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Machine learning based cardiac care analysis using electro cardio graphs

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ABSTRACT

Accurate classification of electrocardiogram (ECG) signals is crucial for early detection and management of cardiovascular disorders. With the rise of wearable healthcare technology and increasing volumes of ECG data, the integration of advanced machine learning (ML) techniques has become essential. This study investigates the performance of various ML classifiers—SVC, Random Forest, XGBoost, and Linear SVC—for ECG classification using the PTB Diagnostic ECG Database. To improve predictive accuracy, metaheuristic optimization algorithms, including Enhanced AEO, LevyJA, JADE, and OriginalJA, were employed to fine-tune hyperparameters of the XGBoost model. Principal Component Analysis (PCA) was used for dimensionality reduction, and model performance was evaluated using accuracy, precision, recall, and F1-score. The results demonstrate that the hybrid XGBoost-JADE model achieved superior classification performance with an F1-score of 0.8742, surpassing baseline models and existing literature benchmarks. This work also addresses real-time applicability in resource-constrained environments by discussing strategies for computational efficiency. The findings highlight the potential of metaheuristically optimized machine learning frameworks in enhancing automated ECG interpretation systems.

Keywords: ECG classification, machine learning, cardiovascular disease, real-time monitoring, dimensionality reduction

1. INTRODUCTION

A revolutionary development in healthcare is connected health technology, which is best represented by wearable technology such as the Apple Watch. The diagnosis, monitoring, and treatment of many illnesses, especially those pertaining to the heart, could be greatly improved by these devices [1, 2]. Because they can continuously monitor cardiac activity, remote monitoring devices have revolutionised healthcare for people with periodic heart arrhythmias. The need for trustworthy techniques to automatically interpret ECGs is highlighted by the fact that, despite the significant advantages these devices provide, they produce vast amounts of ECG data that must be interpreted by doctors [3]. A non-stationary signal called an electrocardiogram (ECG) is frequently used to assess cardiac rhythm and pace. To ensure accuracy in ECG signal classification, pertinent features must be extracted. In order to determine the best classification parameters for differentiating between various heart diseases based on the features of ECG signals, swarm optimisation methods are frequently utilised in combination with classifiers [4]. In medical applications, ECG signal classification is essential for the diagnosis of cardiac disorders. ECG data is being analysed and classified using machine learning solutions [5]. The application of deep learning architectures, which have several benefits, is one suggested remedy. Convolutional neurones work as feature extractors in these systems, identifying complex patterns in the ECG data. Following their processing of these data, fully connected layers (FCN) determine the final ECG class. By allowing the model to automatically learn pertinent features from the data, this method has demonstrated promise in increasing the accuracy of ECG classification, lowering the need for manually created features and possibly improving diagnostic capabilities [6].
The ability of deep learning and machine learning algorithms to identify abnormalities in ECG signals for vital patient monitoring is being studied more and more for a variety of healthcare applications [7]. Although ECGs are trustworthy instruments for tracking the operation of the cardiovascular system, precise classification of heartbeats has received more attention lately. However, rather than emphasising learning and using transferable knowledge across many tasks, many studies in this field prefer to focus on identifying circumstances using annotated datasets [8]. Lower classification accuracy

and less-than-ideal feature selection may arise from this dependence on heuristic features and shallow feature learning architectures [9].

