Fetal Health Classification based on CTG using Machine Learning

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Abstract

The UN has estimated that 24 million babies were born in India in 2017 and 35,000 mothers died during or shortly after birth, with MMR at 145 per 100,000 live births, or 12% of parental deaths worldwide. Classification of fetal health is an important aspect of child care and can help prevent negative consequences. Cardiotocography (CTG) is a method often used to monitor fetal health, but its interpretation can be subjective and inaccurate. In recent years, machine learning methodologies and techniques have been proposed as a solution for improvement in the accuracy of CTG-based classification of fetus. In this study, we developed a classifier that automatically predicts fetal health using different learning machines. We used a database of CTG data from the University of California, Irvine's Machine Learning Repository containing 2126 subjects and 21 features, including 1655 healthy subjects, 295 unhealthy subjects and pathologically diseased there are 176 subjects. The proposed model has the potential to improve the accuracy and purpose of CTG-based fetal health classification, leading to better prenatal care and better outcomes for mothers and foetuses. As a comparison, the best model for prediction is random forest with 96% accuracy.

I. INTRODUCTION

The Government of India has signed on to the United Nations (UN) Sustainable Development Goals (SDGs) reaching the maternal mortality rate (MMR) target of less than 70 deaths per 100,000 children born by 2030. This requires reliable measurement of maternal deaths and conditions and an understanding of the root causes of these deaths at the local level. Like many countries with a high maternal mortality rate, India recorded only a few births, deaths and significant events. Parental deaths occur concentrated in rural areas and are the least likely to be recorded in the country. However, India already has a very successful Registration System (SRS) to track births and deaths, including over 1 million national representatives over 50 years.

The UN has estimated that around 24 million babies were born in India in 2017, and about 35,000 mothers died during or shortly after birth, with the MMR of 145 per 100,000 live births. This is 12% of worldwide maternal deaths. According to the World Health Organization (WHO), the female mortality rate in the world fell from 342 in 2000 to 211 in 2017, reducing global maternal deaths from 451,000 to 295,000. About 40% of this decline is due to lower rates of maternal mortality in India.

Pregnancy can be complicated by the need for additional procedures to assess fetal health. These conditions include the mother's medical problems that can affect the fetus, pregnancy-specific problems, and defect or abnormality in birth that can affect the health of the fetus. Maternal medical problems associated with fetal risk include essential hypertension, preeclampsia, kidney and autoimmune diseases, maternal diabetes, and thyroid disease. Other conditions that pose greater risks to the health of the fetus during pregnancy include prolonged pregnancy, reduced fetal growth, vaginal bleeding and elongation of the membrane. These risks include neurodevelopmental issues such as brain malformations, developmental delays, and hearing and vision loss in infants.

Fetal health monitoring is a critical aspect of prenatal care that involves assessing the well-being of the developing fetus during pregnancy. One method that is used method for monitoring the fetal health is cardiotocography (CTG), which records the fetal heart rate and uterine contractions over time. CTG is a non-invasive and widely available technique that can provide important information on fetal health, such as fetal distress or hypoxia, which may cause to adverse birth outcomes if left untreated.

However, the interpretation of CTG can be subjective and prone to errors, which can result in unnecessary interventions or missed cases of fetal distress. The subjective nature of CTG interpretation is due in part to the complex and dynamic nature of the fetal heart rate pattern, which can vary greatly depending on fetal age, activity level, and other factors.

To address the limitations of traditional CTG interpretation, researchers have proposed the use of machine learning techniques for fetal health classification based on CTG. Machine learning is a subset of artificial intelligence that involves training algorithms to recognize patterns in data and make predictions or decisions based on those patterns. Machine learning techniques have the potential to improve the accuracy and objectivity of fetal health classification, which could lead to better outcomes for both mother and fetus.

The goal of this proposed solution is to develop and evaluate a machine learning-based classification model for fetal health based on CTG. We will use a dataset of CTG recordings from a cohort of pregnant women and assess the accuracy and performance of various machine learning algorithms in classifying fetal health. The results of this study could have important implications for improving fetal health monitoring and reducing adverse birth outcomes.

