Risk Level Prediction of Antenatal Period Using Machine Learning Approaches

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Abstract. This research looks at the use of machine learning to predict the risk levels of antenatal complications, presenting a novel approach to improving proactive antenatal care. In this study, we have collected dataset of 800 entries with eight key attributes such as Age, Weight, BMI, systolic BP, diastolic BP, BloodglucoseLevels, BodyTemperature, and HeartRate. The target attribute, "Labels" categorizes pregnancies as "Low Risk," "Medium Risk," and "High Risk," with possible level percentages (Low: 43.38%, Medium: 38.62%, High: 18%).A variety of machine learning models are used, including Gaussian Naive Bayes, Logistic Regression, Random Forest Classifier, Perceptron, and Voting Classifier. The results highlight the exceptional performance of the Random Forest Classifier, outperforming others with an accuracy of 99.21%. The ability of the model to collect multiple factors and minimize overfitting shows its potential to predict antenatal risk. The ethical considerations of the study ensure privacy for patients and avoid judgments, focusing on responsible implementation of models. The purpose of this study follows from its ability to change antenatal care by promoting an active structure that enhances healthier pregnancy and better outcomes for both the mother and the baby. The findings call for more research on understanding machine learning outputs, long-term effect evaluations, and the ability to adapt the proposed model in a number of healthcare settings. This study prepares the way for future studies that aim to improve maternal care through the use of advanced machine learning techniques.

Key words: Prediction Risk Level, Antenatal Period, ML, Gaussian Naive Bayes, Logistic Regression, Random Forest Classifier, Perceptron, EDA

1 Introduction

During the maternal period, women experience a variety of changes in their bodies that affect not only their physical health, but also their psychological[17] well being, which will sometimes be a concern for the baby's health, so important. As they require early identification and intervention to reduce the negative effects.

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Traditional risk assessment systems are not always as specific or rapid a way to provide ideal antenatal care, and tend to use in general limit which can fail to recognize individual differences. The latest innovations in machine learning provide a significant solution, as they allow analyzing complex health data, diagnosing the level of risk with increased precision. This study focuses on using machine learning techniques to predict the risk level of antenatal complications, providing a proactive approach to antenatal care.

For this Study, we have collected datasets in a wide range of attributes, including maternal age, weight, BMI, blood pressure measurements, blood glucose levels, body temperature, and heart rate and carefully labeled with three different risk levels - "Low Risk," "Medium Risk," and "High Risk" serves as the foundation for developing reliable machine learning models.

Most existing works focusing on specific complications, such as fetal health status [1], sepsis in pregnancy [2], stillbirth prediction [3], or preeclampsia detection [4] using Machine Learning models.They are often focused on specific conditions and are typically based on narrow or specialized datasets, like electronic health records[9] or small clinical groups. This research aims to address the gap by using machine learning models to antenatal risk prediction. By applying deep learning models like Gaussian Naive Bayes, Logistic Regression, Random Forest Classifier, Perceptron and Voting Classifier were used to enhance the accuracy of predictions. The model assessments, cross-validation and testing on data unseen were done to make sure that models are accurate and generalizable[4].

This study will equip healthcare workers with timely and informed decision making assistance to reduce negative consequences and promote healthier pregnancies by overcoming the divide between traditional and modern AI tools.

The key contributions are as follows:

- Created a specialist prenatal dataset that includes eight health indicators of the mother and three risk-level classifications
- The application and comparison of some machine learning algorithms, such as Logistic Regression, Gaussian Naive Bayes, Perceptron, Random Forest and Voting Classifier.
- Using Random Forest model that was predicting 99.21% accurately which means a reliable prediction of antenatal risks.

This study aims to contribute in medical sector by offering a effective model for the early detection of antenatal risks in pregnancy period. In future, we would like to grow and modify our primary data sets and train our model more effectively for real time application in medical sector.

2 Literature Review

In this part of our research, we look at current studies in the field where several researchers have applied different types of machine learning model to predict antenatal risks.

Akbulut et al.[1] focused on improving the prognosis of fetal congenital defects by utilizing e-Health and machine learning applications with conventional pregnancy diagnostics.They have used decision forest models based on used clinical questionnaires to determine the fetal health status and they were able to achieve almost 89.5% accuracy, but their study was constrained due to small number of respondents.

