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Prediction of Risk Levels in Maternal Health Care Using Machine Learning Algorithms

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Abstract
The health of women during pregnancy, childbirth, and the postnatal period is a critical aspect known as maternal health. Between 50% and 98% of maternal fatalities are due to direct obstetric factors such as bleeding, infection, complications from high blood pressure, uterine rupture, liver conditions, and anemia. The latest data from 2020 indicates a maternal mortality ratio of approximately 224 deaths per 100,000 live births. Current predictive models only offer limited effectiveness as they fail to fully integrate the prognostic and analytical dimensions present in extensive data sets, which include multiple risk factors related to maternal health. In the quest to harness large medical data sets for better prediction of diseases, data experts are testing various machine learning methods. This research scrutinized a range of algorithms such as K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, Extreme Gradient Boosting (XGBoost), and Decision Trees. Upon evaluation, Logistic Regression was observed to have the lowest prediction accuracy at 59%, with Random Forest at 86%, KNN at 73%, and Decision Tree close by at 85% accuracy. The study identified XGBoost as the superior machine learning tool, demonstrating a remarkable 93% prediction accuracy.

Keywords: Maternal health, KNN, Random Forest, Logistic Regression, XGBoost.

1. Introduction

Maternal health is a comprehensive term that refers to the physical, mental, emotional, and social wellness of women at all stages surrounding pregnancy. The majority of maternal health complications are preventable, making the correct identification of such issues crucial to averting potential critical consequences later on. An increase in maternal mortality has been linked to inadequate knowledge about maternal healthcare practices during and after pregnancy. It is vital to pinpoint the root causes of maternal health challenges and to pay close attention to the early warning signs. Key risk factors include obesity, the intervals between pregnancies, and tobacco use. The primary direct culprits of maternal morbidity and mortality include severe hemorrhage, infections, hypertension, complications from unsafe abortions, and obstructed labor. There are also indirect causes to consider, such as anemia, malaria, and cardiovascular conditions, which significantly contribute to the risks associated with maternal health.

In 2020, the maternal mortality ratio marginally rose to 152 deaths per 100,000 live births from a previous figure of 151 in 2019, based on the data recorded [1-2]. Common medical conditions such as diabetes, cancer, hypertension, infections, and sexually transmitted diseases, including HIV, alongside kidney issues, epilepsy, and anemia, can pose significant risks during pregnancy [3]. Potential complications during this period include disorders related to amniotic fluid, hemorrhage, ectopic pregnancies, spontaneous abortion or loss of the fetus, complications with the placenta, and the onset of pre-eclampsia or eclampsia [4]. The condition known as macrosomia describes infants born with a higher than average birth weight, which can lead to an increased risk of delivery-related trauma, the necessity for neonatal resuscitation, and a likelihood of scoring below seven on the Apgar scale after five minutes post-birth [5].

Diagnostic tools for maternal health issues:

MRI scans, through magnetic resonance imaging, are pivotal for identifying conditions like inflammation, hemorrhage, and obstructions within the intestines. This imaging technique is commonly used to investigate maternal conditions in the abdomen and pelvic regions during and after pregnancy [6]. Laparoscopy serves as a diagnostic tool for a variety of conditions within the abdominal or pelvic cavities [7]. The primary determinants influencing women's proactive measures in obtaining maternal healthcare include their level of education, the number of previous births, and their awareness of potential pregnancy complications. Addressing women's tendencies to seek healthcare is critical, and can be improved through prioritized health education and counseling services provided by empathetic and attentive healthcare personnel [8].

The significance of maternal healthcare: Maternal health is a cornerstone of a nation's efforts to advance equity and combat poverty, with the well-being of mothers being integral to tackling broader economic, social, and developmental obstacles. Key indicators of maternal health care include prenatal screenings, institutional deliveries, presence of skilled birth attendants, and postpartum care [9]. In today's medical landscape, delivering top-tier services and precise diagnostic assessments presents a substantial challenge. The criticality of maternal healthcare becomes most evident in the instances of sudden maternal mortality. Nonetheless, with timely detection, maternal health complications can be efficiently identified and subsequently treated, controlled, or managed. To systematically categorize issues in maternal healthcare and pinpoint difficulties within it, there is a call for a diagnostic framework that integrates MRI scan data with machine learning techniques. Machine learning (ML), a subset of artificial intelligence (AI), is increasingly being leveraged to make accurate diagnoses, detections, and predictions across various healthcare challenges. The application of machine learning is becoming paramount in autonomously processing input data and executing relevant actions without human intervention. Model-based ML approaches utilize input data to project outcomes through mathematical or statistical models and are applied across diverse sectors, including healthcare. Research is continually expanding to better predict and assess the severity of medical conditions [6-9]. Ensemble learning models, in particular, enhance accuracy by overcoming challenges faced by single machine learning algorithms, such as the arduous nature of data collection, susceptibility to errors, and the complexity of selecting the most appropriate algorithm. These models are a sophisticated amalgamation of various approaches, designed to deliver more reliable and robust healthcare diagnostic solutions.