II.LITERATURE SURVEY

Some related works have been studied under this topic. In [1] after performing all the steps needed to get the results from preparation to pre-processing to feature engineering and finally performing the models(SVM, random forest, logistic regression and naive bayes) the authors have concluded that the model which performs the best out of all these is the logistic regression model with 99.5 percent accuracy.

In [2] the classification model developed using XGBoost technique had the highest prediction accuracy for an adverse fetal outcome. Lay health care workers in low and middle income countries can use this model to triage pregnant women in remote areas for early referral and further management.

In [3] a comparative analysis among the built models was executed. According to the comparative analysis, the best model to automatically detect fetal health was the extreme gradient boosting algorithm-based model with an accuracy of 96.7% and an F1-Score of 0.963 in the pathologic class.

In [4] This paper endeavour to perform under-sampling with Cluster Centroids, Condensed Nearest Neighbour, All KNN, Repeated ENN, Edited Nearest Neighbours, Instance Hardness Threshold and Near Miss methods..

III. METHODOLOGY

Various steps are involved in the methodology that are explained below. Figure 1 depicts flow diagram of proposed solution.

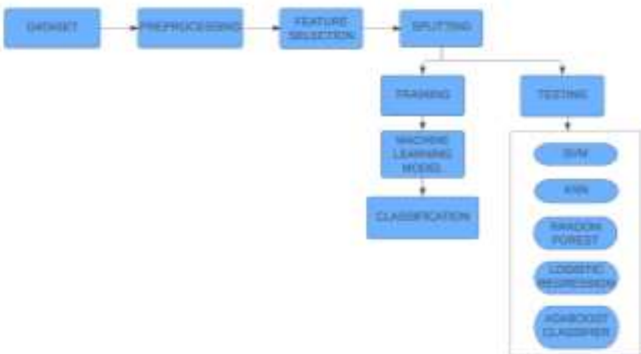

Figure 1: Flow Diagram of Proposed Solution

Data Collection: The dataset used in this study consist of CTG recordings collected from University California Irvine Machine Learning Repository which consist of 2126 instances. These women were in third trimester during the observations.

Data Pre-processing: The CTG recordings underwent pre-processing to remove any artefacts and to extract relevant features for classification. The pre-processing steps included detection of anomaly and rounding it off the upper limit and also check for the null value was carried out. The data was already thoroughly cleaned upon obtaining the dataset, there is very minimal cleaning tasks carried out in this particular project, some outlier detection, but chose to include any existing outliers as they could be important towards the analysis given the size of the dataset and the integrity of how the data was collected.

Feature Selection: To reduce the dimensionality of the dataset and improve the performance of the classification model, feature selection techniques are applied. The feature selection process used here is PCA(Principal Component Analysis) and LDA(Linear Discriminant Analysis).

Splitting: Dataset is being split into training set and testing set. It is in the ratio of 3:1 which means 75% testing data and 25% testing data.

Model Building: Before building any models, including of linear discriminants from LDA application as well as clusters created from applying KMeans Clustering to the dataset as new features. We evaluated the performance of several machine learning algorithms for fetal health classification based on CTG. These algorithms include logistic regression, support vector machines (SVM), decision trees, random forests, and artificial neural networks (ANN).

Model Evaluation: We will evaluate the performance of the machine learning algorithms based on several performance metrics, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC). We will also compare the performance of the machine learning algorithms to the performance of traditional CTG interpretation. The random forest has the best performance with an accuracy of 95%. Figure 2 shows system architecture.