Kopanitsa et al.[2] used 15,000 births among 74,000 electronic medical records. Machine learning models that were trained to predict sepsis during pregnancy had 95% of accuracy. Primarily, the technique used only medical history and vital signs and was therefore clinically feasible in comparison to lab intensive models.

Using large cohort data from Western Australia,Malacova et al.[3] compared several models, such as NN, XGBoost, Logistic Regression, Decision Trees, and Random Forest using 10-fold cross validation, and the XGBoost model demonstrated a 45% of accuracy in stillbirth prediction, which compares slightly better than logistic regression. The limitation of the study lies in low sensitivity and only modest gains from the ensemble methods.

Table 1. Comparison of Studies in Antenatal Risk Prediction

Study info	Dataset	Model	Accuracy	Limitations
[1]	Clinical questionnaires on 96 pregnant women	Decision Forest	89.5%	Small sample size,limited application
[2]	Electronic medical records	Ensemble ML models	95%	Single-center dataset; dependent on EHR coding
[3]	Population cohort (Western Australia)	XGBoost, RF, LR, NN	Moderate Accuracy; XGBoost best performer	Class imbalance; limited sensitivity for rare outcomes
[4]	Clinical antenatal data	Gradient Boosting, LR, RF, SVM	97.3%	Requires external validation
[5]	EMR data (108,557 pregnancies)	ML on pregnancy trajectories	92% (37 weeks), 83% (labor), 89% (postpartum)	Complex trajectory modeling; not routine in clinics
[8]	Demographic Health Survey (Kenya)	Random Forest, XGBoost	95.7%	Relies on survey data; lacks clinical variables
[14]	Multi-site labor admission data (US Consortium)	XGBoost, RF, LR	93%	Retrospective design; needs real-time validation

Li et al.[5] work Models were trained to predict pre-eclampsia at different stages utilizing a massive EMR of 108,557 pregnancies of the Mount Sinai Health System and 60,879 records. Two independent cohorts confirmed the following reported accuracy of 92% on 37 weeks, 83% at labor, and 89% postpartum. The method was effective in detecting new and existing risk variables although the complexity of trajectory based modeling may limit typical clinical application and necessitate additional validation.

Sharon et al.[8] used secondary data of Kenya Demographic Health Survey, comprising of women between the ages of 15 and 49. The models that were analyzed were LR, DT, RF, SVM, GB, and XGBoost, with Random Forest being the most effective accuracy of 95. 7% and accuracy of 98. 8%. The indicators of greatest importance were maternal weight, maternal height, maternal age, and prenatal visits. Survey data is very reliable but has some limitations in regard to clinical usefulness.

A study of 17 articles about machine learning-based Clinical Decision Support Systems (CDSSs) to prenatal care has been conducted by Du et al. [12]. The review revealed that there were high dependency on single-center datasets, inadequate validation, and lack of model explainability. There was scarcity of cultural and ethnic consideration, and the user testing was inadequate, which restricted the use of CDSS in different communities.

Venkatesh et al. [14]. Based on 152,279 labor admission data on the United States Consortium of Safe Labor, the authors forecasted postpartum bleeding risk by RF, XGBoost, and logistic regression. XGBoost model was more clinically useful as it gave the best performance (C-statistic = 0.93) across sites and time. The models were not future-oriented and had to be validated in real-time clinical practice, although they were very strong.

Finally, past studies have shown that machine learning can effectively predict issues such as as sepsis, stillbirth, preeclampsia, low birth weight, and postpartum hemorrhage, and ensemble models often perform better than single models, seen in Table 1. However, the limitation of most studies are the limited focus on endpoints, single-center datasets, or the absence of clinical validation. These limitations underscore a more comprehensive risk prediction model.

3 Methodology

This part covers the information on collecting the dataset, the data preprocessing techniques, and the methodology overall that applied to this research, as seen in Fig. 1.

3.1 Dataset Collection

In this research, the data collection was conducted through structured questionnaire sessions with the patients of various hospitals to establish a comprehensive dataset on the risk of prediction during antenatal care. The data consists of 800

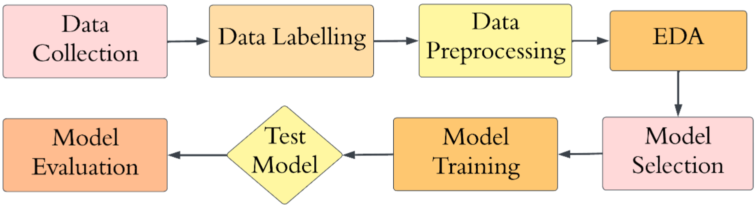

Fig. 1. Workflow Diagram of the Proposed Model

records and eight crucial features each, including age, weight, BMI, systolic and diastolic blood pressure, blood glucose, body temperature, and heart rate. The target attribute categorizes pregnancies as one of three categories of risks; low, medium and high.

