Forest Model

The construction of the random forest prediction model through hyperparameter tuning is covered in this subsection. The total dataset is 3479 is used for validation or testing. So in this algorithm by using parameters like a number of estimators or a number of trees, maximum depth, and minimum sample splits we can evaluate the performance of this algorithm. This combination of parameters aims to create a model that is robust and generalizes well to unseen data while avoiding the drawbacks of overfitting by controlling tree complexity and the size of the splits and leaves. The following are the Python programs for change hyperparameters and their values. which is a popular ensemble learning method used for classification and regression tasks. Here’s a breakdown of each parameter.

In this experiment, the RF technique is used to develop a prediction model. The dictionary format class_weight parameter value is determined using a cost-sensitive weight computing approach. We used the following Python function code to determine the values of the class_weight argument

```
'Random Forest Algorithm': {
    'n_estimators': [40, 50],  # Few trees
    'max_depth': [2, 10],  # Shallow trees
    'min_samples_split': [80, 150],  # Large minimum split size
    'min_samples_leaf': [40, 150],  # Very large minimum leaf size
    'max_features': ['sqrt', 'log2']  # Limiting the number of features considered for splits
},
```

Random Forest model to balance between bias and variance. The chosen values suggest a cautious approach to prevent overfitting while still allowing the model to learn from the data effectively. Adjusting these hyperparameters can significantly impact the model's performance, and they are often optimized through techniques like grid search or random search during model training. Evaluating Model Performance and Classification Report

Random Forest Algorithm: Classification Report:

	precision	recall	f1-score	support
Normal	0.95	1.00	0.98	186
Low	1.00	1.00	1.00	233
Moderate	0.99	0.94	0.96	234
High	0.89	0.95	0.92	43
accuracy			0.98	696
macro avg	0.96	0.97	0.96	696
weighted avg	0.98	0.98	0.98	696

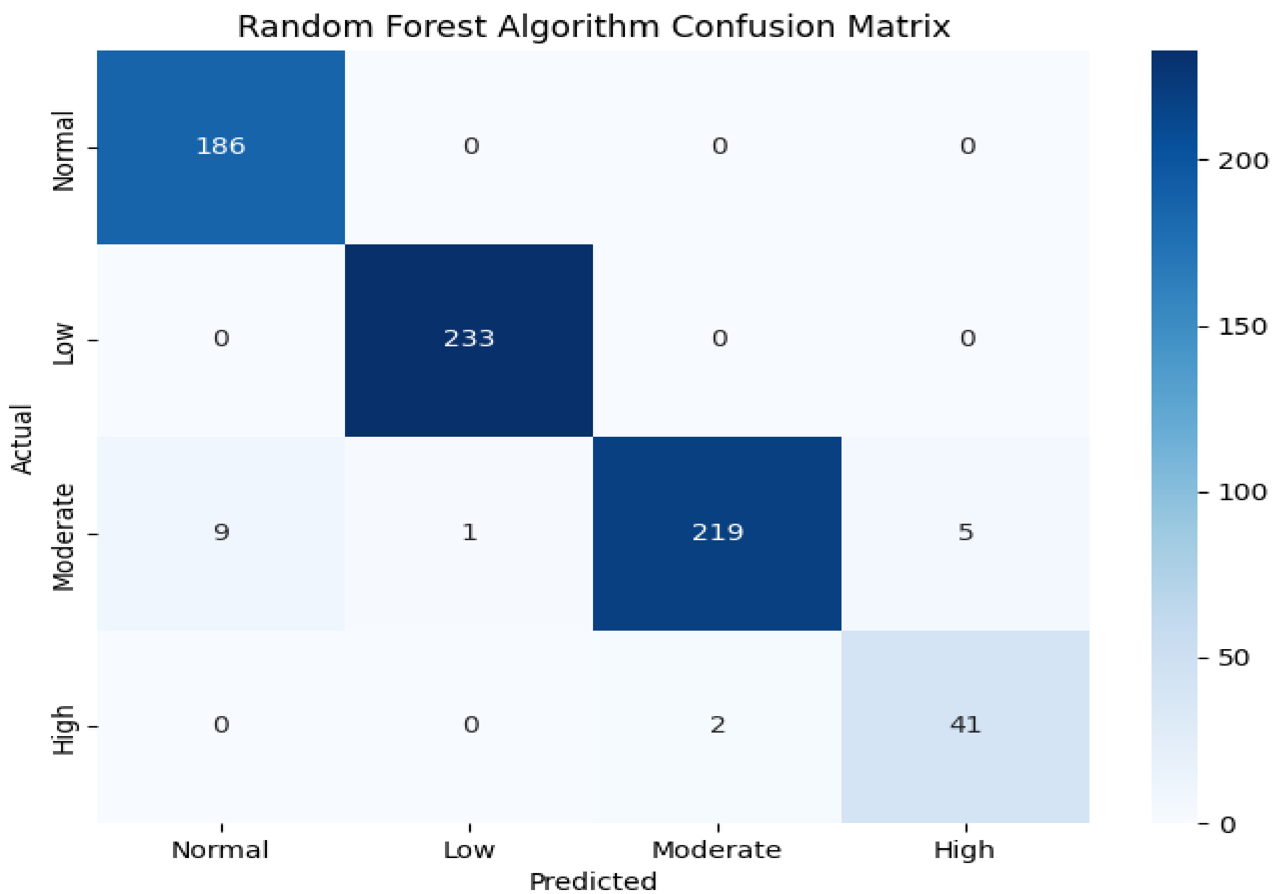

Figure 4.1:Comparision for each algorith

As we have shown in the above Figure 4. 1. The confusion matrix shows that the random forest algorithm performed very well on this classification task, with a high number of true positive predictions 186, 233, 219, and 41 for each class normal, low, moderate, and high respectively, and no false positives or false negative values. This indicates that the model was able to accurately distinguish between the positive and negative classes. The confusion matrix can be used to calculate various performance metrics, such as accuracy, precision, recall, and F1-score, which can give a more comprehensive understanding of the model's overall performance. General Interpretation for Random Forest Confusion Matrix The model performs well in predicting the "Normal" and "Low" classes, with high true positive counts and no false positives. The Moderate class has some misclassifications, with 9 instances incorrectly predicted as Normal and 1 as Low. The High class also shows some misclassifications, with 2 instances incorrectly predicted as Moderate.

4.2.2. Logistic Regression Model

This subsection describes how the logistic regression technique was used to create the PIH-level prediction model. With the other part being discrete, logistic regression is used to predict descriptive variables or order variables based on a collection of independent factors as though some of them were continuous variables [60]. In particular, multivariate logistic regression was used, meaning that there are multiclassification possible values for the dependent variable that are normal, low, moderate, and high. regression using logic. The model is constructed using Python libraries together with other libraries that are described in the data pretreatment section. classification report from a Logistic Regression model, summarizing its performance across different classes. The report indicates that while the model is effective for certain classes, there is room for improvement, particularly in predicting the "High" category. Further analysis and potential model adjustments may be necessary to enhance performance across all classes.

Evaluating Model Performance and Classification Report

Logistic Regression: Classification Report:

	precision	recall	f1-score	support
Normal	0.85	1.00	0.92	186
Low	0.99	0.96	0.97	233
Moderate	0.96	0.57	0.72	234
High	0.35	0.91	0.50	43
accuracy			0.84	696
macro avg	0.79	0.86	0.78	696
weighted avg	0.90	0.84	0.84	696