The significant contributions in the article include: An ensemble learning model is developed by integrating various machine learning techniques to form a collective decision-making framework. This method capitalizes on the strengths of individual models while mitigating their weaknesses, thereby enhancing the overall predictive accuracy. Within the domain of maternal healthcare, the implementation of ensemble learning methods, particularly XGBoost (Extreme Gradient Boosting), has been proposed for early-stage detection and intervention. XGBoost stands as a potent example of ensemble learning, which has been successful in tackling complex issues by building a series of decision trees in a sequential manner where each tree corrects the errors of its predecessors. This approach has shown promise in identifying and predicting maternal health complications efficiently, thus allowing for timely and effective medical responses. The model's ability to handle various types of data and its robustness against overfitting make it a valuable tool in predicting outcomes with greater precision, which is crucial in the sensitive context of maternal health care.The Synthetic Minority Over-sampling Technique (SMOTE) is an innovative approach designed to tackle the issue of class imbalance in data sets used for machine learning. Class imbalance occurs when there are significantly more instances of some classes than others in the training dataset, which can lead to biased models that do not perform well on the minority class.SMOTE works by creating synthetic samples from the minority class instead of creating copies. This is done by taking samples from the feature space for each target class and its nearest neighbors, and generating new examples that combine features of the minority class with features of its nearest neighbors. This approach leads to a more diversified and representative dataset, which can improve the performance of machine learning models. By effectively balancing the class distribution, SMOTE helps in building predictive models that are more general and fair, which is particularly important in critical fields like healthcare where the cost of misclassification can be very high. In the context of maternal health, using SMOTE to balance datasets can help in better identifying and predicting rare but severe complications, ultimately contributing to more effective and responsive healthcare interventions.When evaluating the effectiveness of the proposed approach, which in this case might involve an ensemble model enhanced by techniques such as SMOTE for class imbalance and XGBoost for improved prediction, it's important to compare its performance against other established machine learning and ensemble models. This comparative analysis typically includes a variety of metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC), depending on the specific requirements of the domain, which for maternal health care, would be centered on reliability and precision due to the serious nature of potential outcomes. The essay is comprised of five additional sections. Section 2 encompasses a comprehensive review of existing research on forecasting maternal health outcomes. Section 3 describes the proposed research method in detail. Section 4 outlines the experimental framework, detailing the empirical data gathered, data preprocessing steps, the simulation setting, parameters used, and the selection of comparative techniques and performance metrics utilized to authenticate the proposed method.

2. Literature Survey

In their study, Akbulutet.al[10] The authors suggestedan assistive e-Health application for physicians and pregnant patients that, along with standard techniques, uses machine learning techniques for identifying congenital anomalies.

In another research effort, Author's in [11] introduced an entropy-based method for selecting features. Their model applied three distinct classifiers to predict preterm birth (PTB): decision tree (DT), logistic regression (LR), and support vector machine (SVM). Upon evaluating the classifiers' performance with metrics such as accuracy, specificity, and sensitivity, the SVM classifier was found to surpass the others, achieving an accuracy of 90.9%.

In their comparative analysis, Author's in[12] evaluated two classifiers to predict preterm birth among a cohort of pregnant women diagnosed with diabetes mellitus (DM) or gestational diabetes mellitus (GDM). Their findings concluded that the Support Vector Machine (SVM) classifiers, utilizing both linear and radial bases, attained an accuracy level of 86% on the dataset. The research identified several risk factors that contribute to the prediction of preterm births, underscoring that both DM and GDM are significant predictors for such adverse pregnancy outcomes.

In their research, Author's in [13] developed a model that examined six widely-used machine learning classification algorithms to determine their precision in predicting health outcomes. Upon application to the dataset, it was found that the accuracy of these algorithms varied, with the Decision Tree algorithm emerging as the most accurate. This particular algorithm was then employed for predicting pneumonia in newborns and conducting a statistical analysis of maternal conditions, aiming to reduce infant mortality rates. The insights gained from this study have the potential to support governmental efforts in public health education and awareness campaigns.