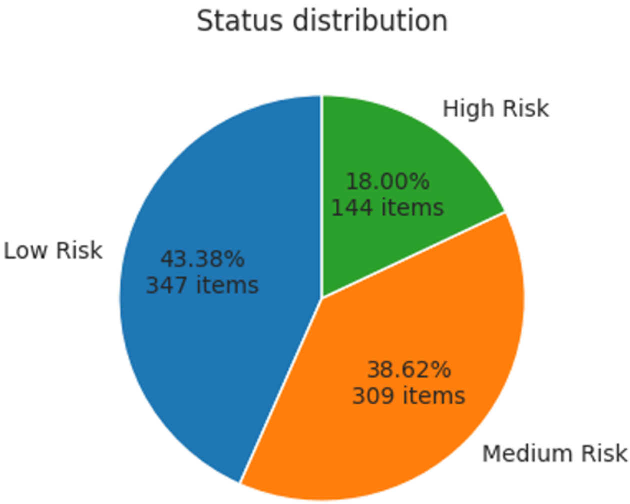

Fig. 2. Number of target attribute

The data was collected by a variety of patients of different ages, weights, and health parameters to be representative. The risk level distribution captures the prevalence in real world where 43.38% are low risk, 38.62% are medium risk and 18% are high risk, as seen in Fig. 2. This equal distribution makes the dataset more effective in training machine learning models since they will be able to generalize the patterns in various situations of antenatal risks. The dataset can more accurately capture the complexity of the real world by including the responses of various hospitals, and it can be used to produce strong and generalizable prediction models.

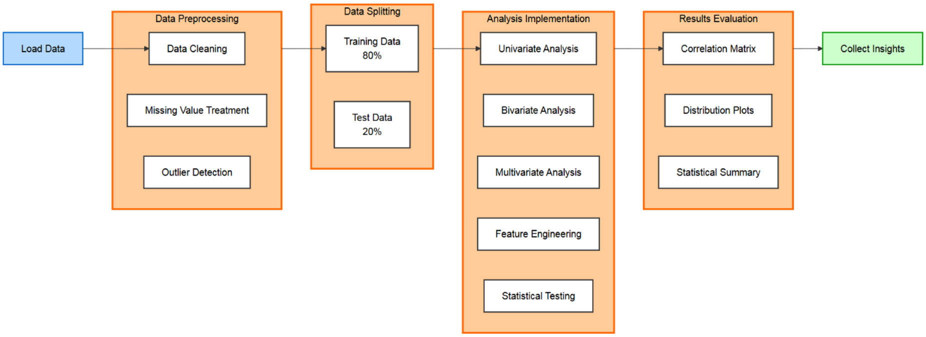

Fig. 3. Workflow Diagram of EDA

The EDA workflow is presented in Fig. 3. The data set has 22 features such as age, blood pressure, BMI, smoking habits, physical activity, and income, having 798 records . The part of the example offering a target variable "HeartDiseaseorAttack" which reports 22% Yes, 78% No and therefore indicates an imbalance, for which the model training was managed. On the other hand, features like age and less healthy lives generally, had a perfectly positive relationship with the odds of heart disease, while a higher income had a perfectly negative relationship. This in turns helps us to choose the most useful features, and the prediction model becomes accurate.

3.2 Data Pre-processing

In our study, data pre processing was a key area and was used to enhance data quality before the models were applied to the data sets. The data set was classified in three groups such as 'Low Risk','Medium Risk' and 'High risk' to reflect the target feature of the supervised machine learning. This classification established a clear structure for model development and evaluation. Before training the machine learning models, we cleaned and prepared the data in a manner that made it more useful and accurate. Exploratory Data Analysis (EDA) is an important step in the data analysis process that involves looking into and understanding the underlying patterns, trends, and characteristics of a data set. To conduct EDA, we addressed missing values. Mean, median, and standard deviation were used to get a better idea of the basic data patterns and how they changed over time. Graphs and charts were applied such as histograms, scatter plots, and box plots to show the data visually to see patterns and outliers. Then, use correlation analysis to look at how variables are related to each other. Identify possible issues, anomalies, or trends in the data using descriptive statistics and visualizations. EDA helps to develop hypotheses, pre processing, and future analytical decisions. Occasionally reviewing EDA during a project is a sure way of understanding the data well.