2. LITERATURE REVIEW

In keeping with this part, subsequent studies have concentrated on classifying ECG signals through the use of deep learning and machine learning techniques. Working along with other experts in the field, these investigations investigate novel methods and algorithms to increase the precision and effectiveness of ECG categorisation. Using a linear discriminant criterion, Mar et al. [10] presented the sequential forward floating search (SFFS) algorithm for categorising ECG arrhythmias. Using a multilayer perceptron, this technique evaluated the robustness of the model while looking at a wide range of features. The method met the standards for ambulatory monitoring and outperformed comparable research. A novel technique for creating wavelets that accurately depict ECG beats was presented by Daamouche et al. [11], who emphasised the wavelets' capacity for discrimination. This method formulates the design problem in a particle swarm optimisation (PSO) framework and makes use of the wavelet filter bank's polyphase representation. Experimental results utilising a state-of-the-art support vector machine classifier on the MIT/BIH arrhythmia database showed that the suggested approach performed better in terms of classification stability and accuracy. In order to categorise heartbeats, Kachuee et al. [12] developed a deep convolutional neural network (CNN) method that demonstrated great accuracy in classifying five different forms of arrhythmias. They were also successful in using this information to categorise myocardial infarction (MI). The technique achieved remarkable classification accuracy rates of 93.4% for arrhythmias and 95.9% for MIs. The MIT-BIH and PTB Diagnostics data sets from PhysionNet were used to validate these findings. A deep-learning technique for classifying single-lead ECG signals was presented by Mathews et al. [13]. They particularly identified ventricular and supraventricular heartbeats using deep belief networks (DBN) and the Restricted Boltzmann Machine (RBM). At a modest sampling rate of 114 Hz, the algorithm remarkably achieved high average recognition accuracies for both supraventricular and ventricular ectopic beats (95.57 % and 93.63%, respectively). This study highlights the potential of deep learning techniques for precise ECG classification and implies that they can be applied to a wider variety of physiological signal classifications, such as studies of heart rate variability, arterial blood pressure, and nerve conduction. Walsh's study focused on the advantages of using Support Vector Machine Learning for ECG monitoring. The study demonstrated the feasibility of Support Vector Machines as a machine learning technique by demonstrating their capacity to effectively identify ECG signals. Its successful application to the Kaggle ECG Heartbeat Categorisation Dataset served as proof of this. A thorough analysis of current deep learning (DL) techniques for classifying ECG data was carried out by Ebrahimi et al. CNN, Deep Belief Network (DBN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) were among the DL techniques they investigated. The fact that CNN was used in 52% of the 75-research carried out between 2017 and 2018 indicates that it was the most effective technique among them for feature extraction. The DL techniques demonstrated remarkable accuracy in properly diagnosing Ventricular Ectopic Beats (99.7%), Supraventricular Ectopic Beats (99.8%), and Atrial Fibrillation (100%).
Deep CNN was used by Weimann and Conrad [14] to classify ECG recordings, a procedure that usually requires expensive annotated samples. They used transfer learning to overcome this difficulty, first pre-training the CNNs on the biggest publically accessible dataset before optimising them for the classification of atrial fibrillation. This pretraining phase reduced the need for annotations and significantly improved CNN performance, increasing it by up to 80%. Furthermore, the investigators investigated both supervised and unsupervised pretraining methods, emphasising their capacity to improve relevance without requiring costly ECG annotations. By utilising developments in machine learning and deep learning techniques, ongoing research is continuously improving ECG classification systems. Although electrocardiograms (ECGs) are reliable instruments for cardiovascular surveillance, current work has focused on improving heartbeat classification for more accurate diagnosis. Nonetheless, a prevalent constraint in several research endeavours is their emphasis on categorising circumstances through annotated datasets, neglecting the possible advantages of acquiring and utilising transferable knowledge in other activities. More reliable approaches are required since this dependence on heuristic features and shallow learning architectures might result in less-than-ideal feature selection and decreased classification accuracy. Recent research has created approaches to solve these issues by attempting to decrease computational resources and enhance classification performance. These developments are especially pertinent to ambulatory settings, where precision and efficiency are critical. Notwithstanding these initiatives, the field continues to struggle to achieve the best possible classification accuracy and generalisability across a variety of datasets. To ensure more dependable diagnosis and monitoring in clinical settings, more research is required to create more flexible and transportable methods for ECG classification.
To overcome the shortcomings of earlier techniques, hybrid machine learning techniques including metaheuristic algorithms were applied in this study. Although machine learning techniques such as SVC, RandomForest, XGBoost, and LinearSVC have proven successful in classification tasks, the incorporation of metaheuristic algorithms to improve accuracy was not investigated in earlier research. This work suggests using metaheuristic algorithms—more especially, the JADE algorithm—to optimise learning models and raise their precision and effectiveness in order to close this gap. To further improve the performance of the machine classification models, the paper also presents the Enhanced AEO, LevyJA, JADE, and OriginalJA algorithms as techniques for hyper-parameter optimisation of learning models.