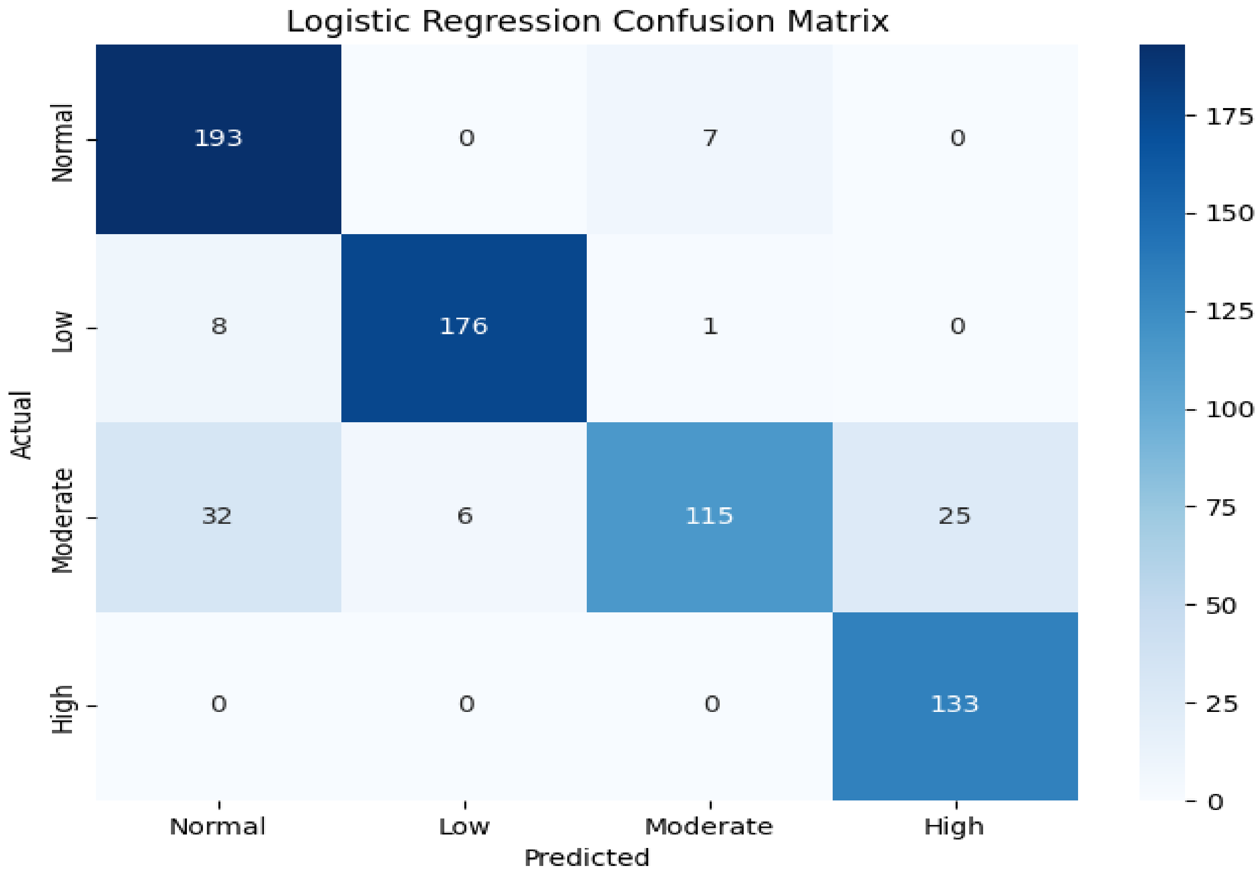

Figure 4. 1:Confusion matrix for logistic regression

Confusion matrix for logistic regression

The confusion matrix from figure 4.2 is a logistic regression model, which is used to evaluate the performance of a classification algorithm. The vertical axis (Actual) shows the true classes Normal, Low, Moderate, and High. The horizontal axis (Predicted) shows the predicted classes. Each cell in the matrix indicates the number of instances classified into each category. For example, the model correctly predicted 193 instances as Normal and 176 as Low, but misclassified some instances, such as 32 instances of Moderate predicted as Low. The performance of the model performs well for Normal and Low categories but has some misclassifications in Moderate and High categories, particularly with 25 instances of Moderate misclassified as High. This matrix helps in understanding where the model is performing well and where it needs improvement.

4.2.3. Support Vector Machine Model

Effective classification can result from using SVM to predict PIH levels, particularly when the data shows complicated patterns. Its capacity to handle non-linear separations and high-dimensional data makes it an invaluable tool for healthcare predictive modeling. The model to predict the risk of PIH level was constructed using the SVM algorithm. By maximizing the margin between four data groups, this algorithm creates the best multidimensional hyperplane to discriminate between two classes and conduct a classification [61].

performance evaluation and classification report

Support Vector Machine: Classification Report:

	precision	recall	f1-score	support
Normal	0.91	1.00	0.95	186
Low	1.00	0.97	0.99	233
Moderate	0.99	0.88	0.93	234
High	0.71	0.95	0.81	43
accuracy			0.95	696
macro avg	0.90	0.95	0.92	696
weighted avg	0.96	0.95	0.95	696

confusion matrix for the SVM algorithm

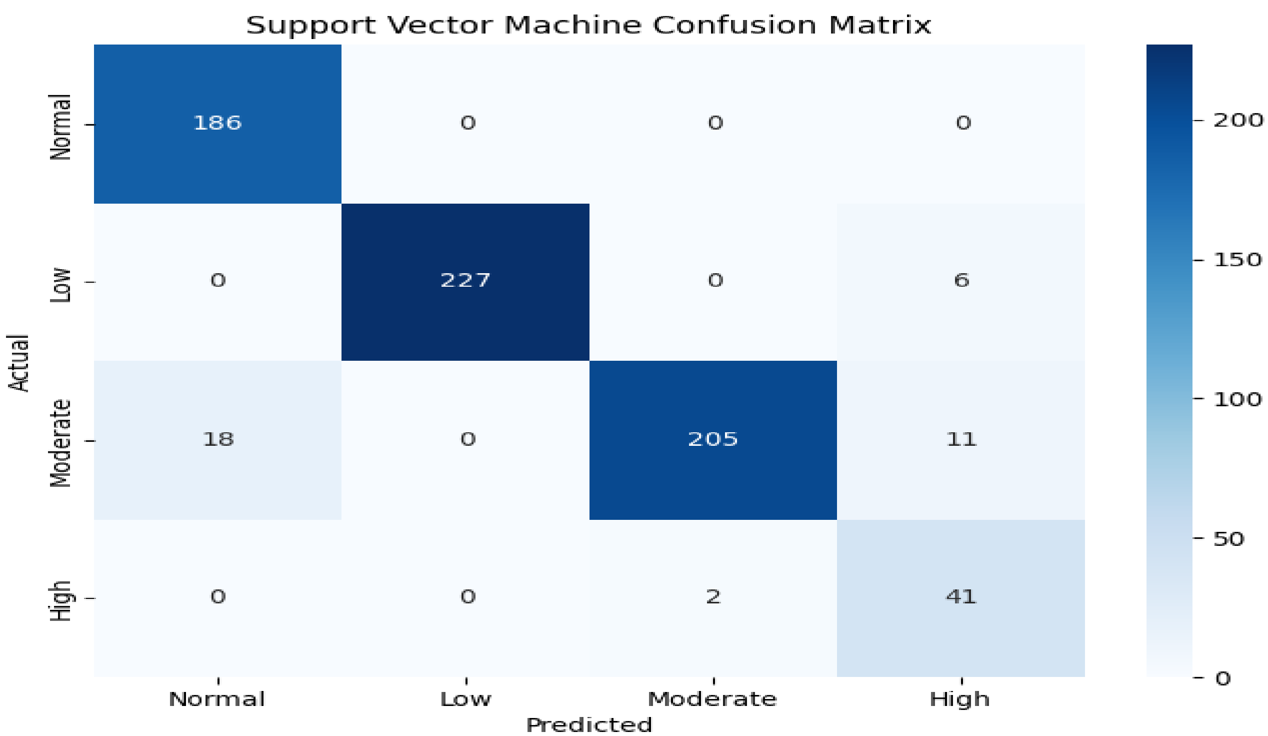

Figure 4. 2: SVM confusion matrix

Support Vector Machine (SVM) classification model, which is used to evaluate the performance of the model in predicting different classes. Stands from figure 4.3 Vertical Axis (Actual) represents the true classes of the data. The categories are normal, low, moderate, and high. Horizontal Axis (Predicted) represents the classes predicted by the SVM model. Diagonal values represent the number of correct predictions for each class. The predicted value for Normal 186 instances correctly predicted as Normal, Low 227 instances were correctly predicted as Low, Moderate 205 instances were correctly predicted as Moderate, and High 41 instances were correctly predicted as High. The othe indicated misclassifications for Normal**-** 0 instances were misclassified as Low, Moderate, or High. In Low**-** 6 instances of Low were misclassified as High, in Moderate -18 instances of Moderate were misclassified as Normal, and 11 as High. And High -2 instances of High were misclassified as Moderate.

4.2.4. Decision Tree Algorithm

For the most accurate forecasts for the PIH level, the decision tree algorithm automatically identify the critical features and their thresholds. Understanding the model's decision-making process can be assisted by the decision tree's visual representation. decision tree technique in the context of machine learning to forecast levels of pregnancy-induced hypertension. Performance metrics and particular dataset features can be used to inform adjustments and revisions.

