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HealthBloom: Machine Learning for Fetal Well-being

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ABSTRACT

Fetal mortality, a significant public health concern in the U.S., impacts over a million pregnancies yearly, with 26,000 occurring post 20 weeks of gestation. Despite advances, the U.S. fetal mortality rate remains unchanged. This project employs machine learning alongside accessible cardiotocograms (CTGs) for more effective fetal health assessment, focusing on indicators like heart rate, movement, and contractions. This proactive approach allows healthcare professionals to intervene early, reducing risks for both mother and child.

The methodology involves gathering diverse CTG recordings and corresponding clinical data. Feature engineering techniques extract key information. Machine learning models will be trained and validated, creating a robust classification system. Evaluation metrics include sensitivity, specificity, and area under the receiver operating characteristic curve.

This research is a pivotal step in transforming prenatal care and substantially lowering fetal and maternal mortality rates. Through the fusion of machine learning and accessible clinical data, the aim is to enhance outcomes for infants and mothers nationwide, underscoring the vital role of technology in addressing critical public health challenges.

Keywords: Fetal mortality, Machine learning, Cardiotocograms (CTGs), Fetal health assessment, Prenatal care, Maternal health, Public health intervention, Classification system.

1.INTRODUCTION

The prenatal health of pregnant women and their fetuses is of paramount concern in modern healthcare. This research endeavors to develop an early diagnostic tool for assessing crucial fetal parameters, including heart rate, accelerations, movements, and uterine contractions, employing a machine learning algorithm on the widely recognized Cardiotocography Data Set. However, one of the principal challenges in this field lies in the scarcity of comprehensive medical data from pregnant women, underscoring the significance of this study. This work conducts rigorous statistical significance testing to evaluate the impact of employing a multi-class neural network and multiclass random forest on the Cardiotocography Data Set. The integration of machine learning algorithms holds immense promise for enhancing complex decision support systems in healthcare. By presenting an effective approach to leveraging data for disease diagnosis, particularly in addressing fetal concerns for pregnant women, this paper contributes significantly to the advancement of prenatal healthcare. The study introduces two distinct machine learning techniques tailored for detecting fetal issues in pregnant women. Notably, the multi-class neural network exhibits superior predictive capabilities, outperforming the multi-class random forest methodology.

2.METHODOLOGY

2.1.Data Set Description

In this proposed study, the dataset sourced is from the UCI, encompassing information on uterine contraction and fetal heart characteristics from 2126 CTG recordings. This dataset has undergone thorough evaluation by skilled obstetricians, resulting in distinct classifications for each entry. Specifically, among these entries, 1655 have been categorized as exhibiting normal fetal characteristics, while 295 were labeled as suspicious, leaving 176 classified as pathological. The distribution of fetuses across these categories is summarized in Table 1, providing a comprehensive overview of the dataset composition.

Table 1. Complete Dataset details

Type	Number of fetuses
Normal	1655
Suspicious	295
Pathological	176
Total	2126

Table 1 encapsulates the specific counts of fetuses falling into the categories of normal, suspicious, and pathological, offering a detailed breakdown of the dataset's composition.

2.2.Data Preprocessing

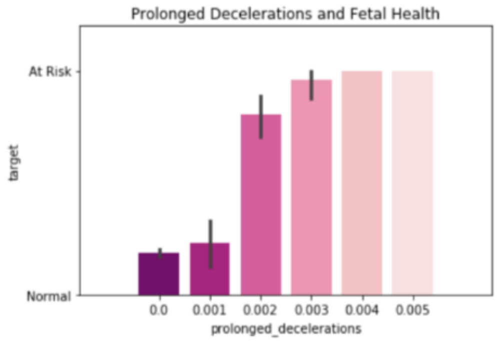
Importing data from reputable sources, followed by rigorous cleaning, processing, and scaling to ready it for model training. Notably, steps were taken to address class imbalance, a pivotal preprocessing measure to prevent bias towards the majority class. Descriptive statistics and visualizations were instrumental in revealing data trends and identifying influential factors for fetal health predictions. The establishment of pipelines, along with grid search functions, played a crucial role in iterating through models and determining optimal hyperparameters. The selection of the best-performing model, based on the recall metric, followed a comprehensive evaluation process to ensure informed recommendations. Additionally, the transformation of the multi-class problem into a binary classification problem was integral in simplifying the analysis for enhanced focus and clarity.