3. METHODOLOGY

Using the PTB Diagnostic ECG Database for the categorisation job, the study used a methodical approach. Samples of both normal and arrhythmia-affected heartbeats were included in the dataset. Data cleaning, normalisation, and imputation of missing values using the mean were all part of the preprocessing of the datasets. A proportionate 70% and 30% of the data were then separated into training and testing sets, respectively. To find the top-performing model, a number of machine learning models were put into practice and assessed, including SVC, RandomForest, XGBoost, and Line-arSVC. After the initial model evaluation, the optimisation procedure concentrated on improving the prediction skills of the top-performing model by fine-tuning its parameters. Enhanced AEO, LevyJA, JADE, and OriginalJA were among the optimiser algorithms used in this optimisation. In order to determine the best model and optimiser combination for better performance in diagnosing cardiovascular disease, a thorough evaluation was carried out in the study's final stages, considering metrics including accuracy, precision, recall, and F1-score. gives a graphic depiction of the processing flowchart used in the study, showing the steps that were followed in order as part of the research methodology.

3.1. Evaluation of the performance

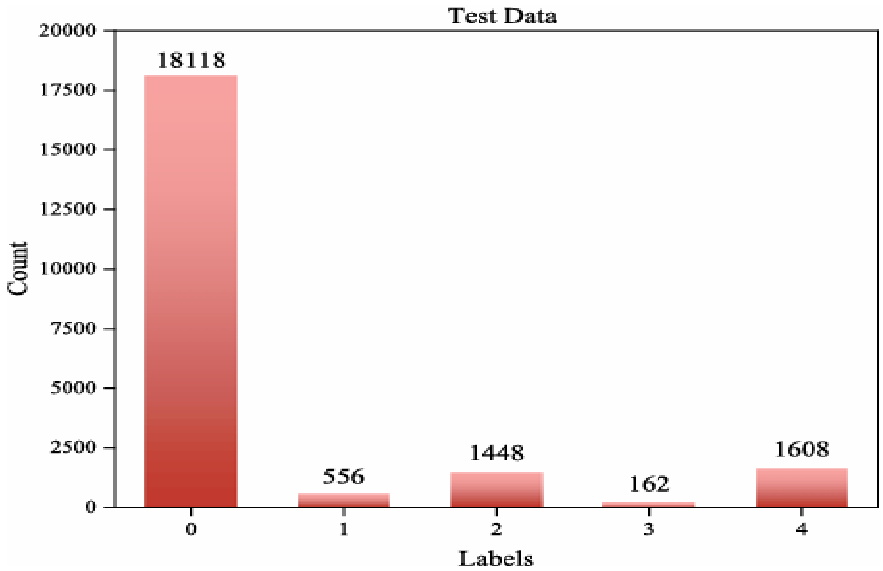

Fig. 1. The number of samples in each testing class

A key indicator that measures the proportion of accurate forecasts to all of a model's predictions is accuracy. It provides a thorough evaluation of the model's overall accuracy, considering predictions from every class. A larger percentage of accurate predictions compared to the total number of predictions the model made is indicated by a higher accuracy score.

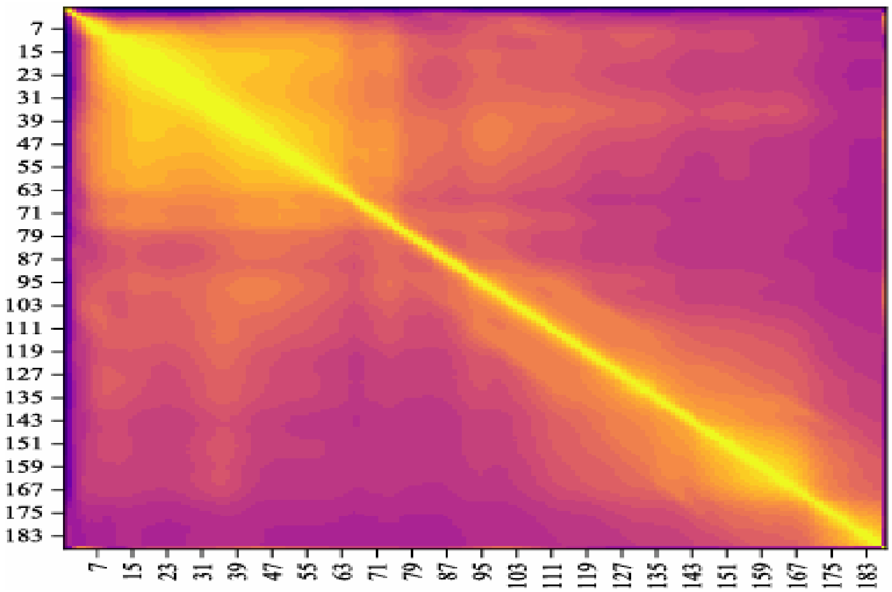

Fig. 2. The heatmap of datasets

Because it considers both precision and recall, the F1 score is a more trustworthy statistic for unbalanced datasets. According to the results, XGBoost outperformed the other four models in categorising ECG datasets, obtaining the greatest F1 score. Metaheuristic techniques were used to optimise the XGBoost model's hyperparameters in order to further improve its performance. Enhanced AEO, LevyJA, JADE, and OriginalJA were among these algorithms. through default configuration optimisation.