Performance evaluation and classification report

Decision Tree Algorithm: Classification Report:

	precision	recall	f1-score	support
Normal	0.95	1.00	0.98	186
Low	1.00	1.00	1.00	233
Moderate	1.00	0.84	0.91	234
High	0.60	1.00	0.75	43
accuracy			0.95	696
macro avg	0.89	0.96	0.91	696
weighted avg	0.96	0.95	0.95	696

Confusion matrix for decision tree algorithm

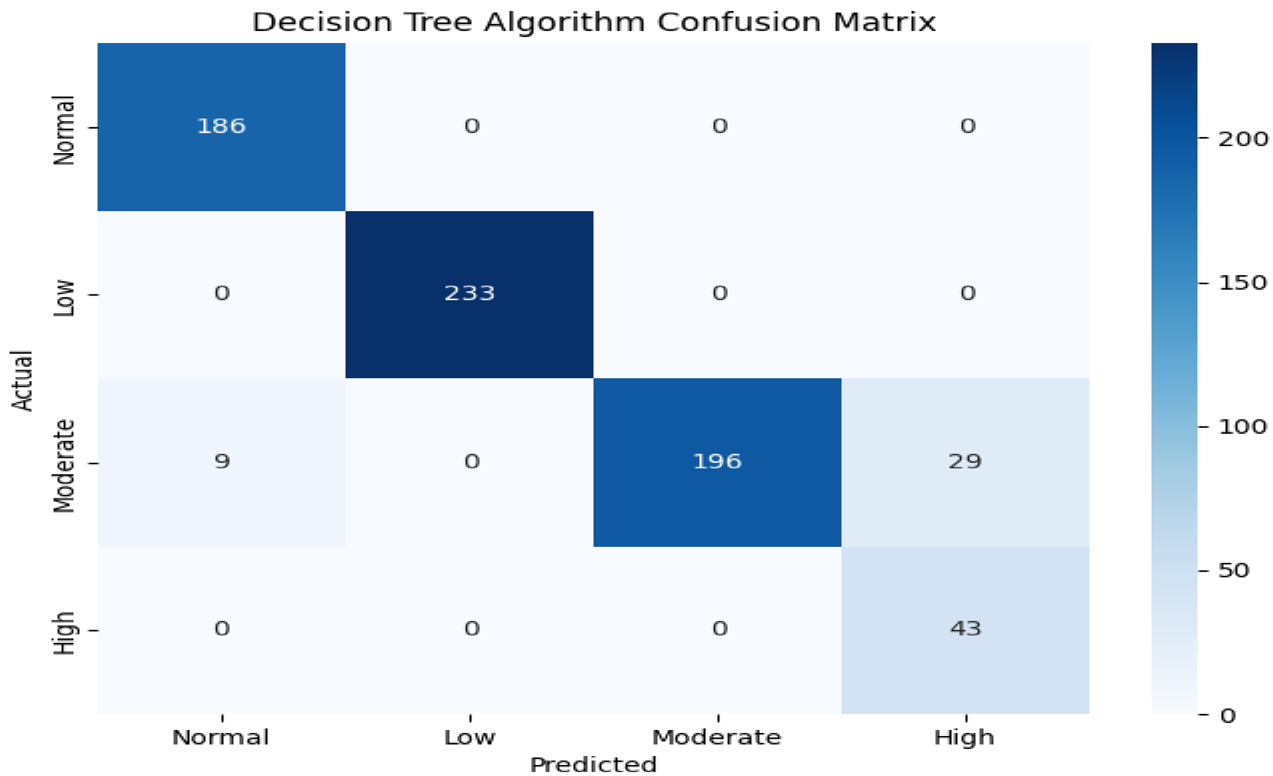

Figure 4. 3: Confusion matrix for decision tree

From this confusion vertical axis matrix Horizontal Axis (Predicted) represents the classes predicted by the Decision Tree model. Diagonal Values represent the number of correct predictions for each class. Normal-186 instances were correctly predicted as Normal, Low-233 instances were correctly predicted as Low, Moderate-196 instances were correctly predicted as Moderate, and High 43 instances were correctly predicted as High. These indicate misclassifications for Normal- 0 instances of Normal were misclassified as Low, Moderate, or High, Low- 0 instances of Low were misclassified as Normal, Moderate, or High, Moderate- 9 instances of Moderate were misclassified as Normal, and 29 as High, High-0 instances of High were misclassified as Normal or Low, but 0 instances were misclassified as Moderate.

RQ2. Which ML models were used to predict PIH?

4.2.5. Xgboost Algorithm

A strong gradient-boosting technique applied to both regression and classification problems applied in the XGboost model. Utilize suitable metrics to assess the model's performance after it has been trained. Common metrics for classification tasks like PIH prediction are F1-score, accuracy, precision, and recall.

Confusion matrices can be used to comprehend how well the model performs at various PIH levels. To get better performance we have to use the following parameters**:**

```
'XGBoost Algorithm': {
    'n_estimators': [10, 20],  # Very few trees
    'learning_rate': [0.01, 0.05],  # Very low learning rate
    'max_depth': [1, 2],  # Very shallow trees
    'subsample': [0.5],  # Use only half of the data for each tree
    'colsample_bytree': [0.5],  # Use only half of the features for each tree
    'min_child_weight': [10, 20]  # Large minimum sum of instance weight needed in a child
}
```

The XGboost algorithm's behavior can be fundamentally controlled by these hyperparameters. By adjusting them, you can ultimately affect the performance of the model by balancing the trade-off between variance and bias. A focus on simplicity is suggested by low values for n_estimators, max_depth, and learning_rate, which can assist prevent overfitting. Randomness is introduced by subsampling and feature sampling, which helps strengthen the flexibility of the model. A preference for stronger child nodes is shown by higher values for min_child_weight, which lowers the likelihood of fitting to noise. To maximize the performance of the XGboost model for your particular dataset and problem carefully adjust these models.

Performance evaluation and classification report

XGBoost Algorithm: Classification Report:

	precision	recall	f1-score	support
Normal	0.95	1.00	0.98	186
Low	1.00	1.00	1.00	233
Moderate	1.00	0.96	0.98	234
High	0.98	1.00	0.99	43
accuracy			0.99	696
macro avg	0.98	0.99	0.99	696
weighted avg	0.99	0.99	0.99	696

Calculating the macro average is a method commonly used in classification tasks to evaluate the performance of a model across multiple classes. For each metric calculated, find the average across all classes. The formula for macro average for a metric is

$$micro\ avarage = 1/4 \sum_{i=1}^{N} mi$$

Calculating a weighted average involves assigning different weights to different values, reflecting their importance or contribution to the overall average. The formula for calculating the weighted average is as follows:

