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VITALBEAT AI: PREDICTIVE CLASSIFICATION OF FETAL WELLBEING USING DATA ANALYTICS

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ABSTRACT

Fetal health monitoring is a vital component of prenatal care, as early detection of abnormal fetal conditions helps reduce risks to both mother and child. Cardiotocography (CTG) is commonly used to monitor Fetal Heart Rate (FHR) and uterine contractions; however, manual interpretation of CTG data requires expert knowledge and may lead to subjective judgment, inconsistencies, and delayed clinical decisions. These systems are prone to human error, limited scalability, inconsistent prediction outcomes, and difficulty handling imbalanced class distributions. Therefore, there is a strong need for an intelligent and automated system capable of providing accurate, fast, and reliable fetal health predictions. This research proposes a machine learning-based framework for automated classification of fetal cardiotocogram data into three categories: Normal, Suspect, and Pathological. The system incorporates preprocessing techniques such as missing value handling, categorical encoding, and class imbalance correction using the Synthetic Minority Over-sampling Technique (SMOTE). Multiple machine learning models, including Decision Tree Classifier (DTC), Logistic Regression Classifier (LRC), Gaussian Naive Bayes Classifier (GNBC), and a proposed Light Gradient Boosting Machine (LGBM), are implemented and evaluated to identify optimal performance. A Graphical User Interface (GUI) ensures accessibility and ease of use of research work. The proposed system enhances predictive accuracy, reduces reliance on subjective analysis, and provides consistent classification outcomes. By integrating advanced machine learning models with an interactive application interface, it supports clinical decision-making and contributes to intelligent healthcare solutions for effective antepartum monitoring.

Keywords: Fetal Health Monitoring, Predictive Analytics, Machine Learning, Healthcare Data Analytics, Clinical Decision Support, Health Risk Prediction

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1. INTRODUCTION

The widespread occurrence of health complications during pregnancy represents a significant global health concern, particularly in developing and underdeveloped countries [1, 2]. These complications often result in fetal morbidity and mortality. Fetal death is clinically characterized as the loss of a fetus from human reproduction, regardless of gestational age, and not including medically induced terminations [3], occurring prior to the fetus being fully expelled or removed from the mother's body [4]. This conclusion arises from the lack of essential vital signs, such as breathing, heart function, umbilical cord pulsations, and voluntary muscle movements, as noted right after the fetus is delivered or removed. To improve maternal and fetal health outcomes, particularly in settings with limited resources where accessing quality prenatal care might be challenging, it is crucial to address the underlying causes and mitigating factors linked to fetal death [5].

Fig. 1 displays the fetal healthcare monitoring system process. Here, Fig. 1 (a) contains a digital monitoring interface showing fetal and maternal heart rate data, Fig. 1 (b) contains a pregnant woman using a wireless fetal monitoring system in a clinical setting, Fig. 1(c) contains an abdominal patch with integrated electrodes for electrophysiological monitoring, and Fig. 1(d) contains the components of a portable fetal monitoring kit, including sensors and a display unit.

These are used to determine the compromised fetal status [6] to avoid hypoxic injury and pregnancy-related complications [7]. The CTGs contain imperative information with respect to FHR and uterine contraction based on the fetus's acceleration, deceleration, baseline heart rate, and heart rate variability. These parameters indicate the fetus's hypoxic status and serve as a baseline for medical interventions. The complex CTG patterns are poorly understood, and their visual interpretation by clinicians is challenging [8]. It is now well understood that the linear features in the CTG datasets have a more pronounced effect than the nonlinear ones in the modelling of fetuses [9]. Hence, the feature selection algorithms for CTG patterns allow dimensionality reduction with a slight compromise on the sensitivity and selectivity parameters.

Fig. 1. Fetal healthcare monitoring. (a) a digital monitoring interface, (b) a pregnant woman using a wireless clinical setting, (c) an abdominal patch with integrated electrodes, and (d) components of a portable fetal monitoring kit.

2. LITERATURE SURVEY

Das et al. [10] proposed a machine-learning-based model, which was applied separately to both stages of labor, using standard classifiers such as SVM, random forest (RF), multi-layer perceptron (MLP), and beginning to classify the CTG. The outcome was validated using the model performance measure, the combined performance measure, and the ROC-AUC. Though AUC-ROC was sufficiently high for all the classifiers, the other parameters established a better performance by SVM and RF. Daydulo et al. [11] monitored and evaluated the level of fetal distress. Even though CTG is the most widely used device to monitor and determine the fetus's health, the existence of a high false-positive result from the visual interpretation has a significant contribution to unnecessary surgical delivery or delayed intervention. Park et al. [12] developed a clinically applicable model using a large-scale, nationwide CTG dataset with reliable annotations provided by a board-certified obstetrician. Our study utilized 22,522 deliveries from 14 hospitals, each including CTG recordings of up to 75 min in length. The CTG signals were segmented into

5-minute intervals, resulting in a total of 519,800 person-minutes of analyzed data. Mehbodniya et al. [13] assessed the influence of various factors measured through CTG to predict the health state of the fetus through algorithms like support vector machine, random forest (RF), multi-layer perception, and K-nearest neighbors. In addition to this, the regression analysis and correlation analysis revealed the influence of the attributes on fetal health.

