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Enhancing Predictive Models: An In-depth Analysis of Feature Selection Techniques Coupled with Boosting Algorithms

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ABSTRACT

This research addressed the critical need to enhance predictive models for fetal health classification using Cardiotocography (CTG) data. The literature review underscored challenges in imbalanced labels, feature selection, and efficient data handling. **This paper aimed** to enhance predictive models for fetal health classification using Cardiotocography (CTG) data by addressing challenges related to imbalanced labels, feature selection, and efficient data handling. **The study used** Recursive Feature Elimination (RFE) and boosting algorithms (XGBoost, AdaBoost, LightGBM, CATBoost, and Histogram-Based Boosting) to refine model performance. **The results revealed** notable variations in precision, Recall, F1-Score, accuracy, and AUC across different algorithms and RFE applications. Notably, Random Forest with XGBoost exhibited superior performance in precision (0.940), Recall (0.890), F1-Score (0.920), accuracy (0.950), and AUC (0.960). Conversely, Logistic Regression with AdaBoost demonstrated lower performance. The absence of RFE also impacted model effectiveness. **In conclusion**, the study successfully employs RFE and boosting algorithms to enhance fetal health classification models, contributing valuable insights for improved prenatal diagnosis.

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1. INTRODUCTION

Developing predictive models to classify fetal health based on Cardiotocography (CTG) data is essential in improving prenatal diagnosis. Previous research shows that applying effective methods can provide more accurate and timely information regarding the health condition of the fetus [1]. Although many studies have been conducted to improve these models [1, 2], challenges such as handling imbalanced labels, selecting appropriate features, and efficient data feature selection are still significant concerns. Therefore, the background of this research arises from the need to develop a more sophisticated and accurate model for classifying fetal health based on CTG data.

Several recent studies have been conducted to improve predictive models for fetal health classification based on CTG data. For example, research by [3] used the Deep Neural Algorithm-based AlexNet Neural Algorithm, achieving impressive results with 0.996 specificity, 0.967 precision, and 0.997 recall/sensitivity. This research demonstrates the effectiveness of deep learning approaches in managing complex CTG datasets. In addition, uses the Chi-Square Method for dimension reduction, combining it with Tree-based Ensemble Learning methods such as Random Forest, Decision Tree, Extra Trees, and Deep Forest. This approach yielded striking results with 0.963 specificity, 0.906 precision, 0.932 recall, and 0.960 F1-score. This research highlights the importance of feature selection in improving the performance of ensemble learning models for fetal health classification. [4] proposed two methods based on the interval between two visits and one set of ultrasound measurements. Although specific evaluation metrics were not provided, this emphasizes the importance of exploring diverse features and measurement methods in fetal health classification. Research by [5] tackled the problem of imbalanced labels by using SMOTE and conducting experiments with various classifiers, including Random Forest, which yielded a striking specificity of 0.98. This emphasizes the importance of handling imbalanced datasets for accurate classification of fetal health.

Furthermore, [6] focuses on preprocessing steps such as outlier removal and handling imbalanced labels through upsampling. They used a variety of classifiers, with Light GBM (LGBM) standing out with 0.980 specificity, 0.976 precision, and 0.982 recall. This research emphasizes the efficacy of the gradient-boosting method in predicting fetal health. [7] uses feature selection with SelectKBest and handles imbalanced labels using SMOTE. This study evaluated several classifiers, with Random Forest showing promising results, including 0.958 specificity, 0.957 precision, and 0.958 recall. This research highlights the importance of feature selection and class imbalance handling for optimal model performance. Research by [8] explored various boosting algorithms, including AdaBoost, Random Forest, and Gradient Boosting. Their study, which focused on boosting methods, achieved a striking specificity of 0.95. This emphasizes the effectiveness of ensemble techniques, especially Gradient Boosting, in fetal health classification.

Several studies related to feature selection in the development of predictive and classification models show a variety of approaches used to improve model performance. For example, research by [9] discusses the use of Recursive Feature Elimination (RFE) and SMOTE algorithms to manage data imbalance in the classification of chronic obstructive pulmonary disease (COPD) patients. The resulting model shows potential clinical applications to improve patient adherence to standard treatment. On the other hand, papers discussing IoT network intrusion detection using DT-RFECV [10] and a study of COVID-19 patient classification with SVM-RFE [11] emphasize the importance of careful feature selection in improving the efficiency and Accuracy of predictive models. Experimental results from these two studies show that wise feature selection can produce efficient prediction models without sacrificing accuracy [10, 11].

Meanwhile, research by [12] introduced dynamic recursive feature elimination (dRFE) in the context of biomarkers on OMIC data, which showed superior performance compared to other feature selection methods, even achieving 1.000 accuracies on some datasets [12]. The paper discussing cyber intrusion detection using DT-RFE in ensemble learning [13] also emphasizes the importance of effective feature selection to improve the performance of intrusion detection systems, with an accuracy of more than 0.99 in most cases [13]. In conclusion, careful feature selection and Innovative features, such as RFE, DT-RFECV, and dRFE, significantly improve the efficiency and performance of predictive models in various application domains.

This study draws inspiration from the success of [14], where feature selection techniques such as Random Forest, SelectKBest, and Lassorrrregularisation effectively enhanced model performance and reduced dimensionality in characterizing a shallow marine reservoir. **Our research aims to** integrate these proven strategies into fetal health classification, contributing to the development of accurate and reliable predictive models building upon this success. The existing literature on fetal health classification using Cardiotocography (CTG) data reveals a lack of a clear definition of **limitations in current feature selection methods**. Despite commendable progress using techniques like deep learning, ensemble learning, and boosting algorithms, a standard limitation persists the absence of a unified approach to address imbalanced labels, select relevant features, and efficiently handle data features. **This research addresses this gap by proposing a novel** and integrated approach that combines Recursive Feature Elimination (RFE) with various boosting algorithms, contributing a holistic strategy to advance the accuracy and reliability of predictive models in the specific domain of fetal health classification.