3.3 Proposed Method

In order to achieve strong and rich evaluation, we used the set of well-established and high-performing machine learning models[2] such as LogisticRegression, Random Forest (RF), GNB and Voting Classifier for ensemble learning. These models were chosen because of their efficacy in classification tasks and the different grades of performance in managing structure, tabular healthcare information.

Machine Learning Models

- **LogisticRegression:** Logistic regression (LR) is a widely used statistical tool that used to perform binary and multiclass classification. In this study, LR was used to estimate the probability of prenatal issues after modeling the probabilities of different types of risks. Its understandability and computational efficiency are suitable in medical processes where it is required to comprehend what effect can be achieved on results of specific traits. The findings built the LR paradigm, which was later applied to create a clear and clinically useful risk assessment for maternal and fetal care. The accuracy in the Logistic Regression model[21] in predicting antenatal risks during experiment evaluation was 84.06, which validates the effectiveness of the model.
- **Random Forest (RF):** Random Forest Classifier[18] is an ensemble learning algorithm that trains a number of decision trees and produces the mode of classifying the problems. It can deal with complex relationships and find the relevance of features very well. Random Forest Classifier will be suitable in this study as it gives the accuracy of 99.21%, which is the highest accuracy among all the models. The capability of dealing with non-linear interactions across various data enables prediction of the risk levels associated with prenatal issues. This provides important information to healthcare professionals. The interpretability, accuracy, and resiliency of the algorithm make it useful in trend identification and in aiding prenatal risk assessment.
- **GaussianNB:** Gaussian Naive Bayes (GNB) is a probabilistic classification algorithm that makes the assumption that features are normally distributed and are conditionally independent of the class. In this research, GNB [15] was used to forecast the level of antenatal risk because it is suitable in the handling of numerical information of health-related data. It is a very strong competitor in the medical field because its simplicity, efficiency and the capability to address continuous variables render it a very good choice where dataset often contains a number of physiological measurements. Through the integration of GNB, the research was intended to investigate latent associations between maternal characteristics and add to the overall perspective of prenatal risk factors. The result of the Gaussian Naive Bayes model was the 80.62 percent accuracy, which indicated moderate accuracy in antenatal risk prediction.
- **Perceptron:** The Perceptron is a simple binary classification method used in machine learning. To calculate a decision boundary, the linear model repeatedly adjusts weights based on the incorrectly classified instances. Perceptron proved to be the most suitable model in my research because it was the most effective in linearly separable tasks, interpretability, and simplicity. The data

do not necessarily fit into linear models, however, the accuracy 55.62% which is much lower. This demands the implementation of more complex algorithms in order to capture the complexities of prenatal issues to the latter. The feature architecture and model testing in my specific study setting will have to be carefully considered to ensure the highest possible level of prediction.

VotingClassifier: A Voting Classifier is a machine learning technique in ensemble learning, and it employs several independent models to generate outputs. The final prediction will be the one based on majority vote, or weighted average of the prediction of various algorithms, including logistic regression, decision trees, and support vectors machines. With a positive aspect we have chosen Voting Classifier[24] to be the focus of this study because it will be able to combine the finest features of various models that may result in improved accuracy of prediction. The entire method enables the model to discover many patterns and associations in the data, resulting in a more robust and accurate prediction of risk levels at the antenatal stage, especially, due to the complexity of the perinatal problems.

3.4 Performance Evaluation

Several performance evaluation metrics were computed, as outlined below. These metrics were used to identify the most effective classifier for this scenario based on the given characteristics.

In this part of our research, we determine the efficacy of using accuracy, precision, recall, and the f1-score. This four-factor matrix is quite helpful for analyzing predictive data. Equation1. demonstrates the accuracy formula:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Accuracy is attached to the capacity to recognize and categorize situations accurately. Here it defined as the ratio of true positive occurrences to total positive events.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Equation2. shows a mathematical expression regarding accuracy. A factor known as "recall" evaluates the way how well the algorithm identifies those suffering from antenatal risk.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Mathematically, recall is represented by Equation3.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

The term "harmonic mean" describes this method since it reaches a balance between accuracy and memory. A version of the mathematical equation for the F1 score is given by Equation4.