Table.1: Machine Learning Models

S.No	Data set	Method	Performance	Evolution	Reference
1	Dataset from the radio diagnostics center (RadyoEmar, Bakirkoy, Istanbul)	Two-class Decision Forest algorithm, Averaged perceptron, Boosted Decision Tree, Bayes Point Machine, Decision Forest, Decision Jungle, Locally-Deep Support Vector Machine, Logistic Regression, Neural Network, Support Vector Machine	Two-class Decision Forest 89.5%(accuracy)	Accuracy, F1 Score, and AUC	[10]
2	Obstetrical data set from the Community Health Centre of Rural areas	SVM, DT, LR	SVM-90.9%	Accuracy, specificity, and sensitivity	[11]
4	Dataset from the hospitals Mysuru.	Logistic regression, SVM, SMOTE	SVM-86%	Accuracy, sensitivity, Specificity, F-Measure, Precision, Recall	[12]
5	Dataset of 1100 women in Bangladesh	KNN, Naive Bayes classifier, decision tree, SVM, Random Forest, Neural networks	Random forest-90.32%	F1-score, accuracy	[13]
6	Data set Queensland	Gradient boosted trees	AUC=0.879, 95%CI 0.846–0.912	AUC, CI	[14]
7	Data set DHS for Nigeria	(BART), LR (with interaction terms), propensity score matching, RF, boosting, Neural Networks, SVM	Area under the ROC curve sensitivity=77.5%, specificity=61.3%, AUC=0.751 with cutoff=0.488	area ROC, sensitivity, specificity	[15]
8	Public dataset Mendeley Data repository.	Decision Tree	AUC, sensitivity, specificity=90%, Matthew correlation coefficient (MCC)	AUC, sensitivity, specificity, Matthew correlation coefficient (MCC)	[16]
9	Data set wearable sensing devices.	DT, Random Forest, SVM, SMO, LR, Naive Bayes, Logistic Model Tree	Accuracy=87%	Accuracy	[17]

3. Methodology Data Collection

The data utilized for analysis was sourced from the renowned UCI Machine Learning Repository. This particular set encompasses a comprehensive record of medical histories from 1,014 expectant mothers, a resource that was made accessible on the last day of 2020. The information was compiled through an array of health facilities, including hospitals, local clinics, and centers dedicated to the welfare of mothers in the rural districts of Bangladesh. This compilation was made possible via an IoT-based system designed to monitor health risks.

Outlined below is a succinct guide to the seven varied attributes that constitute the dataset. These attributes are categorized into four broad sections: fundamental characteristics, clinical particulars, physiological measures, and lifestyle indicators pertinent to each subject in the study. This dataset is characterized by dichotomous variables such as "Risk level" and continuous variables including "age," "systolic and diastolic blood pressure," "blood sugar (BS)," "body temperature," and "heart rate."

Decision Tree

The Decision Tree algorithm stands as a method within the realm of supervised machine learning and exhibits versatility unlike some of its counterparts, as it can tackle both classification and regression tasks. This algorithm creates a model that makes predictions about a target variable's class or value by deducing decision rules from the training dataset. To predict a record's class label using a Decision Tree, one initiates the process at the tree's root and examines the root attribute's values against the given instance's attribute. Following this comparison, one traverses down the branch that aligns with the instance's attribute value, moving onward to the subsequent node in the path.

KNN

The K Nearest Neighbors (KNN) algorithm is a simple yet effective method utilized for classification tasks. It assigns categories to new instances based on a defined measure of similarity (such as distance functions) and by considering the most common category among the k-most similar instances from the data it has already seen. As a non-parametric technique, KNN has been employed since the 1970s in the domains of statistical estimation and pattern recognition, not requiring the assumption of underlying data distributions.

Random Forest

This technique is a form of ensemble learning that leverages a multitude of decision trees to enhance the robustness and precision of the model. It is equipped to handle tasks related to both classification and regression. Within the context of classification, each individual tree in the ensemble casts a 'vote' on the class of a given instance based on its attributes, with the final class decision reflecting the majority vote from the forest. For regression problems, the technique takes the approach of averaging out the outputs of all the trees to arrive at a decision.