A thorough analysis of the findings will be provided in this section of the study. This assessment will shed light on the performance of the various models, the efficiency of the PCA preprocessing step, and the effect of hyperparameter optimisation on the classification performance of the XGBoost model. It provides a thorough summary of the performance metrics and demonstrates a comparatively high level of accuracy and efficacy. Notably, the XGBoost model outperforms the others, demonstrating remarkable ability to correctly identify the ECG datasets. This detailed analysis highlights how crucial it is to use the F1-score measure in order to guarantee a thorough evaluation of the models' performance and durability, particularly when working with unbalanced data.

4. RESULTS AND DISCUSSION

Four distinct models—SVC, RandomForest, XGBoost, and Line-arSVC—were used in this study to classify ECG datasets. Prior to using these models, the dimensionality of the dataset was reduced to 30 features using Principal Component Analysis (PCA).

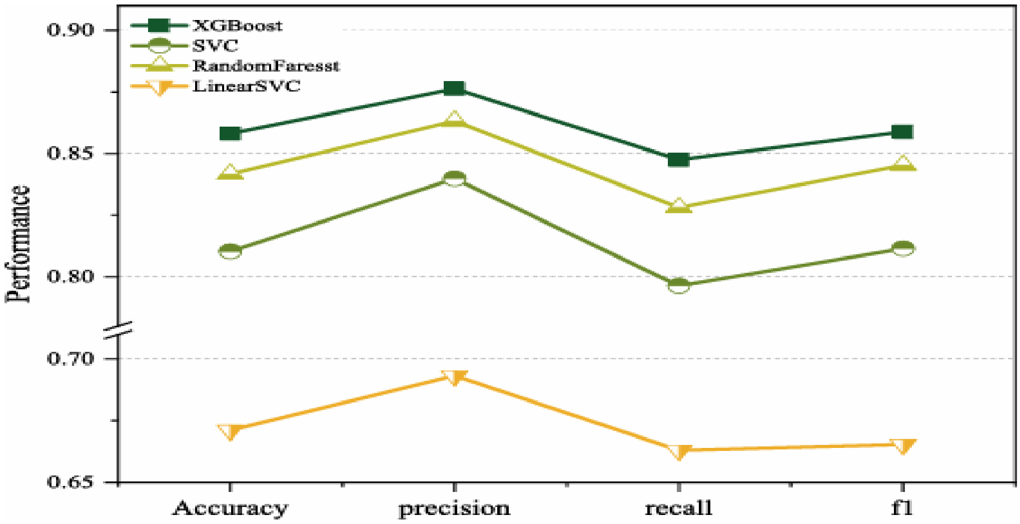

Fig. 3. The performance metrics obtained from XGboost, SVC, random forest, and linearSVC models

This stage was essential for controlling the complexity of the data and enhancing the functionality of the models.