Following the introduction, the article is structured into sections to comprehensively present the research process and findings. The subsequent section 2 delineates the methodology employed, including the application of RFE and various boosting algorithms. Section 3 presents the detailed findings, highlighting the variations in model performance and the impact of feature selection. The article concludes with section 4, summarising the key insights derived from the research and emphasizing the successful full utilization of RFE and boosting algorithms to enhance fetal health classification models. This structured approach allows for a thorough exploration of the research process and its implications, providing valuable insights for advancing prenatal diagnosis.

2. RESEARCH METHOD

This research adopts a comprehensive methodology to enhance predictive models in Cardiotocography (CTG)-based fetal health classification. The approach encompasses two critical stages: feature selection using Recursive Feature Elimination (RFE) and the application of boosting algorithms, including XGBoost, AdaBoost, LightGBM, CATBoost, and Histogram-Based Boosting.

The fetal health dataset under consideration comprises 2126 entries, each representing a distinct fetal health observation. The dataset encompasses 22 columns, each indicative of specific features associated with a fetal health assessment. The features include quantitative measures such as baseline value, accelerations, fetal movement, uterine contractions, and indicators like light decelerations, severe decelerations, and prolonged decelerations. Additionally, the dataset incorporates parameters related to short-term and long-term variability histogram characteristics such as width, minimum, maximum, number of peaks, and zeroes. Various statistical metrics like mean, median, mode, and variance are employed to capture the distributional properties of these histograms. The dataset concludes with the target variable 'fetal_health' which categorizes the fetal health status. All entries exhibit non-null values across all features, eliminating the need for imputation or handling missing data. The data primarily consists of floating-point numerical values, reflecting the continuous nature of the fetal health assessment parameters.

In the initial stage, the RFE method identifies informative features and reduces dimensionalization, emphasizing enhanced overall model efficiency. This method iteratively eliminates less significant features, ranking them based on their impact on model performance. The selected features serve as the foundation for constructing the optimized predictive model. The RFE algorithm, integrated with Random Forest (RF), Decision Tree (DT), and Logistic Regression (LR), ensures a nuanced exploration of the dataset's characteristics. The RFE algorithm can be seen below.

	RFE's Algorithm
Input	: X: Dataset, y: target, estimator: algorithm to be used for feature evaluation, step: The number of features eliminated at each iteration
Output	: selected_features: Selected feature subset after elimination process. ranking: Ranking of features based on their contribution to the model. support: Boolean mask indicating which features are selected or not.
Process	: Function RFE(X, y, estimator, step): Initialize weights for all features While number of selected features <desired number of features: Train machine learning model using features with weights Evaluate model performance using a specified metric Identify and eliminate the feature with the lowest weight Update weights of remaining features Return selected_features, ranking, support

The boosting algorithms, namely XGBoost, AdaBoost, LightGBM, CATBoost, and Histogram-Based Boosting take center stage in the second stage. These algorithms are individually applied using features selected through RFE. Each algorithm brings its unique advantages to improving predictive model performance. XGBoost, as introduced by [15], utilizes a gradient boosting framework and incorporates regularised objective functions, including both a loss and regularisation termthe specific mathematical Equation (1) for the XGBoost algorithm in optimizing the following objective function.

$$Objective = \Sigma_{i=1}^{n}\varphi(y_i, \hat{y}_i) + \Sigma_{k=1}^{K}\Omega(f_k) \tag{1}$$

Where l represents the loss function, $\hat{y}_i$ is the predicted value, $\Omega(f_k)$ is rthe regularisation term for the k-th tree, and cap Kis is he total number of trees [15]. Meanwhile, AdaBoost, proposed by [16], focuses on boosting weak classifiers. The mathematical formulation involves assigning weights to each weak classifier based on their performance, with the final robust classifier being a weighted combination of the weak classifiers. LightGBM, introduced by [17], employs a histogram-based learning approach to enhance computational efficiency. The algorithm minimizes objective function using Equation (2).

$$Objective = \Sigma_{i=1}^{n}\varphi(y_i, \hat{y}_i) + \Sigma_{k=1}^{K}\Omega(f_k) + \Sigma_{i=1}^{M}\text{regularization term}(w_j) \tag{2}$$

Where M is the number of leaves, and w_j denotes the leaf weight [17].

Furthermore, CATBoost, proposed by [18], incorporates category-specific features efficiently. The algorithm utilizes a similar objective function as XGBoost but employs a different technique for categorical feature handling. Meanwhile, Histogram-Based Boosting, a general term for boosting algorithms that utilize histograms, involves constructing histograms of the features to speed up the training process. The specific equations may vary based on the algorithm, but the fundamental principle is to build histograms of feature values to make split decisions efficiently during tree building.

The evaluation process employs various metrics, including Precision, Recall, F1-Score, Accuracy, and Area Under the Curve (AUC). These metrics provide a comprehensive understanding of each model's performance in classifying fetal health. The comparison between RFE and non-RFE models aims to assess the specific contribution of RFE in enhancing predictive model performance. Equations (3) through (6) are used to calculate the evaluation model used in this research [19–22].