Logistic Regression

Logistic regression is a prominent algorithm in machine learning under the umbrella of supervised learning. It is employed to predict the outcome of a categorical dependent variable based on one or more independent variables. This algorithm estimates the probability of the dependent variable falling into a particular category, making it suitable for binary classification tasks where the outcome is dichotomous, such as 'yes' or 'no', 'success' or 'failure'.

Boosting

This ensemble approach constructs a strong predictive model by sequentially integrating several weak classifiers. Initially, a preliminary model is trained on the dataset. Subsequent models are then trained, primarily focusing on correctly predicting the instances that were misclassified by the previous models. This process continues, adding model after model, until either the training dataset is accurately predicted or a pre-set limit of models is reached. This iterative process allows the ensemble to improve its accuracy with each addition, correcting errors from earlier rounds of modeling.

XGBoost

XGBoost, which stands for Extreme Gradient Boosting, is an advanced implementation of gradient-boosted decision trees designed for speed and performance. It is an open-source software library that provides a scalable, portable, and distributed gradient-boosting framework for several programming languages such as C++, Java, Python, R, Julia, Perl, and Scala. This library is engineered to work across various operating systems including macOS, Windows, and Linux.

As a highly favored tool for a wide array of predictive modeling tasks including regression, classification, and ranking, XGBoost is renowned for its efficiency in parallelizing the process of tree construction, thereby enhancing computational speed and performance. Although it shares the gradient descent framework with traditional Gradient Boosting Machines (GBMs), XGBoost elevates the standard by introducing system optimization and algorithmic enhancements. These improvements include regularized boosting to prevent overfitting, a more efficient handling of sparse data, and a suite of features that bolster its utility in practical machine learning challenges.

Data Preprocessing

Data preprocessing is a critical process that transforms raw data into a format that is more meaningful and suitable for analysis. It is a foundational step in enhancing the integrity of original experimental datasets. This primary phase encompasses the collection, organization, and consolidation of the data. Additionally, data preprocessing significantly influences the performance and generalization ability of supervised machine learning algorithms. The preprocessing stage ensures that the dataset is complete, with all missing or null values addressed and validated to ensure consistency and accuracy. Through data preprocessing, unrefined data is converted into a valuable resource ready for analytical models and further processing.

The experiment employs the Synthetic Minority Oversampling Technique (SMOTE) to mitigate issues stemming from an imbalanced class distribution. SMOTE works by either oversampling the underrepresented class or undersampling the overrepresented one. It aims to equalize the class distribution by synthetically generating new minority class instances, rather than merely duplicating existing ones. It does this by interpolating between existing minority instances to create new, plausible data points. In the context of this study, the focus is on oversampling the minority class to rectify the imbalance. The technique of SMOTE was utilized as a preliminary step to enhance the predictive accuracy before feeding the data into the classification models. Instead of simple duplication, SMOTE generates new examples in the minority class by interpolating between existing examples, which enriches the dataset and allows for a more nuanced model fitting.

4. Simulation Environment and Parameter Setting

The experimentation is performed on Intel(R) Core(TM) i3-1005G1 CPU @1.20 GHz, 1190MHz, 2 Core(s), 4 Logical Processor(s), 64-bit operating system, and 8GB RAM.

XGBClassifier=(base_score=0.5,booster='gbtree', max_depth=10)

Confusion Matrix of XGB=(cf_matrix, annot=True, cmap="Blues_r")

plt.title("Confusion Matrix for XGB", fontsize=14, fontname="Helvetica", y=1.03);

LogisticRegressionScore = lr.score(x_test, y_test)

confusion matrix for Logistic Regression=

cf_matrix = confusion_matrix(y_test, y_pred_lr)

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sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")

plt.title("Confusion Matrix for Logistic Regression", fontsize=14, fontname="Helvetica", y=1.04);

KNeighborsClassifierScore = knn.score(x_test, y_test)

confusion matrix for KNN=

cf_matrix = confusion_matrix(y_test, y_pred_knn)

sns.heatmap(cf_matrix, annot=True, cmap="Blues_r")

Rifontname="Helvetica", y=1.03);

DecisionTreeClassifierScore = tree.score(x_test,y_test)

confusion matrix for DecisionTreeClassifier=

cf_matrix = confusion_matrix(y_test, y_pred_tree)

sns.heatmap(cf_matrix, annot=True, cmap="Blues

5. Performance Measures

The proposed use of XG-Boost, or Extreme Gradient Boosting, classifiers is centered on examining clinical patient data to forecast maternal health risks. To verify the efficacy of this approach, its performance is benchmarked against other machine learning and ensemble learning algorithms. This evaluation is conducted using a range of performance metrics that encompass the confusion matrix—which illustrates the instances of true positives, true negatives, false positives, and false negatives—as well as measures of true positive rate (sensitivity), false positive rate (fall-out), precision (positive predictive value), recall (sensitivity), f1-score (a harmonic mean of precision and recall), and overall accuracy. These metrics collectively provide a comprehensive assessment of the classifier's predictive capabilities.