3.Feature Engineering

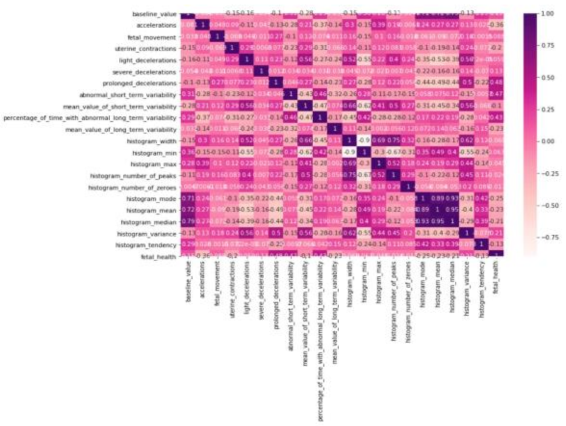
The fetal health classification in the dataset exhibits a notable imbalance, with a predominant occurrence of instances labeled as 1.00, indicating Normal fetal health. The class with the second-highest frequency corresponds to 2.00, denoting Suspect fetal health, while the 3.00 class representing Pathological fetal health records the lowest frequency. To streamline data processing and facilitate a more straightforward binary classification approach, the Suspect and Pathological classes were amalgamated into a singular category termed 'At Risk.' Simultaneously, all instances labeled as 1.00 were retained under the designation of Normal fetal health. This reclassification ensures a clearer focus on distinguishing between 'Normal' and 'At Risk' fetal health states, streamlining the subsequent analysis.

4.Exploratory Data Analysis

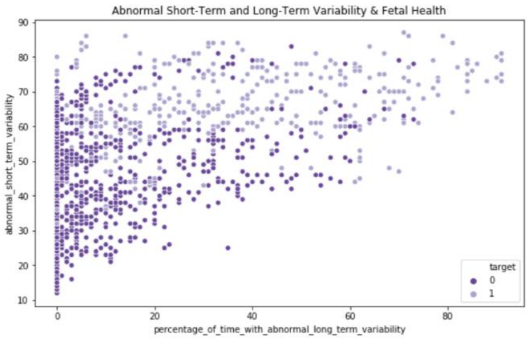
Visible relationship between prolonged fetal heart rate decelerations and fetal health.



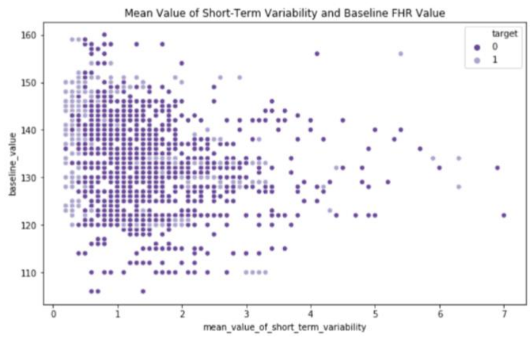
The feature showing the strongest correlation with fetal health is prolonged decelerations, with a correlation of 0.485. There are moderate correlations also observed between fetal health and abnormal short term variability, as well as fetal health and percentage of time with abnormal long term variability.



In the scatter plot, the light purple dots denote the 'At Risk' class, while the dark purple dots signify the 'Normal' class. Notably, points exhibiting elevated percentages of time with short- and long-term variability predominantly belong to the 'At Risk' category, with only a sparse presence of 'Normal' points interspersed within.

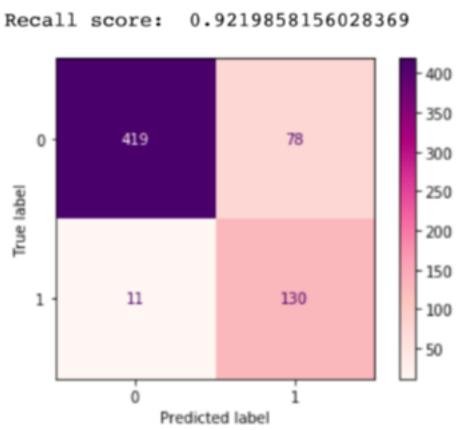


When comparing baseline FHR value and mean value of short term variability, it is not as easy to distinguish a clear relationship between the classes.