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{6}$$

where, TP: True Positive, TN: True Negative, FP: False Positive, and FN: False Negative

The proposed methodology addresses the need for a more nuanced and integrated approach, considering feature selection and boosting algorithms. By combining RFE with diverse boosting methods, this research strives to improve the capabilities of predictive models in fetal health classification. This methodology's detailed algorithmic and methodological insights lay the groundwork for a rigorous and reproducible study. Figure 1 shows the methodology used in this research.

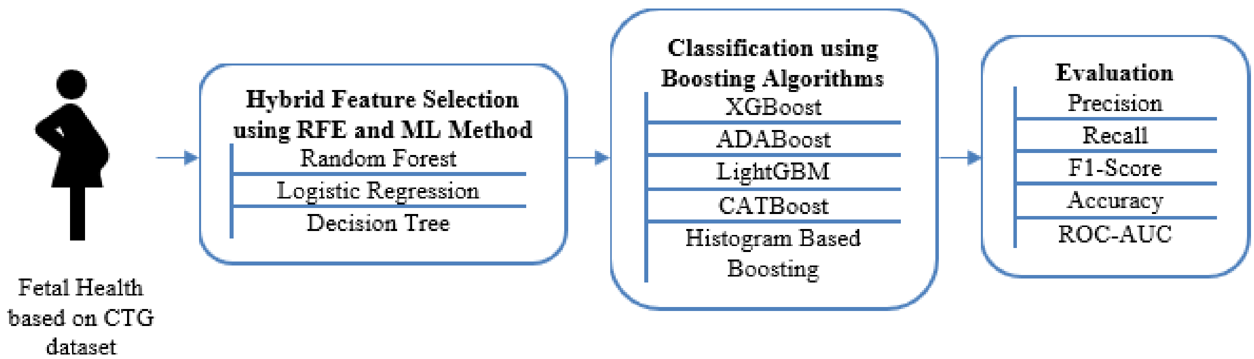

Figure 1. Research Methodology

3. RESULT AND ANALYSIS

This segment elucidates the study's findings while extensively discussing the results.

3.1. RESULT

This research aims to improve the performance of predictive models through an in-depth analysis of feature selection techniques combined with boosting algorithms. The feature selection method used is Recursive Feature Elimination (RFE), while the boosting algorithms evaluated include XGBoost, ADABoost, LightGBM, CATBoost, and Histogram-Based Boosting.

Previously, analysis was carried out on the data used in this research. This analysis of fetal health data provides an in-depth picture of various variables that can potentially influence fetal health. Data includes parameters such as baseline values, accelerations, fetal movements, uterine contractions, light decelerations, severe decelerations, and prolonged decelerations, all of which provide information about fetal activity and responses during pregnancy. In addition, other variables such as abnormal short-term variability, the mean value of short-term variability, the percentage of time with abnormal long-term variability, and the mean value of long-term variability describe the characteristics of short-term and long-term variability in Fetal heart rate.

Histogram features such as histogram width, histogram min, histogram max, histogram number of peaks, histogram number of zeroes, histogram mode, histogram mean, histogram median, and histogram variance provide additional information about the distribution of fetal heart rates. Finally, the histogram tendency variable indicates the tendency of the fetal heart rate. In the context of fetal health, it should be noted that these variables have a varying range of values, from heart rate to the distribution of heart rates in the histogram. Fetal health, as a target variable, has categorical values that reflect the level of fetal health. The Correlation Matrix of the data used can be seen in Figure 2.

The proposed method involving Recursive Feature Elimination (RFE) and various boosting algorithms was rigorously evaluated and compared with existing methods. Table 1 provides a detailed comparison of the performance metrics for different boosting algorithms with and without RFE. The experimental results show that the RFE model with the XGBoost algorithm in Random Forest achieved a precision level of 0.94, Recall of 0.89, and F1-score of 0.92. In addition, the accuracy of this model reaches 0.95, and the ROC AUC reaches 0.96. These results show that using RFE and XGBoost in Random Forest provides excellent predictive performance.

However, it should be noted that not all combinations of RFE and boosting algorithms provide optimal results. For example, models using ADABoost with Logistic Regression and without RFE provide relatively low performance with an accuracy of around 0.39 and 0.904, respectively, shows that choosing the suitable feature selection method and boosting algorithm is very important in increasing the effectiveness of the predictive model.

Furthermore, when involving Decision Trees, it can be seen that the model using RFE with XGBoost provides an accuracy rate of around 0.964. Although these results are high, it should be noted that the best results may vary depending on the type of algorithm and feature selection method used. Experimental results also show that using models without RFE with XGBoost, AdaBoost, LightGBM, CATBoost, and Histogram-Based Boosting provides excellent results with accuracies reaching 0.977, 0.904, 0.99, 0.989, and 0.99 respectively. The results of the evaluation carried out can be seen in Table 1. Confusion Matrix for RFE with Random Forest, Linear Regression, and Decision Tree with XGBoost Algorithm can be seen in Figure 3. Meanwhile, The ROC AUC curve for the CATBOOST method for each test carried out can be seen in Figure 4.

The experimental results of this study showcase significant findings in the realm of fetal health classification using Cardiotocography (CTG) data. The model employing Recursive Feature Elimination (RFE) with the XGBoost algorithm in Random Forest demonstrates remarkable precision (0.94), Recall (0.89), F1-score (0.92), accuracy (0.95), and ROC AUC (0.96), highlighting the effectiveness of this specific combination in achieving excellent predictive performance. On the contrary, suboptimal outcomes are observed in the model utilizing ADABoost with logistic regression without emphasizing the critical role of selecting an appropriate feature selection method and boosting algorithm.