Data preprocessing, as well as the application of machine learning and ensemble learning algorithms, are frequently conducted using Python programming frameworks such as Scikit-learn (often imported as sklearn). This library offers a wealth of tools for effective data manipulation and modeling. For data analysis tasks, the NumPy library is employed for its powerful numerical computations, while the Pandas framework provides sophisticated data structures and functions designed for easy and intuitive data manipulation. Visualization of data is an essential aspect of data science, and in Python, this is often achieved with libraries like Matplotlib and Seaborn. Matplotlib provides a wide array of functions for creating static, interactive, and animated visualizations in Python. Seaborn, on the other hand, is built on top of Matplotlib and provides a high-level interface for drawing attractive and informative statistical graphics. The challenge of class imbalance in datasets—where one class significantly outnumbers the other—is addressed using the SMOTE technique. SMOTE works within the Python ecosystem to synthetically augment the minority class

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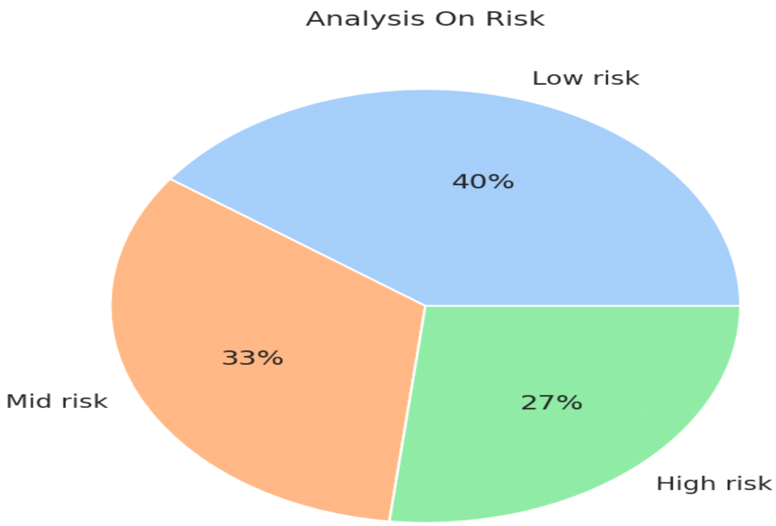
by creating new, similar instances, helping to balance the dataset and improve the performance of classification algorithms. This technique is especially critical in domains like healthcare, where imbalanced data can lead to biased models with poor predictive capabilities for the minority class.

Risk level plotting

This plotting shows the risk level of patients based on the attributes

Analysis on Risk



Analysis on Risk

The pie chart delineates the distribution of patient risk categories: 40% of the patients are classified as low risk, 33% are considered medium risk, and the remaining 27% fall into the high-risk category. Furthermore, the performance of various classification algorithms—Logistic Regression (LoR), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and XGBoost (XGB)—is