4 Results and Discussions

4.1 Experimental Result

The python code used to implement the maternal risk prediction model was Scikit learn, Pandas, Matplotlib, and Seaborn. The data was categorised into Low, Medium and High risk groups according to the heart rate and the body temperature. The accuracy, precision, recall, and F1 score measures were used to determine the model performance on 10-fold cross-validation. Here is a Table 2 summarizing the performance metrics for the different machine learning models in our study:

Table 2. Performance metrics for various algorithms.

Model Name	Accuracy	Precision	Recall	F1-Score
LogisticRegression	84.06%	85%	83%	84%
Gaussian Naive Bayes	80.62%	79%	84%	81%
Random Forest	99.21%	100%	100%	100%
Perception	55.62%	54%	53%	51%
VotingClassifier	96.21%	98%	97%	98%

Table 2 presents the performance comparison of the various models used in this study for predicting Risk Level Prediction of Antenatal Period from raw real-world dataset. The accuracy of logistic regression was 84.06%, showing good prediction with moderate precision and recall. Gaussian Naive Bayes was next with an accuracy of 80.62%, which showed good recall (84%) but much lower precision. However, it was found that the Perceptron model was the least accurate (55.62%), which showed weakness in terms of non-linear decision boundaries. Random Forest classifier was most effective with an accuracy of 99.21% and a 100 percent precision of 100 percent recall and F1-score showing the capacity to absorb the complicated relationship in the data. The Voting Classifier was another good option and achieved high accuracy (96.21%), great precision (98), and recall (97), so it is reliable.

From Table 2, we can come to a conclusion that the Random Forest Classifier model out performed all other models.

4.2 Detailed Analysis of the Best-Performing Model

Since it has better performance, the Random Forest Classifier has been chosen to be analysed in more detail, as this model perform very well with 99.21% accuracy (see Fig. 4) . The main evaluation measures of the model offer the overall picture of its effectiveness as shown in the confusion matrix in Fig. 5.

The confusion matrix is a graphical representation of the performance of the model by all the classes (rows) and the predicted risk levels (columns) and the actual risk levels (rows).

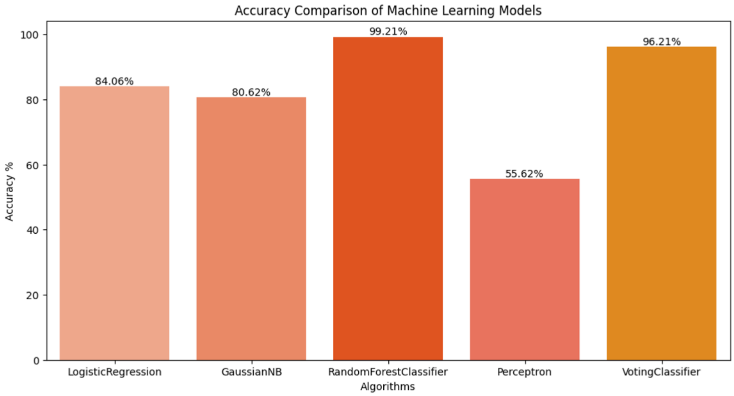

Fig. 4. Accuracy Comparison of Machine Learning Models

Low Risk (Class 0): Number of correctly identified low risk cases was 276. It falsely indicated 2 instances of high risk (Class 2) but critically, it did not show any false negativities of low risk category.

Medium Risk (Class 1): This model performed a perfect classification in this class with no miss-classifications at all and was able to identify all 115 medium risk cases.

High Risk (Class 2): This model was very effective in this critical category, with a very high 247 high-risk predictions. There was no false negativity, which is that no cases at high risk have been overlooked.