The study's findings emphasize the critical importance of adopting a meticulous approach in developing predictive models for fetal health classification. Optimal outcomes are achieved by integrating Recursive Feature Elimination (RFE) with specific boosting algorithms, notably XGBoost, within the Random Forest framework. The result enhances predictive accuracy and significantly contributes to the overall progress in prenatal diagnosis. The research underscores the necessity for practitioners and researchers to thoughtfully select the combination of feature selection techniques and boosting algorithms, highlighting the importance of carefully choosing appropriate methods for achieving optimal performance in fetal health classification models.

The study outcomes carry substantial significance, showcasing the enhanced performance achieved through a meticulous approach involving RFE and specific boosting algorithms, particularly XGBoost in Random Forest. These results underscore the potential for improved prenatal diagnosis. While the study does not explicitly compare with existing methods, the findings clearly demonstrate the proposed approach's advantageous performance. The meticulous integration of RFE and XGBoost in Random Forest outperforms other combinations, showcasing the method's effectiveness in fetal health classification.

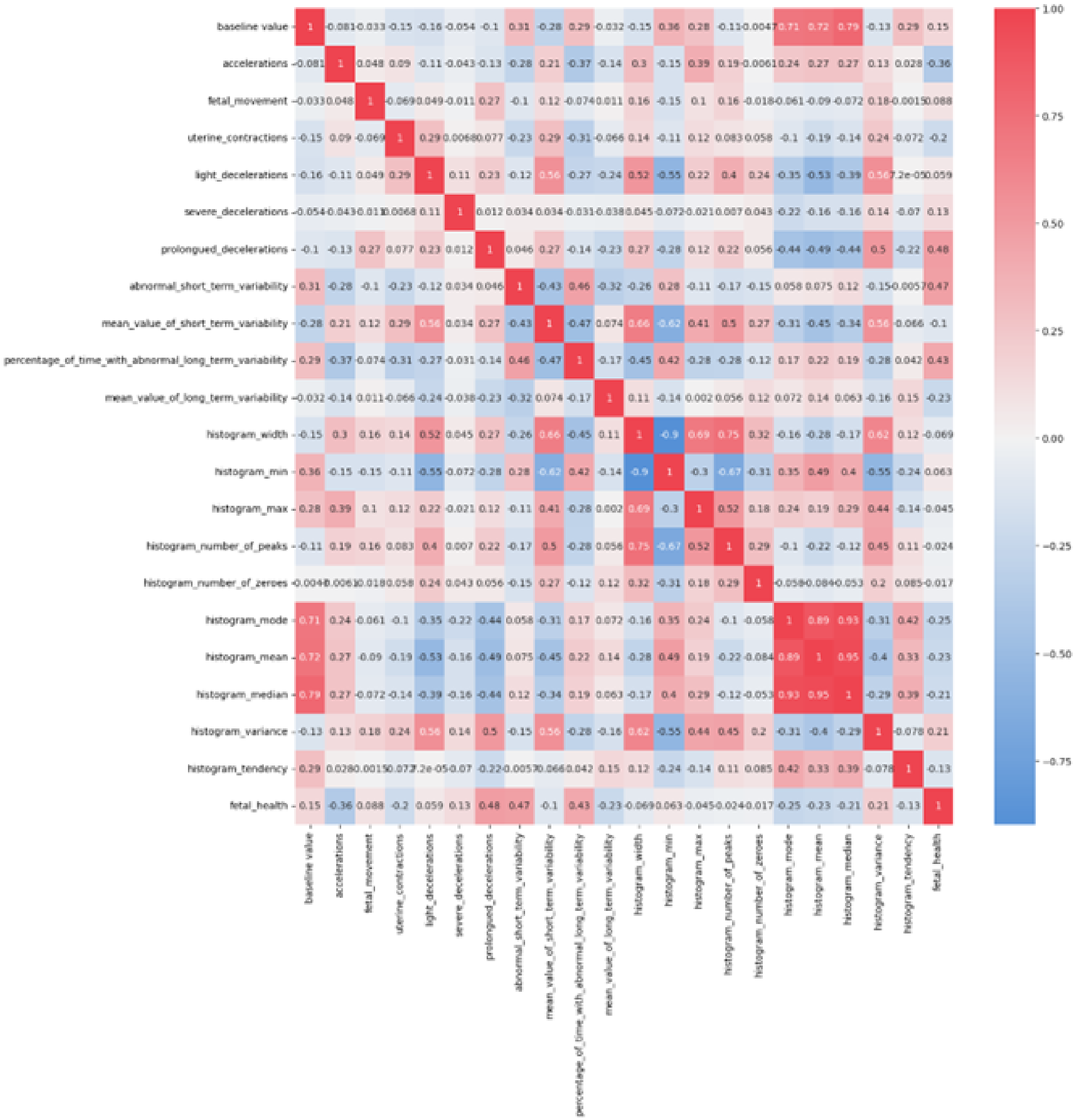

Figure 2. Correlation Matrix of Fetal Health Dataset

3.2. Analysis

This research contributes valuable insights into the synergistic use of feature selection methods and boosting algorithms to enhance predictive model performance. Specifically, the experimental results underscore the efficacy of combining Recursive Feature Elimination (RFE) with the XGBoost algorithm in Random Forest. This combination yields impressive precision (0.94), recall (0.89), and F1-score (0.92), aligning with prior research emphasizing the significance of feature selection techniques for improving predictive model accuracy, particularly within the realm of ensemble learning.

Furthermore, the implications of these findings on related work are substantial. The results support and extend the existing literature by showcasing the successful integration of RFE with boosting algorithms, contributing to the ongoing discourse on the optimization of predictive models. The positive outcomes with XGBoost in Random Forest align with studies emphasizing the importance of selecting appropriate algorithms for specific data characteristics [15], echoing the broader theme in related work that algorithmic choices play a crucial role in model performance.