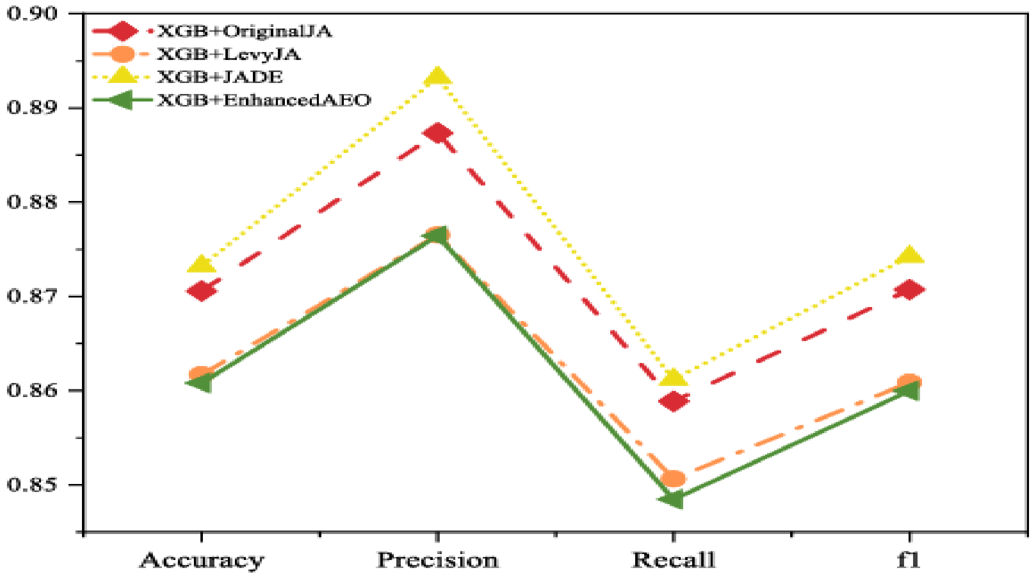

Fig. 4. The performance metrics obtained from XBboost, and XGboost with Original, LevyJA, JADE, and EnhancedAEO hybrid models from testing datasets

The model's performance was carefully assessed in order to adjust key hyperparameters including max depth, N-estimators, and learning rate. When the numbers are closely examined, a recurring pattern becomes apparent: performance measures for all models stay constant in the training dataset, but noticeable differences appear in the testing dataset. In this situation, the XGBoost model first shows comparatively poorer performance measures. However, a noticeable boost in performance measures is revealed by the smart integration of optimiser algorithms. The improved performance seen in the XGBoost model when combined with the JADE optimiser is very noteworthy. Across a range of performance indicators, this coupling continuously exhibits higher performance. Subsequent investigation shows that certain parameter configurations allow the JADE optimiser to operate at its best. Interestingly, the following are the ideal parameters found for the JADE optimiser: {'max depth': 8, 'learning rate': 0.3276316193519062, 'N-estimators': 225}. The effectiveness of the JADE optimiser in improving the XGBoost classification model's performance in the context of this investigation is demonstrated by this precisely calibrated setup. Analysis revealed that JADE was the best-performing of the four hybrid models that combined XGBoost with Original, LevyJA, JADE, and EnhancedAE. Amazingly, after over 300 epochs, using JADE produced an outstanding F1 score of 0.8742. The robustness and effectiveness of the JADE optimiser in combination with XGBoost were demonstrated by the noteworthy fact that this high-performance level remained constant for an additional 200 epochs.

Given the unbalanced nature of the dataset, a thorough evaluation approach was used, utilising macro-precision, macro-recall, and macro-F1 scores to assess performance resilience. Performance data, including accuracy, precision, recall, and F1 score, are carefully displayed in fig. 6 for the XGBoost model's default and optimised hyperparameters using metaheuristic optimisation techniques. The most notable measure across all models is accuracy, which shows a steady strength in accurately identifying affirmative cases. On the other hand, recall, though typically smaller, indicates the model's capacity to identify genuine positive cases out of all real positive cases. Performance metrics are significantly improved by optimising XGBoost with JADE and OriginalJA hyperparameters, demonstrating the effectiveness of metaheuristic approaches in adjusting model parameters for better classification results. With an outstanding F1 score of 0.8742, the XGBoost model integrated with JADE ultimately proves to be the best option for the ECG dataset. With a macro F1 score of 0.82, this notable improvement above Walsh's [1] results highlight the notable advancements made in categorisation accuracy. Additionally, macro measurements are used in the optimisation process, which treats all classes uniformly and ignores data imbalance. Consequently, the averaging procedure is unaffected by the sample size per class. Furthermore, the optimization's primary goal is to increase the F1-score, which is determined macroscopically, meaning that the sample size is irrelevant. As a result, the goal of parameter optimisation is to achieve accurate classification and prediction across all classes. This method is responsible for the outputs' high level of accuracy. The results show that although the classes are unbalanced, each class has very good accuracy.

Even though this study's primary goal is to increase classification accuracy, it is still very motivating to solve problems with inference speed and computational economy while considering how it might be used in wearable medical devices. Fast, low-latency processing is essential for real-time ECG analytics because it allows for prompt response in life-threatening situations.