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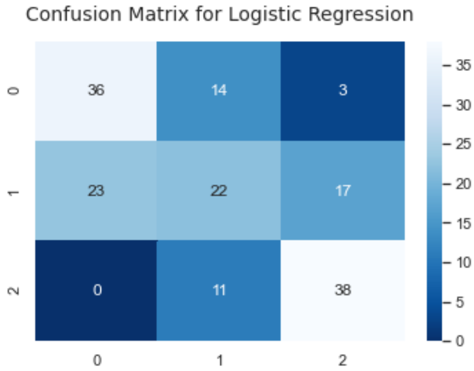
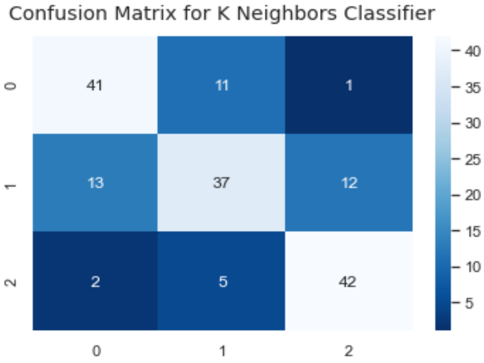
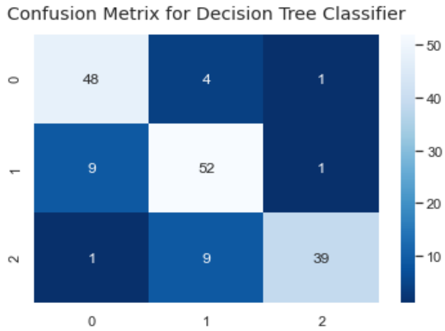
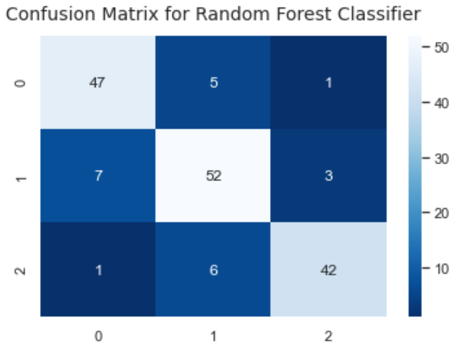
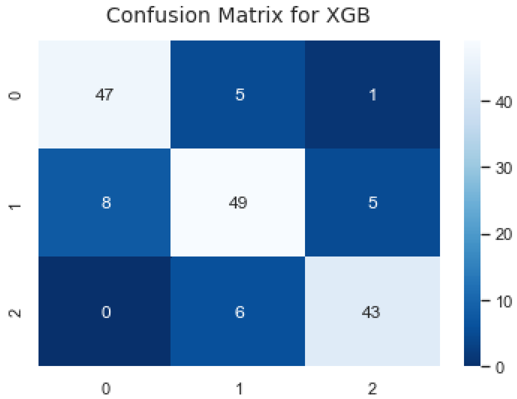
analyzed through confusion matrix graphs, which are depicted as follows:



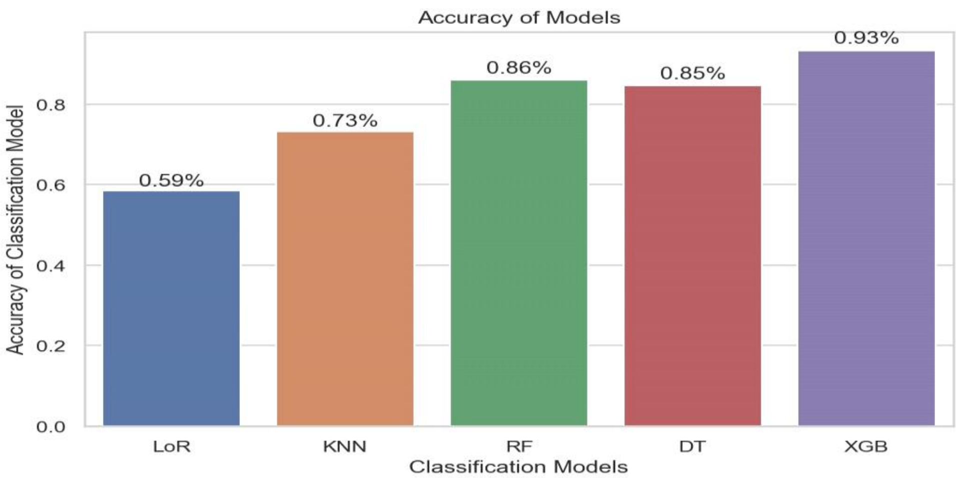








Comparisonof Accuracy



Upon evaluating the effectiveness of the classifiers, the XGBoost classifier emerges as the superior choice, attaining the highest accuracy at 93%. On the other end of the spectrum, Logistic Regression trails with the least accuracy, registering at 59%.

6. Conclusion

The study presented in this paper utilizes a selection of algorithms on a maternal health dataset, including Decision Trees, Random Forests, XGBoost, Logistic Regression, and K-Nearest Neighbors (KNN). The standout is the XGBoost model, which not only demonstrates impressive capabilities but also outperforms the others, achieving the highest measured accuracy of 93%. In contrast, Logistic Regression is noted for its relatively lower accuracy of 59%. Looking ahead, there is potential for the application of more complex models. Deep learning holds promise for addressing future challenges in maternal healthcare. Anticipated advancements could see medical practitioners leveraging computer vision, facilitated by deep learning techniques, to enhance diagnostic and treatment decisions for conditions related to maternal health.

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