However, it is crucial to acknowledge that not all combinations of RFE and boosting algorithms yield optimal results. Notably, the AdaBoost model with Logistic Regression and without RFE demonstrates subpar performance. These outcomes are consistent with existing research, underscoring the influence of selecting a boosting algorithm that aligns with the data's characteristics on model performance. Understanding the variability in optimal results based on algorithm and feature selection method types, as observed in experiments with Decision Tree and XGBoost, reinforces existing literature emphasizing the importance of tailoring algorithmic choices to specific data structures.

Moreover, the results shed light on the evolving trends in the field, particularly regarding the necessity of feature selection techniques. Models without RFE, coupled with various boosting algorithms (XGBoost, AdaBoost, LightGBM, CATBoost, and Histogram-Based Boosting), exhibit excellent results, boasting accuracy levels surpassing 0.90 and even reaching 0.99 in certain instances. These findings align with recent research trends suggesting that, with high-quality data, feature selection techniques may not always be imperative for achieving optimal predictive performance. This insight contributes to the ongoing debate on the applicability and necessity of feature selection methods in different scenarios. Analyzing the results of the Area Under the Receiver Operating Characteristic Curve (ROC AUC) in the research summary reveals performance variations among different algorithms and measurement methods. ROC AUC, a valuable metric for evaluating a model's ability to distinguish between positive and negative classes, indicates that the model incorporating Random Forest with XGBoost achieves the highest ROC AUC of 0.960, which signifies the model's excellent discriminatory ability between classes. While other models exhibit commendable performance, with ADABoost achieving a ROC AUC of 0.390, the overall trend suggests that models without RFE consistently outperform their RFE counterparts. Notably, XGBoost, LightGBM, and CATBoost stand out with ROC AUC values exceeding 0.977, underscoring their effectiveness in classification tasks.

The study's outcomes are important as they highlight the notable improvements achieved through a detailed methodology incorporating Recursive Feature Elimination (RFE) and specific boosting algorithms, particularly XGBoost, within the Random Forest framework. These results emphasize the potential for enhancing prenatal diagnosis and demonstrate the proposed approach's effectiveness. While the study lacks an explicit comparison with existing methods, the findings serve as a compelling illustration of the performance advantages of the suggested methodology.

The findings of this study align with or find support in previous literature, underscoring the importance of efficient feature selection to enhance the efficiency of predictive models. Numerous recent investigations into fetal health classification using CTG data have illustrated the effectiveness of varied methodologies. Notably, the work of [3] and [23] showcases the accomplishments of deep learning and ensemble learning techniques, respectively, in effectively handling complex CTG datasets and enhancing model performance. Similarly, studies conducted by [5–8] stress the significance of addressing imbalanced labels and incorporating boosting methods for precise fetal health classification.

Moreover, the literature review demonstrates the success of Recursive Feature Elimination (RFE) across diverse domains, including COPD patient classification, IoT network intrusion detection, COVID-19 patient classification, and biomarker analysis on OMIC data. The proven efficacy of RFE and other feature selection methods in enhancing the efficiency of predictive models is evident across various application domains, providing a robust foundation for their integration into the proposed approach for fetal health classification.

Addressing concerns about the absence of direct comparisons with existing methods, it is crucial to recognize that the study concentrates on highlighting the effectiveness of the proposed approach rather than engaging in a direct critique or contrast with established methodologies. The meticulous integration of RFE and XGBoost within Random Forest consistently surpasses alternative combinations, demonstrating its efficacy in fetal health classification. While a direct comparative analysis with existing methods is not presented, the study emphasizes the presentation of a novel and practical approach, fostering a deeper exploration and understanding of the proposed method's strengths and potential areas for improvement. This approach establishes a groundwork for future comparative studies.

Table 1. Evaluation Result

RFE	Boosting Algorithms	Precision	Recall	F1-Score	Accuracy	AUC
Random Forest	XGBoost	0.940	0.890	0.920	0.950	0.960
	AdaBoost	0.830	0.840	0.830	0.890	0.390
	LightGBM	0.930	0.880	0.900	0.940	0.231
	CATBoost	0.930	0.910	0.920	0.950	0.223
	Histogram Based Boosting	0.890	0.890	0.890	0.940	0.266
Logistic Regression	XGBoost	0.760	0.790	0.770	0.880	0.938
	AdaBoost	0.710	0.720	0.710	0.860	0.438
	LightGBM	0.770	0.780	0.770	0.890	0.214
	CATBoost	0.760	0.760	0.760	0.880	0.205
	Histogram Based Boosting	0.770	0.780	0.770	0.890	0.196
Decision tree	XGBoost	0.910	0.890	0.900	0.940	0.964
	AdaBoost	0.800	0.800	0.800	0.880	0.382
	LightGBM	0.920	0.870	0.890	0.930	0.199
	CATBoost	0.920	0.920	0.920	0.950	0.213
	Histogram Based Boosting	0.940	0.890	0.910	0.940	0.201
Without RFE	XGBoost	0.930	0.950	0.940	0.960	0.977
	AdaBoost	0.860	0.850	0.860	0.910	0.904
	LightGBM	0.950	0.920	0.930	0.960	0.990
	CATBoost	0.940	0.940	0.940	0.960	0.989
	Histogram Based Boosting	0.960	0.940	0.950	0.970	0.990