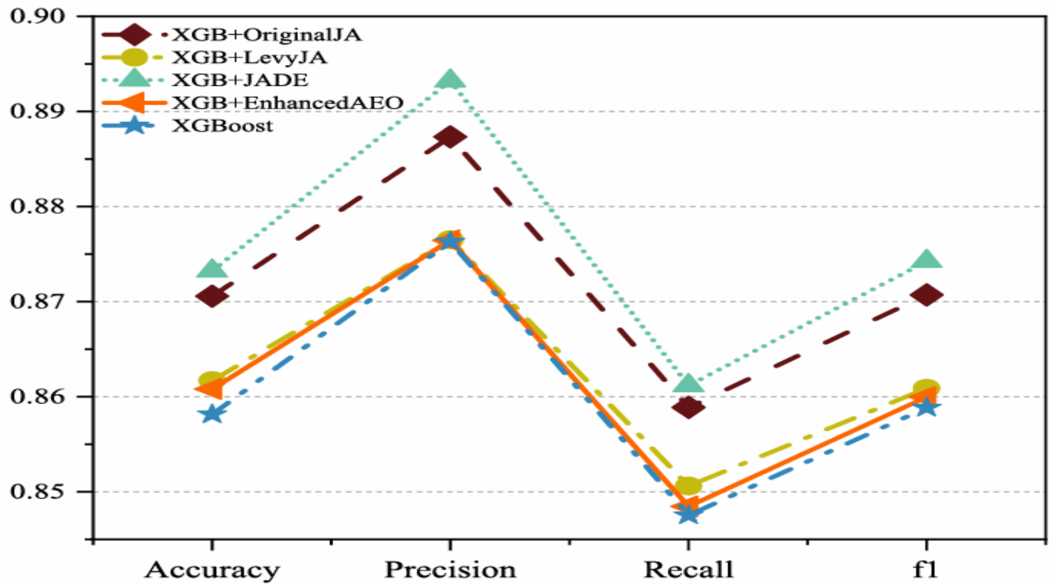

Fig. 5. The performance metrics obtained from XBboost, and XGboost with Original, LevyJA, JADE, and EnhancedAEO hybrid models

This is where the computational complexity of large machine learning models, particularly those from deep learning, becomes a bottleneck. Even though XGBoost performed exceptionally well in this study when compared to other machine learning techniques, it is still necessary to show how effectively they would function in real-world scenarios. Actually, methods like model pruning, quantisation, and hardware acceleration with specialised processors like GPUs or TPUs can all help models infer information faster. In order to find a good compromise that can offer very high accuracy in the classification of electrocardiograms, with the additional guarantee of model lightness and adequate speed for real-time applications on very resource-constrained wearable devices, future work should assess the model's performance in terms of both accuracy and computational efficiency.

Furthermore, investigating edge computing in addition to cloud processing can also lower the computational need of the wearable device, allowing for the use of even more complex models with lower latency. These can be looked into further in order to implement the suggested method for continuous ECG monitoring in real-world healthcare settings. Furthermore, even if the current study has achieved a suitable degree of accuracy for the PTB Diagnostic ECG Database, it should acknowledge that generalisation to a large number of data sets does, in fact, provide robustness and practical applicability. the variety of outcomes in various implementations throughout international healthcare systems. In order to increase robustness and efficacy in a clinical context as opposed to a controlled laboratory setting, the next study will also broaden the pool of data.

The resilience of the XGBoost model when combined with the JADE optimiser was under-scored by a careful analysis of results over various epochs, yielding an astounding F1 score of 0.8742. This significant improvement in performance above previous results demonstrates the significant advancements made in categorisation accuracy. Finally, with notable improvements in classification accuracy and model resilience, the XGBoost model enhanced with JADE is the best option for classifying ECG datasets.

5. CONCLUSION

This study explored and compared the effectiveness of several machine learning models for the classification of ECG signals, with a particular focus on improving classification accuracy through metaheuristic optimization. Among the tested models, XGBoost combined with the JADE algorithm emerged as the most effective solution, achieving a high F1-score of 0.8742 and demonstrating consistent robustness across performance metrics. The use of Principal Component Analysis effectively reduced feature dimensionality, enhancing model efficiency without compromising accuracy. The results confirmed that integrating metaheuristic optimization into the training pipeline significantly enhances the diagnostic capability of machine learning models. Moreover, this research emphasizes the need to consider computational economy and inference speed for potential deployment in wearable devices. Future work should focus on validating the model across diverse datasets and optimizing it further for real-time healthcare applications through edge computing and hardware acceleration techniques. Overall, the JADE-optimized XGBoost framework presents a viable path toward more accurate and efficient ECG classification systems.

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