$$weighted\ avarage = \frac{\sum(wi.Xi)}{\sum wi}$$

Confusion matrix for the XGbost algorithm

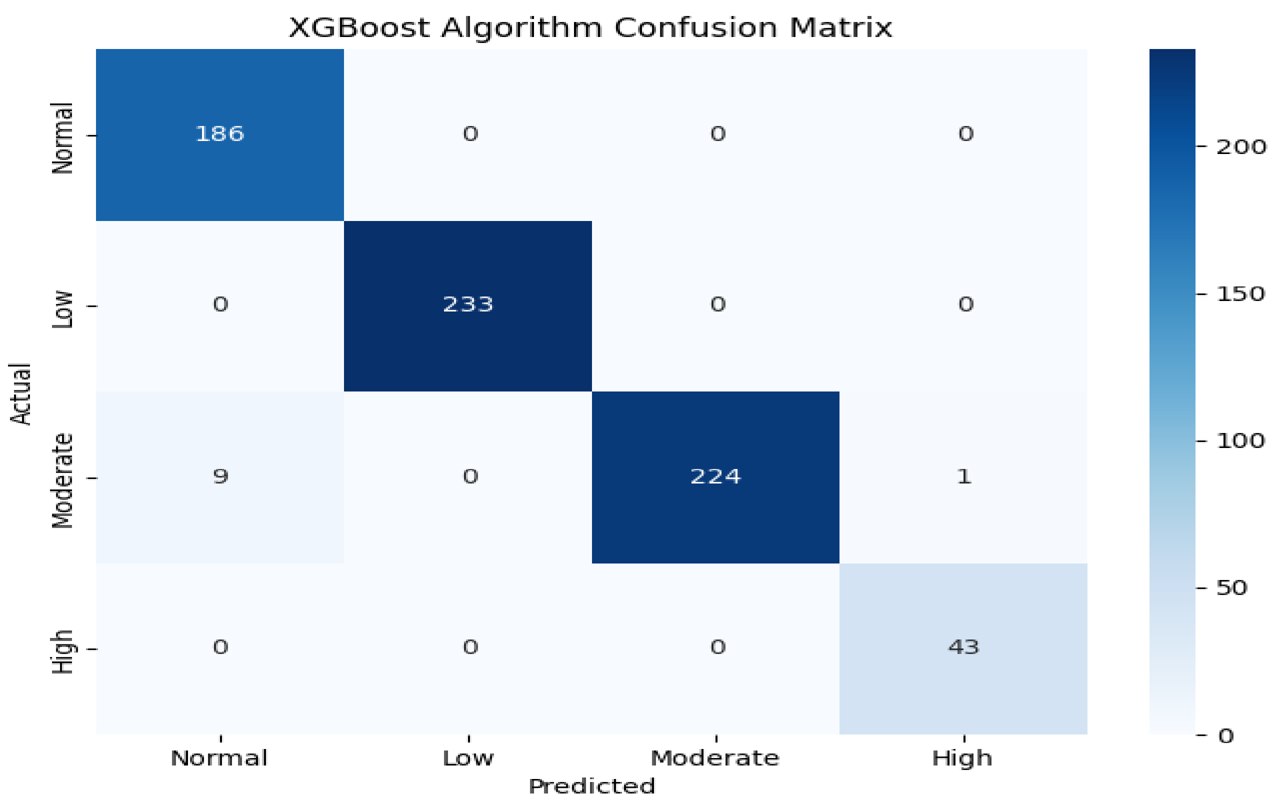

Figure 4. 4: XGboost algorithm confusion matrix

Matrix evaluates the performance of a classification model built using the XGboost algorithm. Us shown figure 4.5 vertical axis (actual) represents the true classes of the data are normal,low,moderate, and high. Horizontal Axis (Predicted) represents the classes predicted by the XGboost model**.** Diagonal Values are represent the number of correct predictions for each class is Normal-186 instances were correctly predicted as Normal, Low-233 instances were correctly predicted as Low, Moderate-224 instances were correctly predicted as Moderate and High-43 instances were correctly predicted as High. These misclassifications indicates for each target variables Normal-0 instances of Normal were misclassified as Low, Moderate, or High, Low-0 instances of Low were misclassified as Normal, Moderate, or High, Moderate-9 instances of

Moderate were misclassified as Normal, 0 as Low, 1 as High, and High-0 instances of High were misclassified as Normal or Low, and 0 as Moderate. Generally High Accuracy fro this confusion matrix the model shows excellent performance, particularly for the Normal and Low classes, with no misclassifications for these categories. In moderate misclassifications are moderate class has some misclassifications, specifically with 9 instances misclassified as Normal and 1 as High. This suggests that the model may have difficulty distinguishing between Moderate and Normal classes. Good performance for high is the High class has a reasonable number of correct predictions (43), with no misclassifications as Low or Normal. We can define in the table the final result of the target variable.

Table 4. 1: The result of each target variable within the measurement value

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Normal	0.95	1.00	0.98	186
Low	1.00	1.00	1.00	233
Moderate	1.00	0.96	0.98	234
High	0.98	1.00	0.99	43

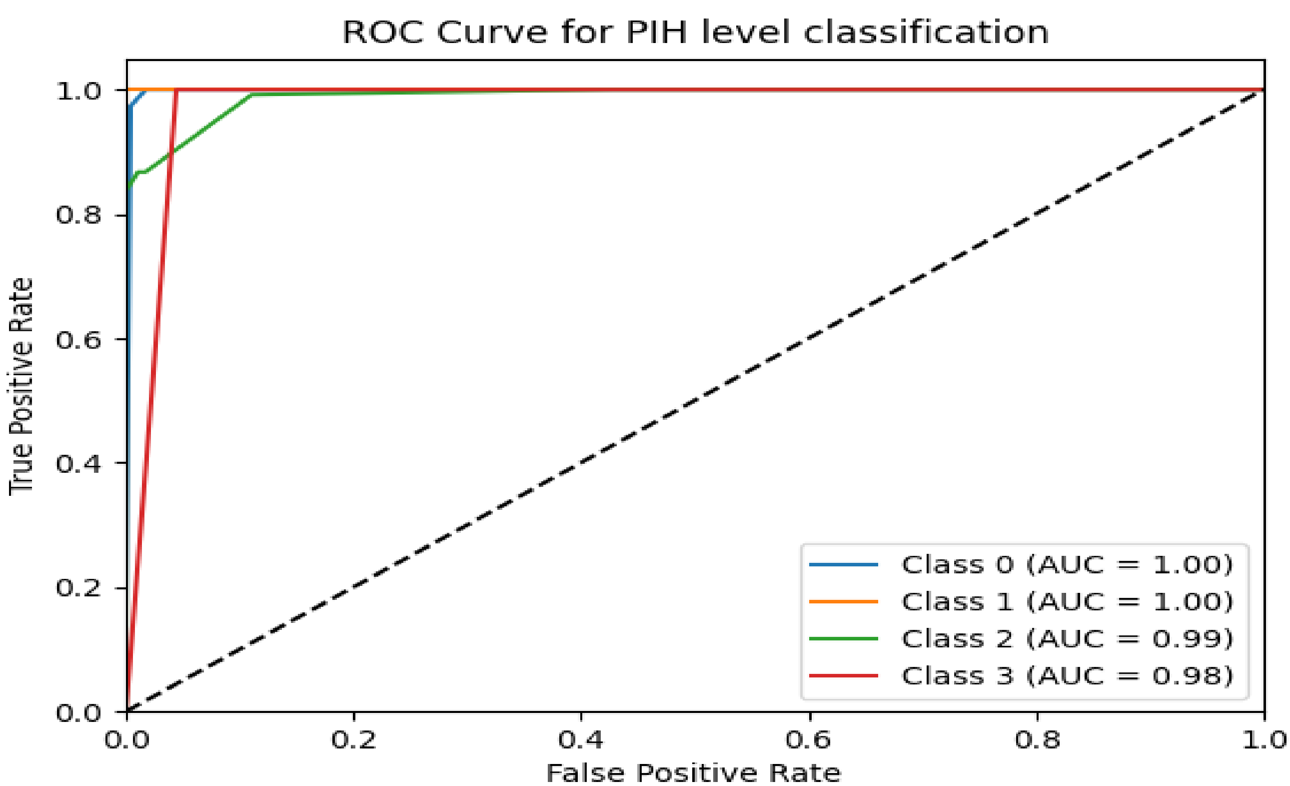

Figure 4. 5: ROC curve for PIH level classification

From the above figure 4.5 encode the target variables for normal,low,moderate, and high assigned 0, 1,2, and 3. Normal TP 186 instances correctly predicted as Normal. FP 0 instances incorrectly predicted as Normal from Low, Moderate, or High. Low TP 23 instances correctly predicted as Low. FP 0 instances incorrectly predicted as Low from other classes. Moderate TP 224 instances correctly predicted as Moderate. FN 9 instances of Moderate were incorrectly predicted as Normal. FP 1 instance incorrectly predicted as Moderate from High. High TP 43 instances correctly predicted as High. FP 0 instances incorrectly predicted as High from other classes.

ROC curve is a fundamental tool for evaluating the performance of binary classification models. Based on this model performs well for the normal, low, moderate, and low classes, showing high true positive rates. The moderate class has a few misclassifications, indicating potential areas for improvement. The high class also has a relatively good prediction rate. The ROC curve is a graphical representation commonly used to evaluate the performance of classification models. The curve illustrates the performance of a classifier on a multi-class problem related to PIH-level classification. The above figure 4.5 describes the X-axis false positive rate: This axis measures the proportion of actual negatives that are incorrectly identified as positives. It ranges from 0 to 1. Y-axis true positive rate also known as sensitivity or recall, this axis measures the proportion of actual positives that are correctly identified. It also ranges from 0 to 1. The broken diagonal line from (0,0) to (1,1) represents the performance of a random classifier. A model that performs no better than random guessing would fall along this line. Each colored line represents the ROC curve for a specific class in the classification problem. Normal PIH (AUC = 1.00) the blue curve indicates perfect classification for normal class, achieving an AUC of 1.00, meaning it can perfectly distinguish this class from others. Low PIH (AUC = 1.00) the orange curve also indicates perfect classification for low hypertension Class with an AUC of 1.00. Moderate PIH Class (AUC = 0.99) the green curve shows a very high performance with an AUC of 0.99, indicating excellent discrimination. high pregnant PIH class (AUC = 0.98) the red curve indicates strong performance for high hypertansion Class as well, with an AUC of 0.98. The AUC quantifies the overall ability of the model to differentiate between classes. Values closer to low PIH class indicate better performance AUC are 1.00 Perfect discrimination. AUC = 0.99 / 0.98 Very strong discrimination, indicating the model performs exceptionally well for these classes. The ROC curves for classes 0 and 1 demonstrate that the model has achieved perfect classification, meaning there are no false positives or false negatives for these classes. While slightly lower, the curves for classes 2 and 3 still indicate very high performance. This suggests that the classifier is highly effective in distinguishing between these classes and the others. Generally, this ROC curve analysis indicates it shows a healthy classification performance, making the model suitable for practical applications in predicting PIH levels. This ROC curve analysis provides valuable insights into the classifier's performance across multiple classes. The high AUC values suggest that the model is well-suited for PIH-level classification, with excellent discriminatory power for each class.