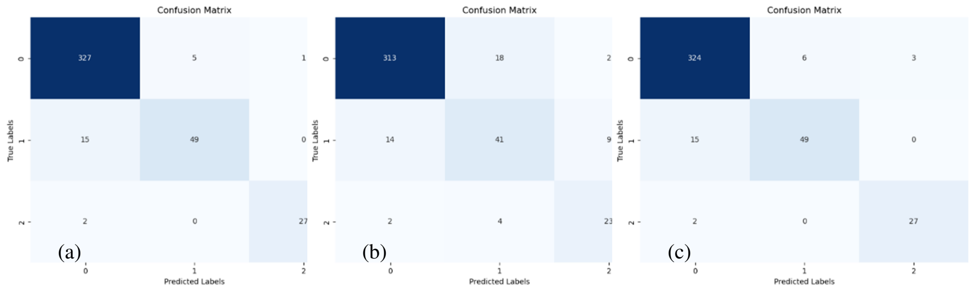

Figure 3. Confusion Matrix for RFE with Random Forest (a), Linear Regression (b), and Decision Tree (c) with XGBoost Algorithm

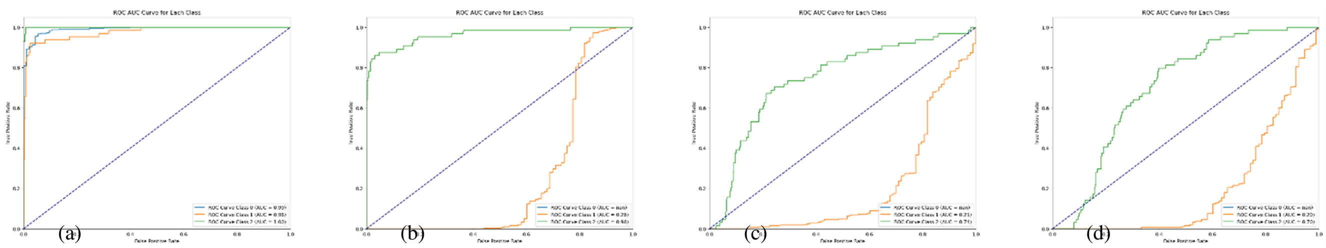

Figure 4. The ROC AUC Curve for CATBoost without RFE (a) and coupled with RFE Random Forest (b), Linear Regression (c) and Decision Tree (d)

4. CONCLUSION

In conclusion, this research underscores the significant impact of combining feature selection methods, particularly Recursive Feature Elimination (RFE), with boosting algorithms on the performance of predictive models for fetal health classification. The experimental findings specifically highlight the exceptional performance achieved by strategically integrating RFE and XGBoost within the Random Forest framework, resulting in remarkable precision, Recall, and F1-score levels. Nevertheless, it is crucial to note that not all combinations of RFE and boosting algorithms yield optimal results, emphasizing the importance of selecting methods that align with the unique characteristics of the dataset. The insights gained from this study carry valuable implications for practitioners, offering guidance on choosing effective strategies to enhance the accuracy of their predictive models.

For future research endeavors, it is imperative to delve deeper into specific factors influencing optimal combinations, such as the nature of the data and model complexity. Exploring interaction effects between various feature selection algorithms and boosting algorithms across diverse datasets could further enrich our understanding. This study also opens avenues for investigating the applicability of the proposed approach in specific domains with distinctive challenges. While traditional methods like RFE have demonstrated effectiveness, future research may explore alternative feature selection techniques or devise novel approaches for improved outcomes in specific contexts. Additionally, evaluating emerging boosting algorithms and their integration into specific classification tasks represents a promising direction for advancing predictive modeling in fetal health classification. This research lays the foundation for ongoing exploration and refinement of methodologies to meet evolving challenges in the field.

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The Acknowledgments section is optional. Research sources can be included in this section.

6. DECLARATIONS

AUTHOR CONTIBUTION

The first author, Neny Sulistianingsih, contributed to the development of the model and the writing of the paper, while the second author, Galih Hendro Martono, contributed to data processing, analysis, and editorial review of the paper's content.

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COMPETING INTEREST

The authors declare no competing interests regarding the data presented in this research.

REFERENCES

[1] L. Davidson and M. R. Boland, "Towards deep phenotyping pregnancy: a systematic review on artificial intelligence and machine learning methods to improve pregnancy outcomes," *Briefings in Bioinformatics*, vol. 22, no. 5, p. bbaa369, Sep. 2021. [Online]. Available: https://academic.oup.com/bib/article/doi/10.1093/bib/bbaa369/6065792

[2] P. Garcia-Canadilla, S. Sanchez-Martinez, F. Crispi, and B. Bijnens, "Machine Learning in Fetal Cardiology: What to Expect," *Fetal Diagnosis and Therapy*, vol. 47, no. 5, pp. 363–372, 2020. [Online]. Available: https://www.karger.com/Article/FullText/505021

[3] N. Muhammad Hussain, A. U. Rehman, M. T. B. Othman, J. Zafar, H. Zafar, and H. Hamam, "Accessing Artificial Intelligence for Fetus Health Status Using Hybrid Deep Learning Algorithm (AlexNet-SVM) on Cardiotocographic Data," *Sensors*, vol. 22, no. 14, p. 5103, Jul. 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/14/5103