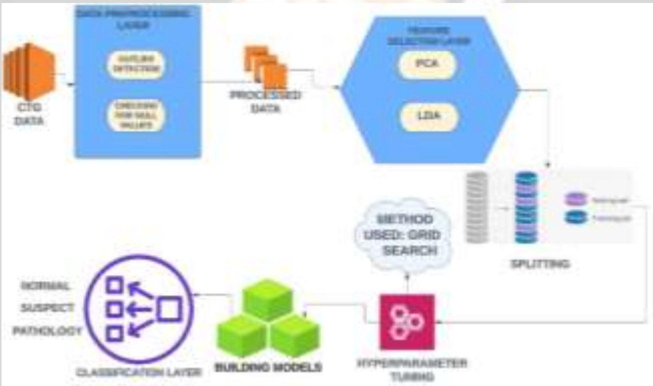

Figure 2: System Architecture of proposed solution

IV. RESULTS

Table 1 shows the accuracy of each machine learning models which is evaluated using different performance metrics.
The estimation of performance is done using below mentioned equations.

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

$$\text{Precision} = \frac{TP}{TP+FP}$$

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

$$\text{F1 – score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision} + \text{Recall}}$$

Precision measures how many of the predicted positive instances are actually positive. Recall measures how many of the actual positive instances are correctly predicted as positive. F1 score is the harmonic mean of precision and recall, and it combines both metrics into a single value. These metrics are for evaluating the performance of a classification model, as they provide a comprehensive assessment of the model's ability to correctly identify positive instances and avoid false positives and false negatives.

Random Forest: Here overall achieved f1 score is 94%. The individual, f1 score for normal is 97%, 79% for suspect and 91% for pathological. Figure 3.1 displays the confusion matrix, the total number of correct predictions are 401 with 24 incorrect.

Logistic Regression: Here overall achieved f1 score is 92%. The individual f1 score for normal is 96%, 71% for suspect and 83% for pathological. Figure 3.2 displays confusion matrix, the total number of correct predictions are 390 with 35 incorrect.

SVM: Here overall achieved f1 score is 92%. The individual f1 score for normal is 95%, 70% for suspect and 89% for pathological. Figure 3.3 displays confusion matrix, the total number of correct predictions are 395 with 37 incorrect.

AdaBoost: Here overall achieved f1 score is 91%. The individual f1 score for normal is 96%, 69% for suspect and 86% for pathological. Figure 3.4 displays confusion matrix, the total number of correct predictions are 376 with 77 incorrect.

Model	Classes	Precision	Recall	F1-score	Support
SVM	Normal	0.94	0.97	0.95	331
	Suspect	0.75	0.65	0.70	59
	Pathological	0.95	0.84	0.89	35
		Accuracy	0.92		425
KNN	Normal	0.91	0.99	0.95	331
	Suspect	0.79	0.44	0.57	59
	Pathological	0.93	0.77	0.84	35
		Accuracy	0.90		425
LgR	Normal	0.94	0.98	0.96	331
	Suspect	0.75	0.68	0.71	59
	Pathological	0.90	0.77	0.83	35
		Accuracy	0.92		425
AdaB	Normal	0.93	0.98	0.96	331
	Suspect	0.85	0.58	0.69	59
	Pathological	0.86	0.86	0.86	35
		Accuracy	0.91		425
RF	Normal	0.95	0.99	0.97	331
	Suspect	0.95	0.68	0.79	59
	Pathological	0.91	0.91	0.91	35
		Accuracy	0.94		425