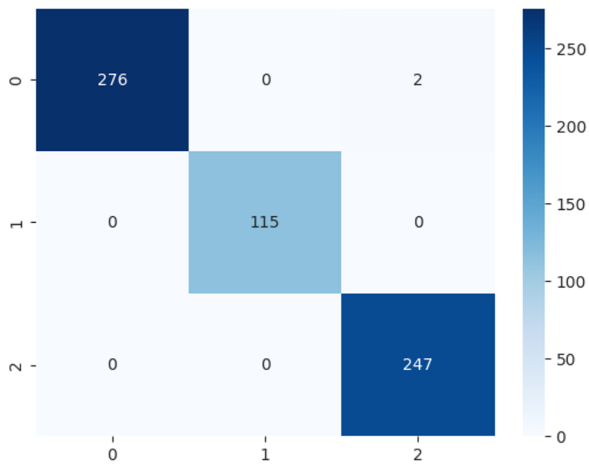

Fig. 5. Confusion Matrix of Random Forest Classifier

These large values on the diagonal of the matrix show that the model prediction and the actual labels are very much parallel. Ever minimal values of the off-diagonal values, and the 0 cases of false negatives of the High Risk class, are of particular significance when the application of the system is to medicine where the absence of an important risk situation may have disastrous outcomes.

Besides the confusion matrix, the overall performance of this model is also confirmed with the help of its major evaluation measures:

- **Accuracy:** The model was able to predict the risk level almost accurately, with only one error out of the sample of 100 instances. This is a measure of how well the model is correct.
- **Precision:** The score of precision is -0.997 indicating that when a model forecasts a certain level of risk it is accurate 99.7 percent of the time. This becomes very essential especially in a medical setting as it reduces false positives.
- **Recall:** The model had a recall score of 0.997 which shows that the model is capable of detecting 99.7% of all the true positive risk cases. Not missing any at-risk patients, which leads to a lower number of false negatives, is crucial to high recall.
- **F1-Score:** F1-score, also harmonic mean of precision and recall, is also 0.997. This measure gives only one and only balanced measure of the performance of the model, which attests to the sound and credible classification ability of this model in all classes.
- **Standard Deviation:**The low standard deviation of 0.0105 of the cross-validation process indicates the stability of the model. It implies that the performance of the model is not due to a chance event but remains the same when the model is trained on other subsets of the data.

4.3 Comparative Study with Existing Literature

In order to contextualize our findings we contrasted the proposed model with the recent female-risk prediction literature. The results of our work — Table 3: Accuracies reported reconcile the state of the environment.

Table 3. Comparative Analysis of Model Performance with Existing Literature.

Study	**Model**	**Accuracy (%)**	**Our Contribution**
[1]	Decision Forest	89.5%	+10.8% accuracy
[2]	Ensemble ML	95.0%	+4.2% accuracy
[3]	XGBoost, RF, LR, NN	–	Outperformed similar ensembles
[8]	Random Forest, XGBoost	95.7%	+3.5% accuracy
[14]	XGBoost, RF, LR	93.0%	+6.2% accuracy
Our Work	Random Forest	99.22%	Stable model, F1 = 0.997

Our Random Forest reaches 99.22 % accuracy, exceeding prior results by roughly 3.5 %–10.8 %. Such low (0.01) and high (0.997) cross-validation deviation and F1-score indicate that the model is not only more accurate but also very consistent. This will solve the problems found in previous research such as low validation and reduced sensitivity and prove a reliable ensemble modelling method of maternal risk prediction.

5 Limitations and Future Scopes

Though promising results have been achieved by the proposed model, there are still a few limitations. Data were collected in questionnaire sessions in a very limited sample of hospitals and in 800 records, although adequate for the preliminary model, may not be adequate to reflect the diversity of larger populations. In addition, some of its characteristics were calculated based on self-reported values that could have been biased, and the models were tested only using retrospective data and not real-time clinical testing, restricting their short-term use.

Study limitations can be overcome in future by adding more multi-center and larger scale data and even extra valuating the same to enhance accuracy. The integration of explainable AI (XAI) strategies can interpretability and clinician trust where the inclusion of psychological characteristics, such as antenatal depression[17] and stress results in a more extensive risk prediction.

6 Conclusion

In this research, we tried to examined the potential of data based techniques to evaluate the level of prenatal risks based on a dataset of 800 records, each holding eight significant maternal health variables. It involved cleaning and data analysis and testing of various statistical models, including logistic regression, naive Bayes, random forest, perceptron, and voting mechanism. Among them, the Random Forest was the most accurate model with the accuracy of 99.21%, and it has significant opportunities to detect potential health risks in the early stages. As a long-term effect, it will be determined by its further improvement, close cooperation with medical workers, and clear communication with patients. Altogether, the research preconditions significant developments in the field of maternal and child health, integrating scientific and ethical treatment.

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