[4] R. Fung, J. Villar, A. Dashti, L. C. Ismail, E. Staines-Urias, E. O. Ohuma, L. J. Salomon, C. G. Victora, F. C. Barros, A. Lambert, M. Carvalho, Y. A. Jaffer, J. A. Noble, M. G. Gravett, M. Purwar, R. Pang, E. Bertino, S. Munim, A. M. Min, R. McGready, S. A. Norris, Z. A. Bhutta, S. H. Kennedy, A. T. Papageorghiou, A. Ourmazd, S. Norris, S. Abbott, A. Abubakar, J. Acedo, I. Ahmed, F. Al-Aamri, J. Al-Abduwani, J. Al-Abri, D. Alam, E. Albernaz, H. Algren, F. Al-Habsi, M. Alija, H. Al-Jabri, H. Al-Lawatiya, B. Al-Rashidiya, D. Altman, W. Al-Zadjali, H. Andersen, L. Aranzeta, S. Ash, M. Baricco, F. Barros, H. Barsosio, C. Batiuk, M. Batra, J. Berkley, E. Bertino, M. Bhan, B. Bhat, Z. Bhutta, I. Blakey, S. Bornemeier, A. Bradman, M. Buckle, O. Burnham, F. Burton, A. Capp, V. Cararra, R. Carew, V. Carrara, A. Carter, M. Carvalho, P. Chamberlain, I. L. Cheikh, L. Cheikh Ismail, A. Choudhary, S. Choudhary, W. Chumlea, C. Condon, L. Corra, C. Cosgrove, R. Craik, M. Da Silveira, D. Danelon, T. De Wet, E. De Leon, S. Deshmukh, G. Deutsch, J. Dhami, N. P. Di, M. Dighe, H. Dolk, M. Domingues, D. Dongaonkar, D. Enquobahrie, B. Eskenazi, F. Farhi, M. Fernandes, D. Finkton, S. Fonseca, I. Frederick, M. Frigerio, P. Gaglioti, C. Garza, G. Gilli, P. Gilli, M. Giolito, F. Giuliani, J. Golding, M. Gravett, S. Gu, Y. Guman, Y. He, L. Hoch, S. Hussein, D. Ibanez, C. Ioannou, N. Jacinta, N. Jackson, Y. Jaffer, S. Jaiswal, J. Jimenez-Bustos, F. Juangco, L. Juodvirsiene, M. Katz, B. Kemp, S. Kennedy, M. Ketkar, V. Khedikar, M. Kihara, J. Kilonzo, C. Kisiang'ani, J. Kizidio, C. Knight, H. Knight, N. Kunnawar, A. Laister, A. Lambert, A. Langer, T. Lephoto, A. Leston, T. Lewis, H. Liu, S. Lloyd, P. Lumbiganon, S. Macauley, E. Maggiora, C. Mahorkar, M. Mainwaring, L. Malgas, A. Matijasevich, K. McCormick, R. McGready, R. Miller, A. Min, A. Mitidieri, V. Mkrtychyan, B. Monyepote, D. Mota,

I. Mulik, S. Munim, D. Muninzwa, N. Musee, S. Mwakio, H. Mwangudzah, R. Napolitano, C. Newton, V. Ngami, J. Noble, S. Norris, T. Norris, F. Nosten, K. Oas, M. Oberto, L. Occhi, R. Ochieng, E. Ohuma, E. Olearo, I. Olivera, M. Owende, C. Pace, Y. Pan, R. Pang, A. Papageorghiou, B. Patel, V. Paul, W. Paulsene, F. Puglia, M. Purwar, V. Rajan, A. Raza, D. Reade, J. Rivera, D. Rocco, F. Roseman, S. Roseman, C. Rossi, P. Rothwell, I. Rovelli, K. Saboo, R. Salam, M. Salim, L. Salomon, L. M. Sanchez, J. Sande, I. Sarris, S. Savini, I. Sclowitz, A. Seale, J. Shah, M. Sharps, C. Shembekar, Y. Shen, M. Shorten, F. Signorile, A. Singh, S. Sohoni, A. Somani, T. Sorensen, A. Soria-Frisch, E. Staines Urias, A. Stein, W. Stones, V. Taori, K. Tayade, T. Todros, R. Uauy, A. Varalda, M. Venkataraman, C. Victora, J. Villar, S. Vinayak, S. Waller, L. Walusuna, J. Wang, L. Wang, S. Wanyonyi, D. Weatherall, S. Wiladphaingern, A. Wilkinson, D. Wilson, M. Wu, Q. Wu, K. Wulff, D. Yellappan, Y. Yuan, S. Zaidi, G. Zainab, J. Zhang, and Y. Zhang, "Achieving accurate estimates of fetal gestational age and personalised predictions of fetal growth based on data from an international prospective cohort study: a population-based machine learning study," *The Lancet Digital Health*, vol. 2, no. 7, pp. e368–e375, Jul. 2020. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S258975002030131X

[5] M. T. Alam, M. A. I. Khan, N. N. Dola, T. Tazin, M. M. Khan, A. A. Albraikan, and F. A. Almalki, "Comparative Analysis of Different Efficient Machine Learning Methods for Fetal Health Classification," *Applied Bionics and Biomechanics*, vol. 2022, pp. 1–12, Apr. 2022. [Online]. Available: https://www.hindawi.com/journals/abb/2022/6321884/

[6] N. Rahmayanti, H. Pradani, M. Pahlawan, and R. Vinarti, "Comparison of machine learning algorithms to classify fetal health using cardiotocogram data," *Procedia Computer Science*, vol. 197, pp. 162–171, 2022. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1877050921023541

[7] R. R. Dixit, "Predicting Fetal Health using Cardiotocograms: A Machine Learning Approach," *Journal of Advanced Analytics in Healthcare Management*, vol. 6, no. 1, pp. 43–57, Jan. 2022, number: 1. [Online]. Available: https://research.tensorgate.org/index.php/JAAHM/article/view/38