4.3. The Proposed Architecture

The processes taken to predict an individual's risk PIH level based on the gathered dataset are displayed in the suggested architecture in Figure 3.1. the data after preprocessing entered into the model to train and evaluate the performance of the algorithm and the dataset includes pregnant who have low, moderate, and high hypertension levels. We make use of the PIH dataset to validate the suggested model. Data collection is done at the Tibebe Ghion Comprehensive Specialized Hospital. Preprocessing operations are performed on the pregnant data dataset to clean up its properties. The dataset is then divided into two parts: the training data set, which comprises 70% of the dataset and is used to train the model, and the test dataset, which comprises 30% of the dataset from this 10% used in validation and is used to assess the system's performance. In the splitting dataset, 70% of the training dataset is run through classification models, such as SVM, logistic regression, Decision Trees, XGboost, and random forest. The developed model-induced hypertension prediction is directly accessed by 30% of the test dataset from this tested data 10% are used for validation testing. finally, the prediction of PIH level is provided at which risk blood pressure prediction model.

4.3. Comparison of machine learning algorithms with their proposed algorithm

The five machine learning algorithms were compared in terms of performance. The evaluation measures outcomes, including accuracy, precision, recall, and F1-score, form the findings' basis. The results indicate that the XGboost prediction models outperformed the random forest, decision tree,logistic regression, and SVM models in terms of accuracy, precision, recall, and F1 score.

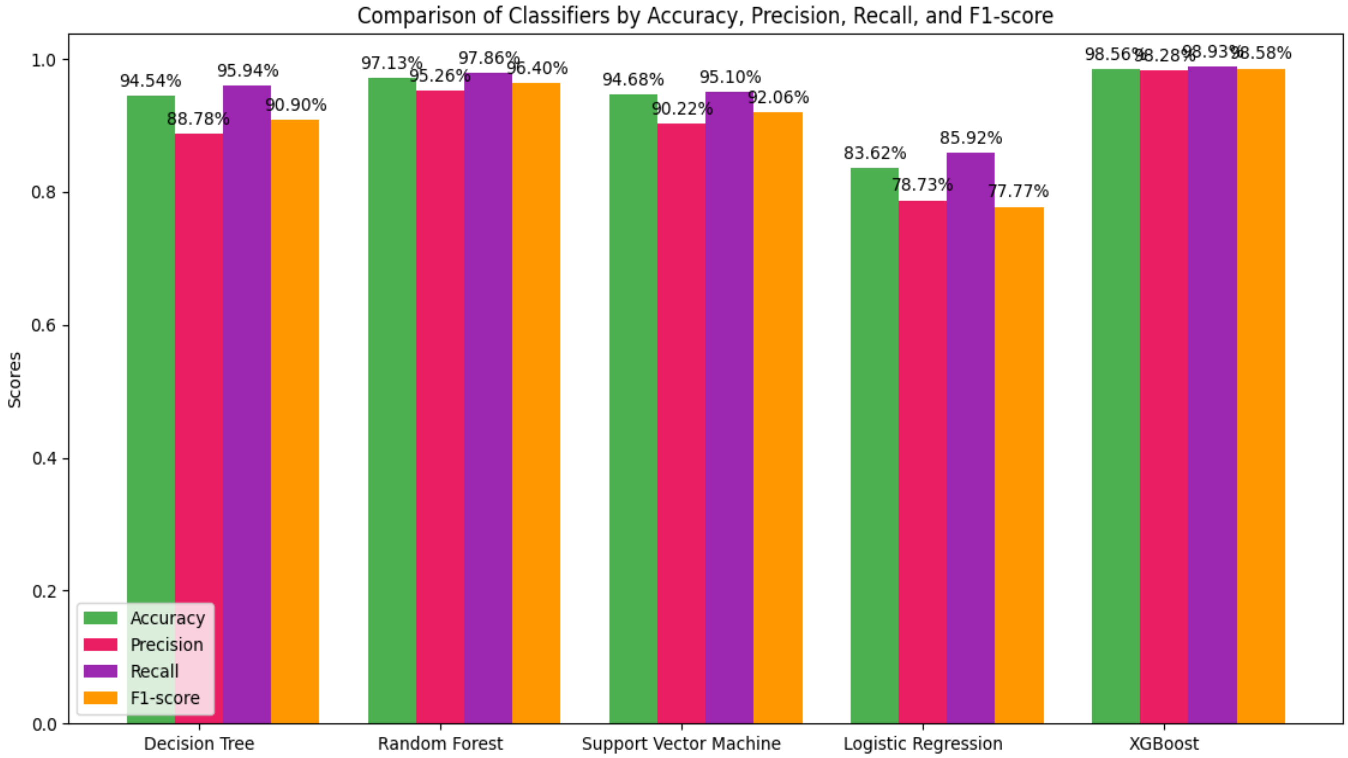

Figure 4. 6: Comparision for each algorithm

The model of XGboost has the highest accuracy, Logistic Regression, Support Vector Machine, Random Forest and Decision Tree are at 98.58%, 83.62%, 94.68%, 97.41%, and 94.54% are the result of each model respectively. The XGboost has the highest precision at 99.33%, Logistic Regression at 85.92%, Support Vector Machine at 95.10%, Random Forest at 97.60%, and Decision Tree at 95.94%. The XGboost has the highest recall at 98.56%, Logistic Regression at 77.77%, from those five model selection XGboost model has the highest Accuracy, Precision, Recall, and Fl-score are 98.56 %, 98.28 %, 98.93 %, and 98.58 % are the result of measurement respectively. Logistic Regression is the lowest result when compared with other models from this 83.62 %,78.73 %,85.92 %, and 77.77 % are the measurement value for Accuracy, Precision, Recall, and Fl-score respectively the final result from this XGboost model better outcome according to the comparison result.

Table 4. 2: Result in each model value in Percent

Algorithm	Accuracy	Precision	Recall	Fl-score
XGboost Model	98.56 %	98.28 %	98.93 %	98.58 %
RandomForest model	97.13 %	95.93 %	97.39 %	96.58 %
Decision tree	94.54%	88.78 %	95.94 %	90.90 %
SVM	94.68 %	90.22 %	95.10 %	92.06 %
Logistic regression	83.62 %	78.73 %	85.92 %	77.77 %

As we adjust for each parameter value, we can observe that, for the PIHLevel class, the XGboost Model is better performance evaluation when making comparisons for each measurement value like accuracy, recall, F1-score, and precision. This XGboost Model provides 98.56 % accuracy in the predicted PIH level class predicted correctly. From the six algorithms, the two models are better measurement values such as XGboost and Random Forest using those key predictor variables including sBP, dBP, BS, heart rate, age, BMI, and protein levels in urine. The high value of accuracy, precision, recall, and F1 scores obtained in the study underscore the potential of these models to predict PIH effectively.

4.4. Identifying Risk Factors of PIH Using RF

We used feature importance to run all tests for the RF technique and to determine the most significant elements influencing the PIH level. According to the World Health Organization, pregnancy exposure to level can be determined by several parameters, including weight, BMI, SBP, DBP, Urine in sugar, and others. These variables have been considered in this study to blood pressure is happening or not on the target of low, mid, normal, and high blood pressure. The feature importance technique was used to identify the features and factors that had the greatest influence. The Gini technique *is* used in RF to calculate the characteristics' relevance. The present study aims to determine which of the 18 parameters in the dataset are most influential in predicting the class/target variable, PIH prediction. The following Python code was then used to determine each feature's feature important scores based on the feature importance variable. We received the following relevance score for each attribute, listed in decreasing order, after running the aforementioned Python code.

```
# Feature importance for  Random Forest
if name in ['Decision Tree Algorithm', 'Random Forest Algorithm', 'Gradient Boosting Algorithm', 'XGBoost Algorithm']:
    feature_importance = grid.best_estimator_.feature_importances_
    features = X.columns
    importance_df = pd.DataFrame({'Feature': features, 'Importance': feature_importance})
    importance_df = importance_df.sort_values(by='Importance', ascending=False)

    plt.figure(figsize=(10, 6))
    sns.barplot(x='Importance', y='Feature', data=importance_df)
    plt.title(f'{name} - Feature Importance')
    plt.savefig(f"{name}_feature_importance.png")
```

The feature importance of a Random Forest technique utilized in a machine learning model is shown by this graph. The y-axis displays the features, and the x-axis, which ranges from 0 to 0.40, indicates each feature's relevance.