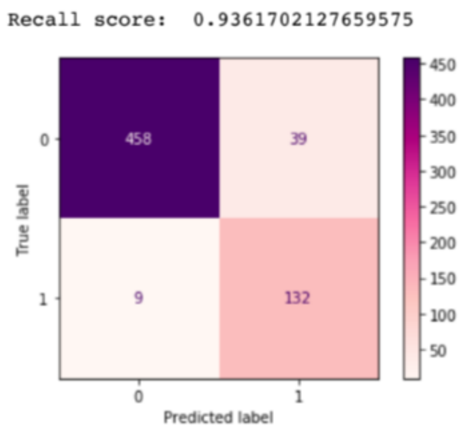
5.Models Used

5.1Logistic Regression



Based on the grid search results, the logistic regression model, even with its optimal parameters, demonstrated commendable performance, albeit not surpassing the effectiveness of the Decision Tree model, which achieved an impressive recall score of 92%

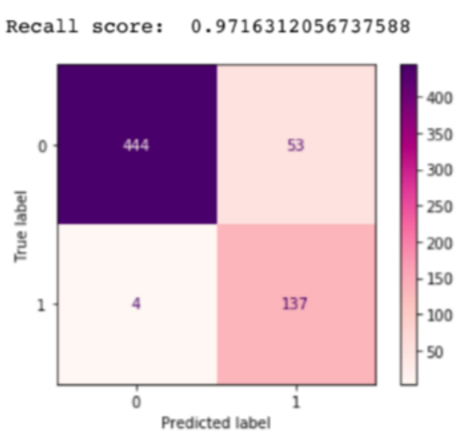
5.2RandomForest



Random Forest model was better, with a recall score of 93.6%.

5.3Extra Trees Classifier

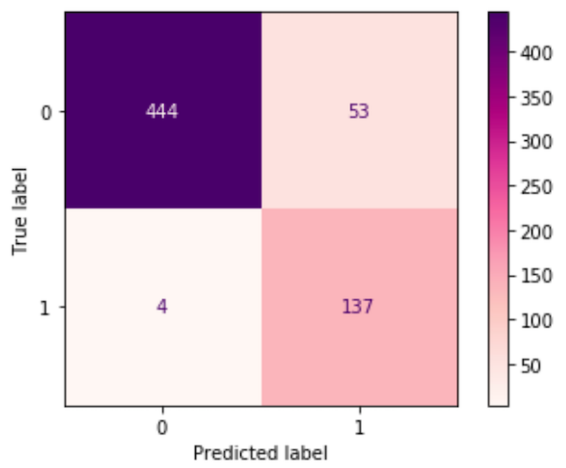
Upon exploring the Extra Trees classifier, its potential suitability for this dataset became apparent. This approach involves employing a multitude of randomized decision trees, also known as 'extra-trees,' on diverse dataset subsets. By leveraging averaging techniques, it enhances predictive accuracy and mitigates overfitting concerns. Although this ensemble method shares similarities with Random Forest, it distinguishes itself by randomly selecting split points rather than computing the optimal ones. This characteristic renders it a more efficient algorithm compared to Random Forest, facilitating faster processing.



This model using the Extra Trees Classifier is the best model, with a recall score of 97.2%.

6. EVALUATION AND RESULTS

The evaluation primarily focused on the recall/sensitivity metric, crucial for minimizing false negatives. Among the seven models assessed, the Extra Trees classifier stood out with an impressive 97% recall rate, signifying its exceptional ability to correctly identify instances of the 'At Risk' class. This model also demonstrated a commendable accuracy of 91%. The precision-recall curve confirmed the model's balanced performance, as evidenced by an F1 score of 83% and an AUC of 94.5%. These metrics underscore the model's effectiveness. Notably, the correlation between prolonged fetal heart rate decelerations and adverse fetal health outcomes was evident. Additionally, the models consistently recognized abnormal short and long-term fetal heart rate variability as critical predictive features.



The Extra Trees classifier excelled in capturing instances of fetal risk, achieving an impressive recall rate of 97%. The model's high accuracy, along with robust performance metrics like F1 score and AUC, reinforced its effectiveness. Furthermore, the observed correlation between prolonged fetal heart rate decelerations and adverse fetal health outcomes, as well as the recognition of abnormal fetal heart rate variability, highlights the model's clinical relevance and potential impact on prenatal care.

7. CONCLUSION

In conclusion, cardiotocogram data provides easily accessible and interpretable insight into fetal health outcomes. ML models are able to predict if a fetus is in distress, using CTG data, with a high level of recall/sensitivity. Between the high predictive power of these models and the expert knowledge of obstetricians, fetal and maternal health could and should be prioritized. By doing this, yearly fetal mortality rates can be effectively reduced.

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