Yin et al. [14] explained the CTG measurements; an algorithm based on Randomized Input Sampling for Explanation of Black-box Models (RISE) was created, called Feature Alteration for Explanation of Black Box Models (FAB). The findings of this novel algorithm were compared to SHAPley Additive explanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME). Haweel et al. [15] examined the growth and safety conditions of the fetus with electronic fetal monitoring (EFM). They used the Newton least mean squares (NLMS) algorithm for training of a polynomial neural network (PNN). They compared the performance of the PNN classifier with functional link artificial neural network (FLANN) classifiers such as a Legendre neural network (LNN) and a Volterra neural network (VNN) and found that the PNN classifier provided better performance.

3. PROPOSED METHODOLOGY

The research work is shown in Fig. 2. introduces a structured methodology for diagnosing fetal health conditions through a combination of traditional machine learning and high-performance gradient boosting. The study is built around a comprehensive pipeline that automates the transition from raw clinical data to real-time diagnostic output. By integrating a secure user management system with a robust analytical engine, the research provides a dual-access framework where medical administrators can manage the model's lifecycle, while healthcare providers can focus on instantaneous fetal risk assessment.

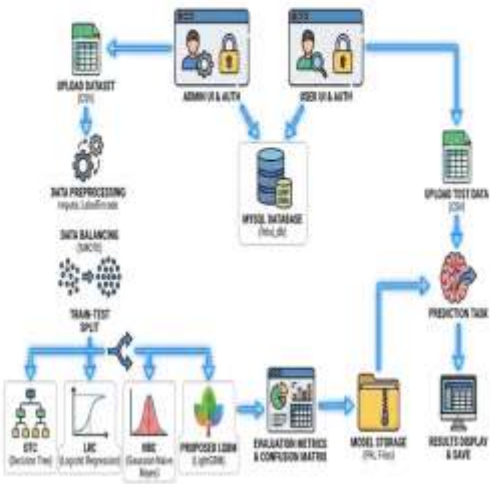


Fig. 2. Proposed system architecture.

LGBM Classifier

The LGBM Classifier as shown in Figure 4.6 operates as an advanced gradient boosting framework that builds a strong predictive model by combining multiple weak learners, typically decision trees, in a sequential learning process. Instead of training all trees independently, it constructs each new tree to correct the errors made by previous ones, gradually improving prediction accuracy. This boosting strategy allows the model to capture complex feature interactions and nonlinear relationships within the data. By using optimized histogram-based learning and efficient leaf-wise tree growth, it achieves high performance while maintaining fast training speed and reduced computational cost.

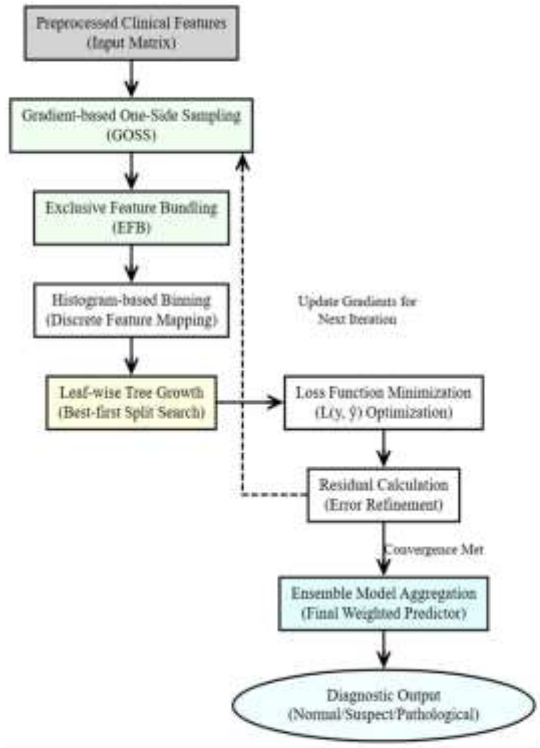


Fig. 3. Internal workflow of LGBM Classifier

Leaf-wise Growth Strategy: Instead of expanding level by level, the algorithm grows the tree by splitting the leaf that results in the largest reduction in error. This selective growth strategy improves accuracy while keeping tree depth efficient. It allows the model to focus computational effort where it is most beneficial.