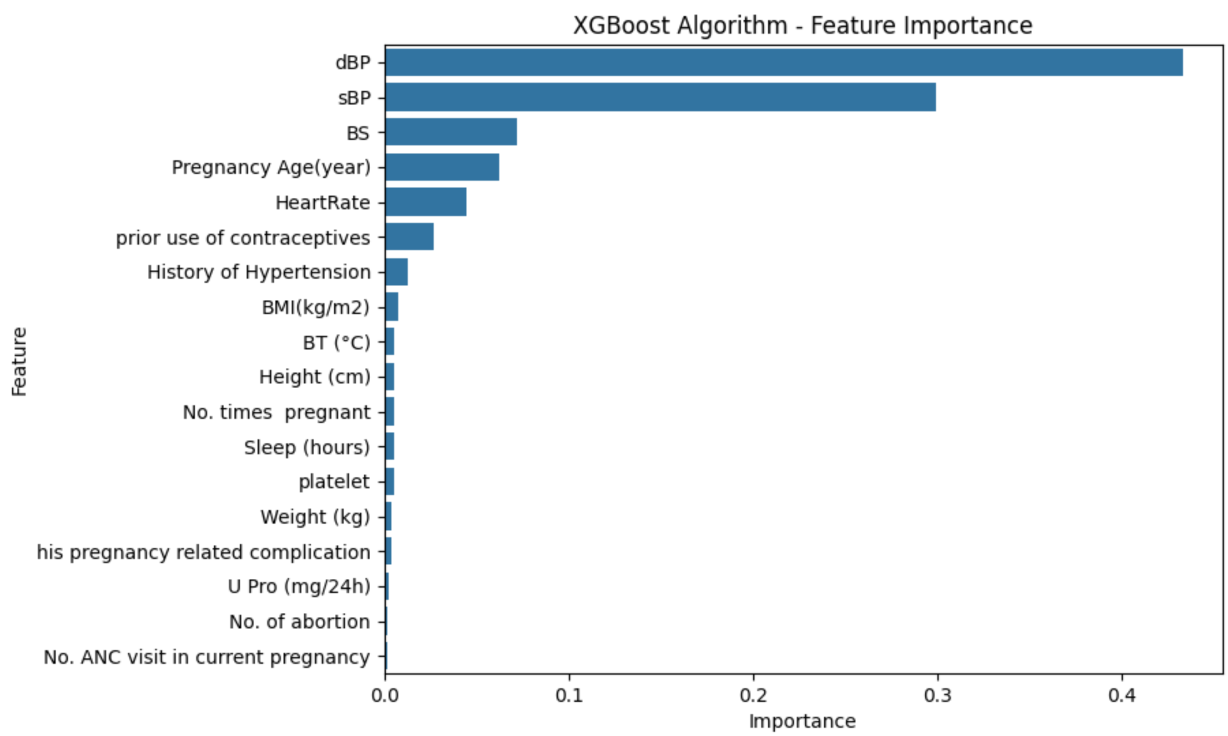

Figure 4. 7: Feature importance for high predictive XGboost model

Indicating that it visualizes which features were most influential in the model's predictions. X-axis his axis represents the importance score of each feature, ranging from 0 to 0.4. The XGboost algorithm identifies several key features that significantly influence the prediction of pregnancy-induced hypertension. The most critical factors, ranked from those features sBP and dBP are the feature of emerged as the most significant predictor of PIH, indicating that higher systolic and diastolic readings are closely associated with increased the level of hypertension . BS elevated blood sugar levels are another important indicator, suggesting that metabolic factors play a role in the development of PIH. Pregnancy Age (years) the duration of the pregnancy is significant; older gestational ages may correlate with higher risks of hypertension. Heart Rate variations in heart rate are also relevant, potentially reflecting the cardiovascular strain associated with PIH. The other factor Prior use of Contraceptives indicates that previous contraceptive use may influence the likelihood of developing PIH. History of Hypertension: A personal or familial history of hypertension is pivotal, highlighting genetic and lifestyle factors in PIH risk. Higher BMI values are linked to increased risk, emphasizing the importance of weight management during pregnancy. Blood Temprature while less significant than other factors, body temperature may still provide insights into maternal health. Height and Weight these proportions and composition of the human body measures contribute to understanding body composition and its relationship to hypertension. Other factors are additional features such as sleep duration, number of times pregnant,platlate ,ANC visits also play roles, and other factores are more predictable variables or features by applaying the prediction factors are important by monitoring and intervention in pregnant women.

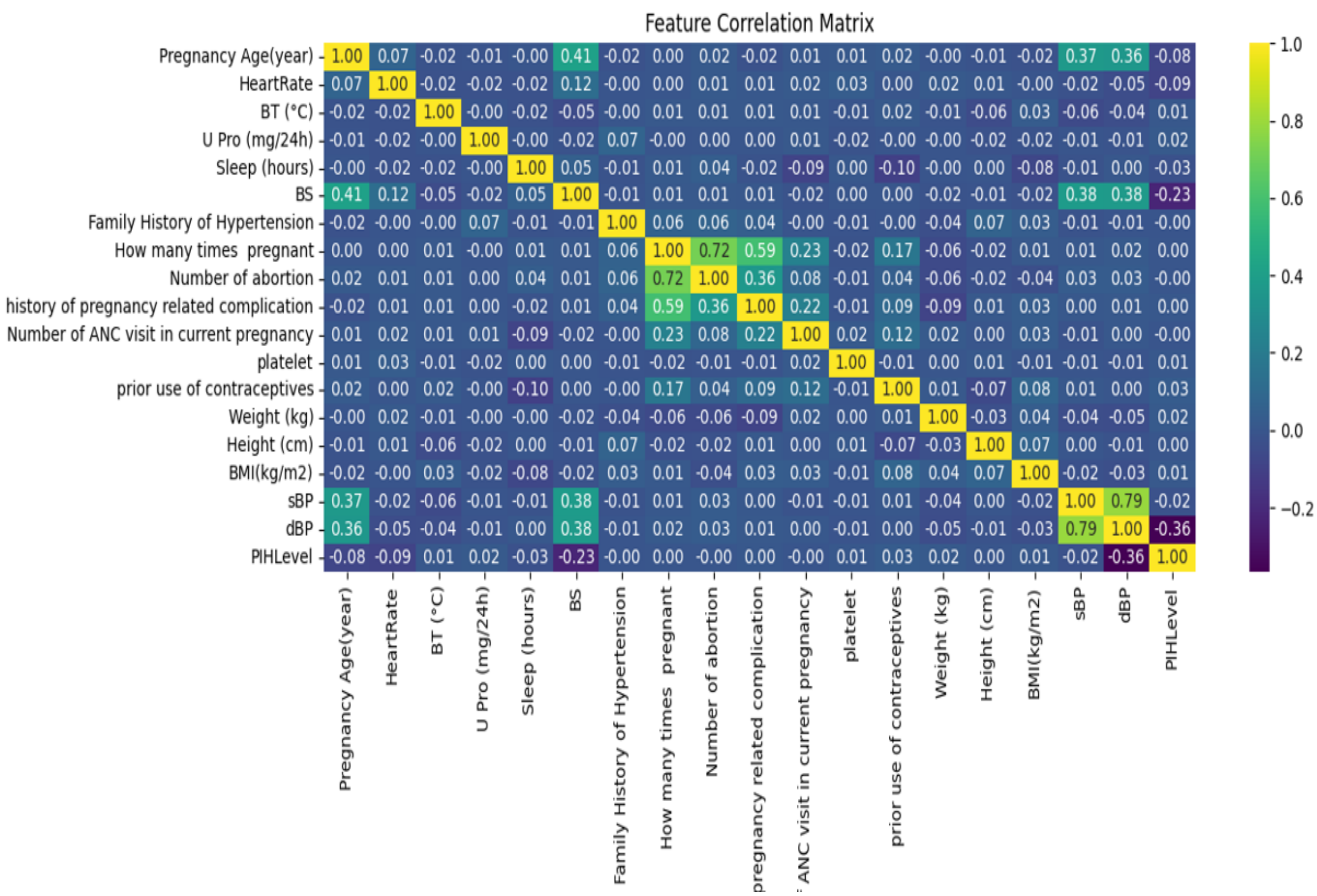

Figure 4. 8: Feature correlation matrix for all factors of PIH level prediction

The features that contribute the most to the model's predictions are those with the highest significance values. In comparison to the top three factors other features like Weight (kg), Heart Rate (bpm), Height (cm), Pregnancy Age (year), Sleep (hours), and Heart Rate (kg) are also important, but not as much. When choosing features, optimizing the Random Forest model, and deciphering the underlying principles of the model's predictions, the figure 4.8 offers insightful information about the relative weights of the various characteristics.