Table 1: Performance table of various models

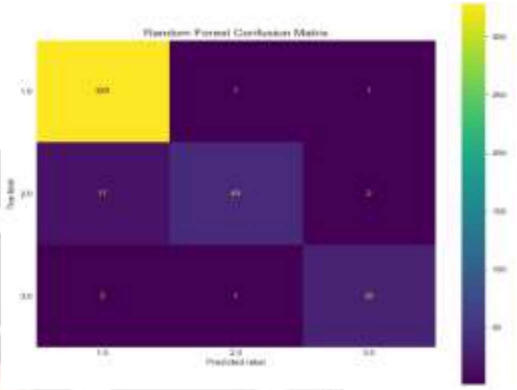

Figure 3.1: Confusion matric of Random Forest

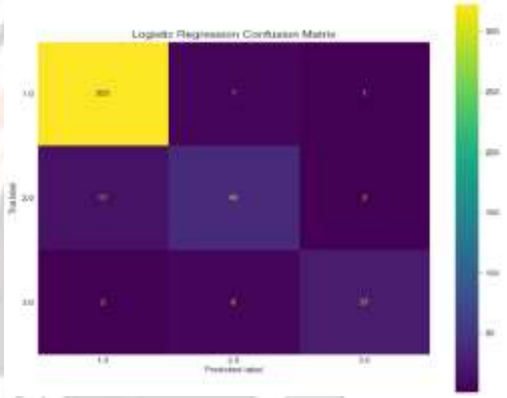

Figure 3.2: Confusion matric of Logistic Regression

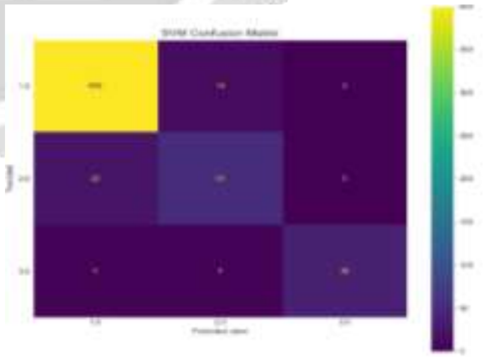

Figure 3.3: Confusion matric of SVM

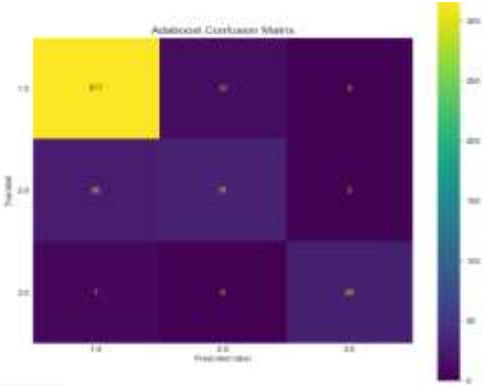

Figure 3.4: Confusion matric of AdaBoost

KNN: Here overall achieved f1 score is 90%. The individual f1 score for normal is 95%, 57% for suspect and 84% for pathological. Figure 3.5 displays confusion matrix, the total number of correct predictions are 383 with 65 incorrect.

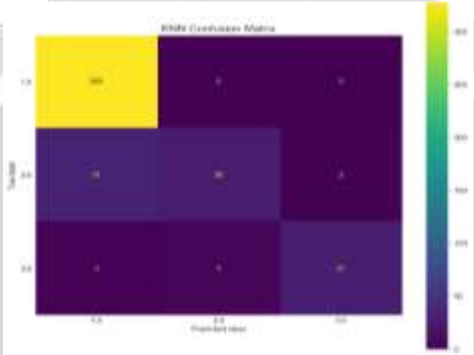

Figure 3.5: Confusion matric of KNN

Below graph in figure 4 shows variation in f1-score from all the models tested for fetal's health. It is clear that random forest records the highest f1 score

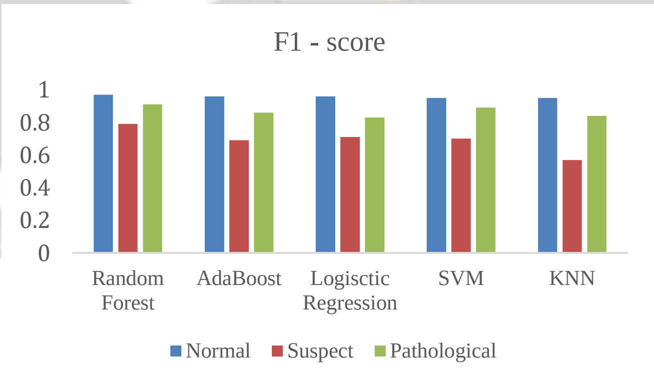

Figure 4: F1-score of models in proposed solution

V. CONCLUSION

This paper is a comparative study of different algorithms that have been used by various methods for the effective prediction of Fetal Health. Among different algorithms used, Random Forest is proven to have highest accuracy. This indicates the potential of machine learning techniques in improving the clinical decision-making process and reducing the risk of adverse outcomes for both the mother and the fetus.

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