Histogram-based Splitting: Continuous feature values are grouped into discrete bins to speed up split calculations. This histogram technique reduces memory usage and computational complexity. It enables faster training without significantly affecting predictive performance.

Prediction Update: After a tree is trained, its predictions are added to the existing model output using a learning rate factor. This incremental update gradually refines prediction values. Each iteration brings predictions closer to actual outcomes.

Iterative Boosting Process: Steps of gradient computation, tree building, and prediction updating are repeated multiple times. With each iteration, the model learns from previous mistakes and improves accuracy. This iterative process continues until performance stabilizes or a predefined limit is reached.

4. Results description

Fig 4 illustrates the count plot comparison before and after SMOTE balancing, providing visual insight into class distribution changes. The figure depicts how imbalance in fetal health categories is addressed through synthetic sampling techniques. It represents the analytical validation stage where data balancing effectiveness is evaluated visually. The visualization emphasizes improved representation of minority classes following preprocessing steps. It demonstrates the importance of data distribution analysis in improving classification model outcomes.

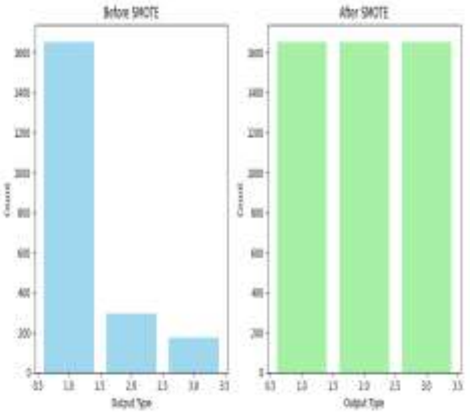
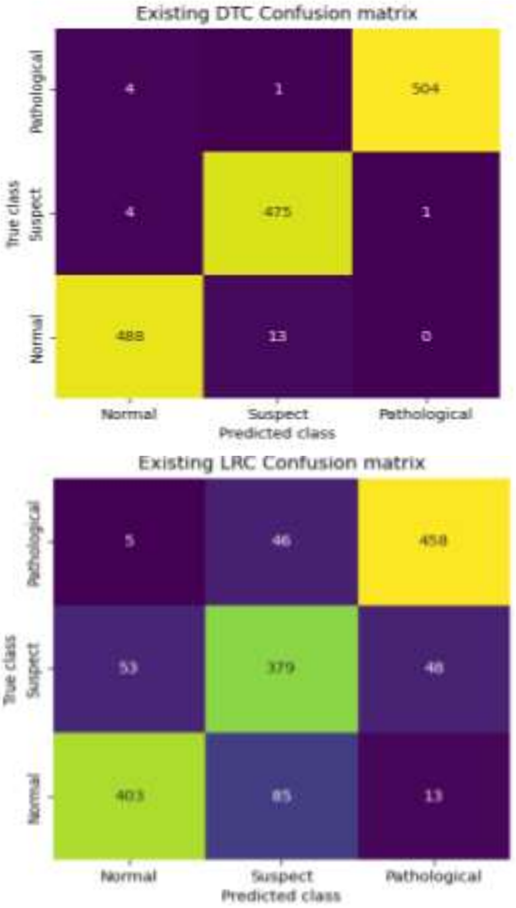
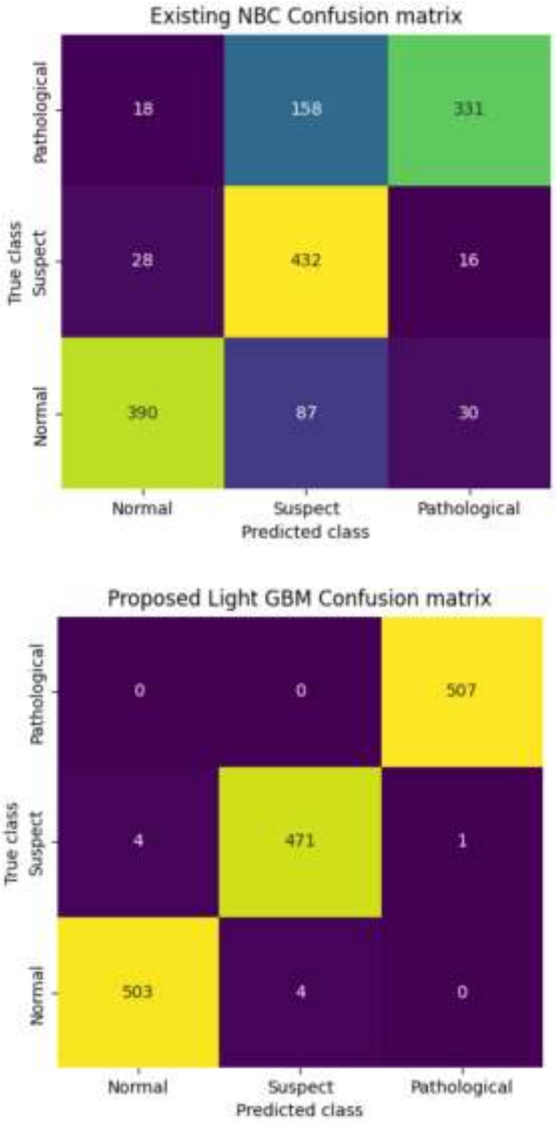