Pregnancy Age (year) this feature has a strong negative correlation (-1.00) with the target variable, indicating that as the pregnancy age increases, the PIH level tends to higher.. BT (°C) this feature has a weak negative correlation (-0.02) with the target variable, implying a limited relationship with the PIH level. U Pro (mg/24h) This feature has a strong negative correlation (-1.00) with the target variable, suggesting that higher levels of U Pro are associated with lower PIH level. Sleep (hours) has a strong positive correlation (1.00) with the target variable, indicating that increased sleep duration is correlated with higher PIH level. BS has a moderate positive correlation (0.38) with the target variable, suggesting that higher blood sugar levels may be associated with higher PIH level. A history of Hypertension has a strong positive correlation (1.00) with the target variable, indicating that a history of hypertension is a significant risk factor for higher PIH level. Number of times pregnant has a strong positive correlation (0.72) with the target variable, suggesting that a higher number of previous pregnancies is associated with increased PIH level 2. Number of abortion has a weak positive correlation (0.06) with the target variable, implying a limited relationship with the PIH level. Pregnancy-related complication has a moderate negative correlation (-0.09) with the target variable, indicating that the presence of pregnancy-related complications associated with lower PIH level.

The pairwise correlations between different variables in a dataset are shown figure 4.8, which is a correlation heatmap. The correlations intensity and direction are shown on the heatmap using a color scale, where blue denotes positive correlations and yellow denotes negative correlations. The x- and y-axis lists of the variables make it simple to determine how any two variables are correlated. The correlations between each variable and itself are represented by the diagonal elements, and they are always 1.0 a perfect positive correlation.

Several outstanding findings variables with the strongest positive correlations dark green include weight (kg) and BMI, as well as SBP and DBP. This is to be expected given their close relationship. Pregnancy Age (year), Number of ANC visits during current pregnancy, and History of pregnancy-related problems are somewhat positive relationships light green. Certain factors, such as pregnancy-related complication show little or no correlations white/light hue) with one another. A few factors, including the one between the number of abortions and the past use of contraceptives, have negative correlations blured green.

Training and Validation Loss for XGboost

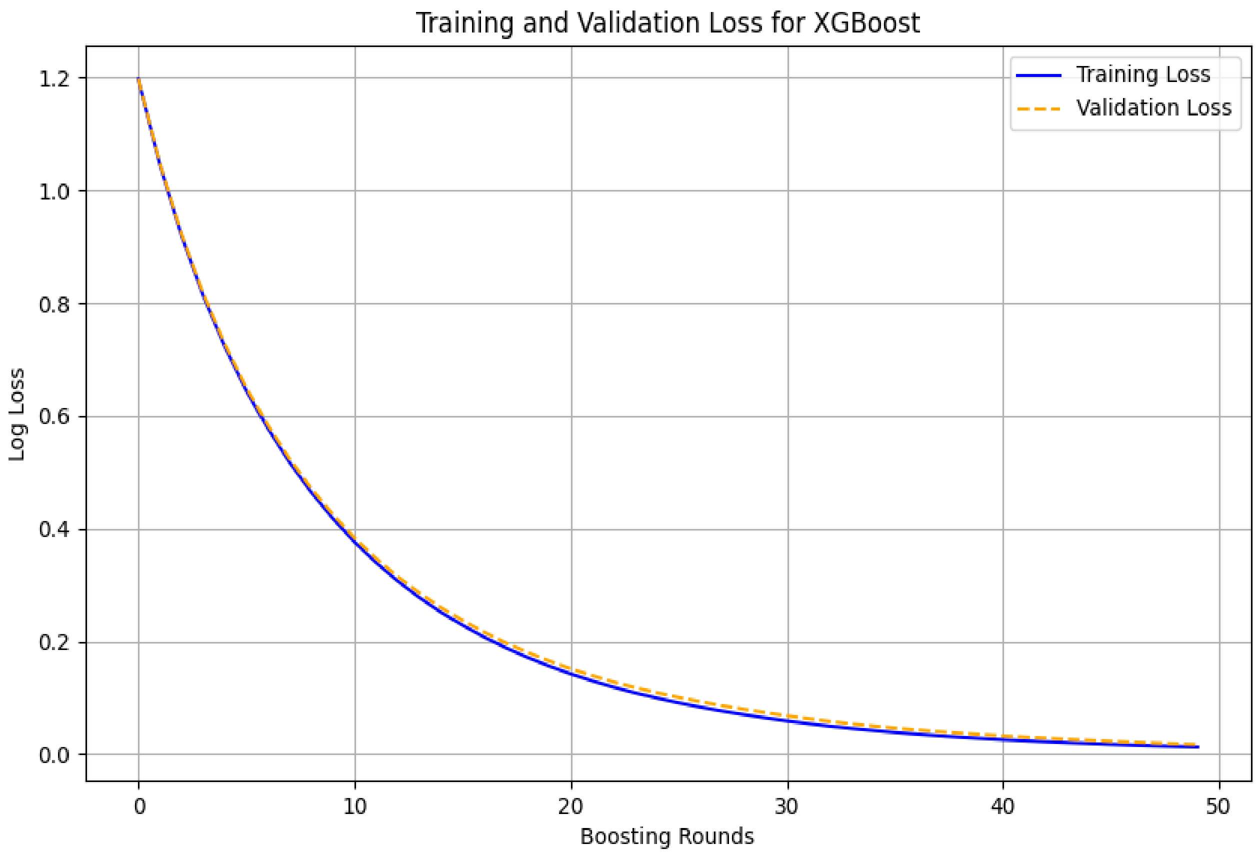

Figure 4. 9: Train and validation loss of XGboost model

To visualizes the above figure the training and validation loss for an XGboost model over a number of boosting rounds. X-Axis labeled as "Boosting Rounds," the x-axis represents the number of boosting iterations, ranging from 0 to 50. Y-Axis Labeled as "Log Loss," the y-axis represents the log loss values, ranging from 0.0 to approximately 1.2. Training Loss represented by a solid blue line, the training loss starts high at around 1.2 and gradually decreases as the number of boosting rounds increases. It stabilizes close to 0.0 after about 50 rounds. Validation Loss represented by a dashed orange line, the validation loss follows a similar pattern to the training loss, starting at the same point and decreasing in tandem with the training loss. The validation loss line is very close to the training loss line, indicating that the model is generalizing well without significant overfitting. The plot that shows both the training and validation losses decrease steadily as the number of boosting rounds increases, indicating that the model is learning effectively. The close alignment between the training and validation loss curves suggests that the model is not overfitting and is performing well on both the training and validation datasets.

4.5. Discussion of Result

In this study, we have developed a prediction model for PIH level and identified the high-risk factors that are highly affected by women during pregnancy. Several studies have been conducted to handle this problem and our study conducts pieces of literature to show their visible critics. [10] A study that was conducted to predict the PIH level by using the decision tree algorithm achieved 90% prediction accuracy from a total of 100 sample sizes. However, our model showed that an XGboost algorithm is better than that of other machine learning algorithms for predicting and identifying the risk factors of PIH level. It shows a result of 98.56% accuracy by using 3479 sample sizes within 18 independent variables. The finding indicates from a total of 18 independent variables seven of them a highly predictor of PIH which are SBP, DBP, BS, heart rate, age of women, body mass index, and urine in protein. The XGboost model's feature importance provides valuable insights into the factors most strongly associated with PIH. Blood pressure metrics dBP and sBP emerge as the top predictors followed by blood sugar levels, maternal age, heart rate, BMI, and urine protein levels. These findings show the multifactorial nature of PIH and the importance of a comprehensive approach to risk assessment and management [6]. By focusing on these key predictors, healthcare providers can better identify women at risk of developing PIH and intervene earlier, potentially improving outcomes for both mothers and their babies. As shown in the result The combination of high SBP and DBP was particularly predictive of high PIH. Machine learning models that included both SBP and DBP as features showed improved accuracy in predicting PIH levels. Women with higher sBP readings were more likely to be classified into higher PIH risk categories [10]. BS is another significant predictor in the models. Women with higher BS levels were more prone to higher PIH levels, making BS a critical factor in the prediction models. Age was consistently identified as a significant factor in the prediction models. Older and very young women were more likely to have higher PIH levels, emphasizing the importance of considering age in the risk assessment.