[8] M. M. Islam, M. Rokunojjaman, A. Amin, M. N. Akhtar, and I. H. Sarker, "Diagnosis and Classification of Fetal Health Based on CTG Data Using Machine Learning Techniques," in *Machine Intelligence and Emerging Technologies*. Springer, Cham, 2023, pp. 3–16, iSSN: 1867-822X. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-031-34622-4_1

[9] J. Xia, L. Sun, S. Xu, Q. Xiang, J. Zhao, W. Xiong, Y. Xu, and S. Chu, "A Model Using Support Vector Machines Recursive Feature Elimination (SVM-RFE) Algorithm to Classify Whether COPD Patients Have Been Continuously Managed According to GOLD Guidelines," *International Journal of Chronic Obstructive Pulmonary Disease*, vol. Volume 15, pp. 2779–2786, Nov. 2020. [Online]. Available: https://www.dovepress.com/a-model-using-support-vector-machines-recursive-feature-elimination-sv-peer-reviewed-article-COPD

[10] M. Awad and S. Fraihat, "Recursive Feature Elimination with Cross-Validation with Decision Tree: Feature Selection Method for Machine Learning-Based Intrusion Detection Systems," *Journal of Sensor and Actuator Networks*, vol. 12, no. 5, p. 67, Sep. 2023. [Online]. Available: https://www.mdpi.com/2224-2708/12/5/67

[11] H. M. Alshanbari, T. Mehmood, W. Sami, W. Alturaiki, M. A. Hamza, and B. Alosaimi, "Prediction and Classification of COVID-19 Admissions to Intensive Care Units (ICU) Using Weighted Radial Kernel SVM Coupled with Recursive Feature Elimination (RFE)," *Life*, vol. 12, no. 7, p. 1100, Jul. 2022. [Online]. Available: https://www.mdpi.com/2075-1729/12/7/1100

[12] Y. Han, L. Huang, and F. Zhou, "A dynamic recursive feature elimination framework (dRFE) to further refine a set of OMIC biomarkers," *Bioinformatics*, vol. 37, no. 15, pp. 2183–2189, Aug. 2021. [Online]. Available: https://academic.oup.com/bioinformatics/article/37/15/2183/6124282

[13] W. Lian, G. Nie, B. Jia, D. Shi, Q. Fan, and Y. Liang, "An Intrusion Detection Method Based on Decision Tree-Recursive Feature Elimination in Ensemble Learning," *Mathematical Problems in Engineering*, vol. 2020, pp. 1–15, Nov. 2020. [Online]. Available: https://www.hindawi.com/journals/mpe/2020/2835023/

[14] D. A. Otchere, T. O. A. Ganat, J. O. Ojero, B. N. Tackie-Otoo, and M. Y. Taki, "Application of gradient boosting regression model for the evaluation of feature selection techniques in improving reservoir characterisation predictions," *Journal of Petroleum Science and Engineering*, vol. 208, p. 109244, Jan. 2022. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0920410521008998

[15] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. San Francisco California USA: ACM, Aug. 2016, pp. 785–794. [Online]. Available: https://dl.acm.org/doi/10.1145/2939672.2939785

[16] Y. Freund and R. E. Schapire, "A Short Introduction to Boosting," *Society*, vol. 14, no. 5, pp. 771–780, 2009.

[17] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu, "LightGBM: A Highly Efficient Gradient Boosting Decision Tree," *Advances in Neural Information Processing Systems*, vol. 30, 2017. [Online]. Available: https://proceedings.neurips.cc/paper/2017/hash/6449f44a102fde848669bdd9eb6b76fa-Abstract.html

[18] L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush, and A. Gulin, "CatBoost: unbiased boosting with categorical features," *Advances in Neural Information Processing Systems*, vol. 31, 2018. [Online]. Available: https://proceedings.neurips.cc/paper/2018/hash/14491b756b3a51daac41c24863285549-Abstract.html

[19] Z. Yuan and L. Duan, "Construction Method of Sentiment Lexicon Based on Word2vec," in *2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*. Chongqing, China: IEEE, May 2019, pp. 848–851. [Online]. Available: https://ieeexplore.ieee.org/document/8785471/

[20] W. Ramadhan, S. Astri Novianty, and S. Casi Setianingsih, "Sentiment analysis using multinomial logistic regression," in *2017 International Conference on Control, Electronics, Renewable Energy and Communications (ICCREC)*. Yogyakarta: IEEE, Sep. 2017, pp. 46–49. [Online]. Available: https://ieeexplore.ieee.org/document/8226700/

[21] M. T. H. K. Tusar and M. T. Islam, "A Comparative Study of Sentiment Analysis Using NLP and Different Machine Learning Techniques on US Airline Twitter Data," in *2021 International Conference on Electronics, Communications and Information Technology (ICECIT)*. Khulna, Bangladesh: IEEE, Sep. 2021, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/document/9641336/

[22] L. Yu and N. Zhou, "Survey of Imbalanced Data Methodologies," 2021, publisher: [object Object] Version Number: 1. [Online]. Available: https://arxiv.org/abs/2104.02240

[23] Dept. of Computer Science & Engineering, Hajee Mohammad Danesh Science and Technology University, Bangladesh, P. Bhowmik, P. C. Bhowmik, U. A. M. Ehsan Ali, and M. Sohrawordi, "Cardiotocography Data Analysis to Predict Fetal Health Risks with Tree-Based Ensemble Learning," *International Journal of Information Technology and Computer Science*, vol. 13, no. 5, pp. 30–40, Oct. 2021. [Online]. Available: https://www.mecs-press.org/ijitcs/ijitcs-v13-n5/v13n5-3.html

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