Fig. 4: Count Plot for Before SMOTE and After SMOTE Screen

Fig 5 presents a comparative evaluation of predictive performance across different algorithms. The figure depicts the classification outcomes for the Existing DTC, Existing LRC, Existing GNBC, and Proposed LGBM. It demonstrates how true class labels and predicted class labels are compared to assess classification accuracy and error distribution. The confusion matrices highlight the ability of each model to correctly identify normal, suspect, and pathological fetal health conditions. Visualization provides insight into model strengths, misclassification patterns, and overall effectiveness, supporting analytical comparison and validation of the proposed approach against existing methods.



(a) (b)



(c) (d)

Fig. 5: Confusion Matrices. (a) DTC. (b) LRC. (c) GNBC. (d) LGBM.

Fig 6 depicts the test data prediction screen, illustrating the stage where trained models generate fetal health predictions based on input test samples. The figure represents the application of machine learning models to unseen data for outcome generation. It demonstrates how individual records are processed and classified into predicted health categories. The screen highlights the inference phase where model outputs are produced for evaluation or practical use. It reflects the final stage of the predictive analytics workflow, where trained models deliver actionable results.

Fig 6: Test Data Prediction Screen

The evaluation metrics presented in Table 1 compare the performance of multiple machine learning models applied to fetal health classification. The Existing DTC demonstrates strong performance with an accuracy of approximately 98.52%, precision of 98.52%, recall of 98.50%, and F1-score of 98.50%, indicating effective classification capability. The LTC model shows moderate performance with accuracy around 82.68%, precision 82.73%, recall 82.61%, and F1-score 82.64%, suggesting limitations in capturing complex feature relationships within the dataset. Similarly, the GNBC achieves comparatively lower results, with accuracy near 77.24%, precision 80.05%, recall 77.17%, and F1-score 77.50%, reflecting the constraints of probabilistic assumptions on prediction performance. In contrast, the proposed LGBM achieves the highest performance across all evaluation metrics, with accuracy approximately 99.19%, precision 99.20%, recall 99.17%, and F1-score 99.18%. The improved accuracy and balanced precision-recall values indicate stronger generalization ability and reduced misclassification rates. These results highlight the effectiveness of ensemble boosting techniques in enhancing predictive performance.

Table. 1: Performance Comparison of Various Fetal Health Classification Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Existing DTC	98.5244	98.5200	98.5035	98.5093
Existing LRC	82.6855	82.7313	82.6191	82.6480
Existing GNBC	77.2483	80.0583	77.1761	77.5000
Proposed LGBM	99.1946	99.2031	99.1791	99.1870

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5. Conclusion

In conclusion, the comparative evaluation of fetal health classification models highlights a clear performance hierarchy across all metrics. The Proposed LGBM model delivers the best results, achieving an accuracy of 99.1946%, precision of 99.2031%, recall of 99.1791%, and F1-score of 99.1870%, reflecting its strong generalization capability and balanced prediction performance. The Existing DTC model also performs competitively with 98.5244% accuracy, 98.5200% precision, 98.5035% recall, and 98.5093% F1-score, but it remains marginally inferior to the proposed approach across all evaluation measures. In contrast, the Existing LRC and Existing GNBC models show comparatively weaker performance, indicating limitations in capturing complex fetal health patterns. The LRC achieves 82.6855% accuracy, 82.7313% precision, 82.6191% recall, and 82.6480% F1-score, while the GNBC records the lowest metrics with 77.2483% accuracy, 80.0583% precision, 77.1761% recall, and 77.5000% F1-score. These results collectively confirm that the Proposed LGBM model offers a substantial improvement in classification reliability and robustness, making it more suitable for accurate and dependable fetal health monitoring applications.

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