The study's findings have several important implications for healthcare practices, particularly in managing and predicting PIH. The identification of key predictors such as systolic and diastolic blood pressure, blood sugar levels, heart rate, age, BMI, and urine protein levels provides a foundation for early detection of PIH. By integrating these factors into predictive models, healthcare providers can identify high-risk individuals sooner, allowing for timely interventions and better management of the condition. The ability to predict PIH with greater accuracy using machine learning models like the XGboost algorithm allows for more personalized care plans. Women who have hypertension identified as high-risk can be monitored more closely, and preventive measures can be tailored to their specific risk profile, improving outcomes and reducing complications associated with PIH. With better predictive tools, healthcare resources can be allocated more effectively. High-risk patients can receive more frequent monitoring and care, while those at lower risk may require less intensive follow-up, optimizing the use of medical resources and improving overall efficiency in healthcare delivery. Understanding the factors that contribute most significantly to PIH risk can also empower patients through education. Women can be made aware of the importance of monitoring blood pressure, maintaining a healthy BMI, and managing blood sugar levels during pregnancy, leading to better self-care practices and potentially reducing the incidence of PIH. Generally, the early identification of factors that contribute to PIH and the accurate prediction of PIH levels can help in timely interventions, potentially reducing complications. In this discussion, we explore how machine learning techniques can be used to identify the most significant predictors of PIH and accurately predict PIH levels in pregnant women.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

Ethiopia's manual and frequently imprecise PIH prediction techniques cause delayed diagnosis and inadequate treatment. Mothers and their children are put at greater risk as a result of this. For this solution, the research proposes using machine learning algorithms to analyze data from pregnant women and predict their PIH levels. This allows for early identification of high-risk pregnancies and timely interventions.

This research focuses on developing a machine learning-based predictive model for pregnancy-induced hypertension (PIH) levels in pregnant women in Ethiopia. The study aims to address the challenges of limited healthcare resources and inaccurate PIH prediction methods in the country. The research successfully develops a predictive model, particularly the Random Forest model, which demonstrates promising accuracy in predicting PIH levels. The study identifies key risk factors for PIH, providing valuable insights for healthcare professionals. Pregnancy-induced hypertension is a disorder that can develop during pregnancy and is characterized by elevated blood pressure. To improve early identification and management measures and eventually improve maternal and fetal health outcomes, a machine learning model that properly identifies risk variables and predicts the likelihood and severity of PIH in pregnant individuals is being developed. When talking about PIH according to machine learning data quality important predictions that aren't accurate can be caused by missing or contradicting data. Model performance may suffer if the most important features are not identified. a model whose generalizability is reduced when it performs well on training data but badly on unknown data. Healthcare practitioners may find it challenging to accept the predictions of complex models (such as neural networks) due to their inherent difficulty in interpretation. The model might not work effectively for all demographic groups if the training data does not represent the general population's concerns about informed consent and patient privacy when using medical data. Certain clinical circumstances may not yield satisfactory results for models trained on particular datasets. Challenges may hamper adoption in incorporating machine learning models into current healthcare workflows. Concern over PIH, which poses serious hazards to both the health of the mother and the fetus, is growing. Even with improvements in prenatal care, early detection is still difficult. A strong machine learning model can evaluate a variety of datasets, pinpoint important variables, and precisely predict the incidence and severity of PIH. We have used methodology starting from data observation up to performance evaluation. The dataset collected from Bahirdar Tibeb Gion Specialized

Hospital from 4130 data used after preprocessing we have used 3479 datasets within 18 independent variables and one dependent variable used, finally 19 features are selected within target variable. After this model selection is applied, there are logistic regression, SVM, random forest, decision tree, and XGboost algorithm. After this divide the dataset into training (say, 70%) and testing (say, 30% within valdation) sets using the train-test split method. To optimize model parameters, employ strategies such as grid Search or Random Search. Finally, the XGboost algorithm was a better performance evaluation when compared to others and the measurement value was Accuracy = 98.56, Precision: 0.95, Recall: 1.00, and F1-Score: 0.98. The XGboost model demonstrates excellent performance in predicting PIH levels, with particularly strong results across all classes, indicating its potential utility in clinical settings for early detection and management of hypertension during pregnancy. The main implication of this research healthcare professionals can effectively control these risks by recommending dietary modifications, medication, or lifestyle changes based on the identification of contributing factors. Healthcare employers can customize monitoring and treatment regimens for each patient based on their unique risk profile by using predictive models, which provide tailored risk evaluations. This could result in the delivery of healthcare that is more effective and efficient, lessening the strain on healthcare systems and enhancing patient outcomes.

5.2. Contribution of the Research

Machine learning in predicting PIH levels and identifying contributing factors holds great potential for enhancing maternal healthcare. By leveraging data and advanced analytical techniques, healthcare providers can improve outcomes, tailor interventions, and ultimately contribute to the well-being of mothers and their child. The system's contribution to better data quality, in this case, the system's better prediction of PIH level is to analyze patient data to identify early signs of PIH, patients are at higher risk, healthcare providers can prioritize monitoring and personalized care, and early identification and intervention can reduce complications, leading to lower healthcare costs. By focusing on comprehensive, high-quality, and ethically gathered data, healthcare systems can enhance their predictive capabilities and improve maternal health outcomes.

5.3. Recommendations

I recommend continued research and development to further enhance the developed model should be implemented in healthcare settings in Ethiopia, particularly in areas with high PIH prevalence, to enhance early detection and intervention. improve the accuracy and robustness of the predictive model by incorporating additional relevant data, exploring new machine learning algorithms, and addressing limitations such as data imbalance and interpretability. I will say Ethiopia can leverage the power of machine learning to significantly improve PIH management, leading to better health outcomes for pregnant women and their infants. Other future work it can be used ultrasound images can be used to detect structural abnormalities or blood flow issues that might correlate with PIH and Advanced image analysis techniques, such as convolutional neural networks can be employed to analyze these images and extract features that may not be evident through traditional clinical observations due to this it should have used large amount dataset to get a better result .

Appendix I

	Bahir Dar University, Tibebe Ghion Specialized Hospital Laboratory	Document No: BDU TGSHL/...
		Version No: 01
		Page: 1 of 1
	Office memo	Effective Date: 30/1/2019

ቀን 14/12/2016 ዓ.ም

ለሚመለከተው ሁሉ

አቶ አዮብ ቢተው በወልድያ ዩኒቨርሲቲ በኮምፒውተር ሳይንስ ትምህርት ክፍል በ pregenancy induced hypertension ጥናትና ምርምሩን እየሰራ መሆኑን የወልድያ ዩኒቨርስቲ ትብብር እንዲደረግላቸው ባጻፉት ደብዳቤ በቀን 24/07/2017ዓ/ም እና ቁጥር ወዩ/ድህ/ምር/82/16 መሰረት የጥበበ ጊዮን ስፔሻላይዝድ ሆስፒታል ዳታውን የሰጠናቸው መሆኑን እንገልጻለን።

ከሰላምታ ጋር

Be... Dimah Taye

... Laboratory Head

በባህር ዳር ዩኒቨርሲቲ
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Authority for Issue: BDUTGSHL	Authorized Date: 30/1/2019
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Sample code for PIH

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split, GridSearchCV

from sklearn.preprocessing import StandardScaler, LabelEncoder

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix,
classification_report

import XGboost as xgb

from imblearn.over_sampling import SMOTE

# Load the data

data1 = pd.read_csv(r"F:\final document\dataset\final pih dataset and code\PIH_level2.csv",
low_memory=False)

# Identify non-numeric columns and encode them

non_numeric_columns = data1.select_dtypes(include=['object']).columns

label_encoders = {}

for column in non_numeric_columns:

    label_encoders[column] = LabelEncoder()

    data1[column] = label_encoders[column].fit_transform(data1[column])

# Split the data into features (X) and target (y)

X = data1.drop('PIH_level2', axis=1)

y = data1['PIH_level2']

# Ensure target variable is numeric

y = LabelEncoder().fit_transform(y)

# Split data into train and test sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the data

scaler = StandardScaler()

X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train), columns=X.columns)

X_test_scaled = pd.DataFrame(scaler.transform(X_test), columns=X.columns)
```

```
# Apply SMOTE for oversampling on training data only
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_scaled, y_train)
# Create and train the XGboost model
xgb_model = xgb.XGBClassifier(eval_metric='mlogloss', use_label_encoder=False)
# Hyperparameter tuning
param_grid = {
    'n_estimators': [10, 20],
    'learning_rate': [0.01, 0.05],
    'max_depth': [1, 2],
    'subsample': [0.5],
    'colsample_bytree': [0.5],
    'min_child_weight': [10, 20]
}
grid = GridSearchCV(xgb_model, param_grid, cv=3, scoring='accuracy', n_jobs=-1)
grid.fit(X_train_resampled, y_train_resampled)
# Best estimator
best_xgb_model = grid.best_estimator
# Predictions
y_pred = best_xgb_model.predict(X_test_scaled)
# Evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='macro')
recall = recall_score(y_test, y_pred, average='macro')
f1score = f1_score(y_test, y_pred, average='macro')
confusionmatrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)
# Print results
print(f'Best XGboost Model: {best_xgb_model}')
```

```
print(f'Accuracy: {accuracy:.2%}')
print(f'Precision: {precision:.2%}')
print(f'Recall: {recall:.2%}')
print(f'F1-score: {f1score:.2%}')
print(f'Confusion Matrix:\n{confusionmatrix}')
print(f'Classification Report:\n{report}')
```