

Performance Comparison Analysis of Random Forest, Support Vector Machine, and AdaBoost in Arrhythmia Classification

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Abstract—Arrhythmia is a condition characterised by irregularities in heart rhythm, where the heartbeat may be excessively fast, abnormally slow, or irregular, potentially leading to severe complications such as heart attacks or sudden cardiac death. Accurate diagnosis of Arrhythmia is essential, but it has traditionally relied on Electrocardiogram (ECG) analysis by medical experts, which can be time-consuming and subject to variability. In recent years, computational methods have gained prominence in arrhythmia classification, improving diagnostic speed, accuracy, and automation. This study investigates the effectiveness of machine learning models, namely Random Forest (RF), Support Vector Machine (SVM), and Adaptive Boosting (AdaBoost), in classifying arrhythmias using features extracted from ECG signals through Discrete Wavelet Transform (DWT). The dataset was sourced from the Massachusetts Institute of Technology—Beth Israel Hospital Arrhythmia Database, and the research involved several stages, including data collection, preprocessing, feature extraction, model training, and performance evaluation. The results indicate that RF achieves the highest accuracy at 97.50%, SVM at 97.20%, and AdaBoost at 90.20%. These findings demonstrate the superior performance of RF in handling arrhythmia classification tasks, highlighting its potential for enhancing automated ECG interpretation and assisting in early diagnosis and clinical decision-making.

Keywords—Discrete Wavelet Transform (DWT), arrhythmia database, Random Forest (RF), Support Vector Machine (SVM), Adaptive Boosting (AdaBoost)

I. INTRODUCTION

Arrhythmia refers to irregularities in heart rhythm, which may manifest as excessively fast, abnormally slow,

or erratic heartbeats. It is considered a serious medical condition that requires timely diagnosis and intervention. Arrhythmia can lead to various complications, including heart attack and sudden death [1]. Arrhythmia diagnosis is an essential step in patient management and treatment. However, diagnosing Arrhythmia often requires medical experts to carefully interpret Electrocardiogram (ECG) signals. In recent years, computational methods for arrhythmia classification have garnered attention as a promising approach to enhance the speed and accuracy of diagnosis [2].

One method used in arrhythmia classification is machine learning algorithms, especially Random Forest (RF), Support Vector Machine (SVM), and Adaptive Boosting (AdaBoost). Random Forest is a powerful machine learning method often used in medical data classification due to its ability to handle large and complex data sets. Conversely, SVM offers a practical approach to classification by maximizing the margin between different classes. Meanwhile, AdaBoost is a boosting algorithm that combines several simple models to improve prediction accuracy. These three algorithms offer various approaches to handling data complexity and can be optimised using feature extraction techniques, such as the Discrete Wavelet Transform (DWT) [3].

Additionally, DWT has been proven effective in extracting features from time signals, such as ECG signals [4]. DWT can produce a more compact signal representation and retain critical information in varying degrees of resolution [5]. Although many studies have been conducted on the use of RF, SVM, and AdaBoost for arrhythmia classification, few studies have specifically explored the effect of DWT on the performance of the three models. This study contributes to addressing this gap

by systematically analysing the impact of DWT on these machine-learning models. By incorporating DWT-based feature extraction, this research aims to enhance the classification accuracy and robustness of arrhythmia detection models. The findings of this study may support the development of automated ECG analysis systems, potentially assisting medical professionals in making timely and accurate diagnoses [6, 7]. Furthermore, the results can be a reference for future research in improving ECG signal processing techniques and optimising classification algorithms for medical applications [8].

The contributions of the study are:

- Extracting ECG signals using DWT for feature extraction and time-frequency analysis.
- Evaluating and comparing RF, SVM, and AdaBoost classification performance in arrhythmia detection.
- Demonstrating the impact of DWT on improving machine learning model accuracy for ECG signal classification.
- Providing a benchmark for using DWT in combination with machine learning models for enhanced ECG interpretation and automated arrhythmia diagnosis.

II. MATERIALS AND METHODS

A. Retrieval Dataset

The dataset used in this research was obtained from the MIT-BIH Arrhythmia Database, a widely recognized and validated dataset hosted on the official PhysioNet platform. This database contains 48 half Hour recordings of two-channel ambulatory ECG signals collected from 47 subjects, including a diverse range of standard and abnormal heart rhythms [9]. The tapes were initially selected to represent a variety of arrhythmias commonly encountered in clinical practice. Fig. 1 illustrates a sample ECG signal visualisation for Subject 100 on Google Colab, demonstrating the raw waveform representation used in this study.

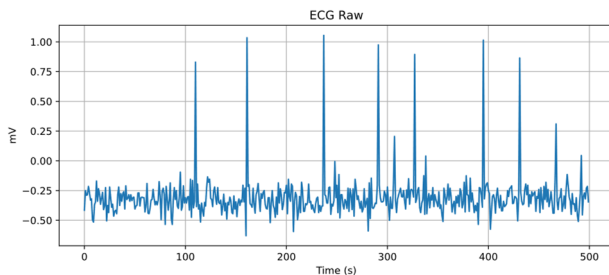


Fig. 1. Raw ECG signal display subject.

In this study, only five individual records from the MIT-BIH database (subjects 100, 101, 103, 105, and 106) were utilized due to time and resource constraints. While this subset does not fully represent the diversity of arrhythmia cases in the complete dataset, it serves as an initial step in evaluating the effectiveness of classical machine learning models. Future research should expand this approach to include a broader range of subjects and

incorporate subject-independent validation to enhance generalizability.

Each ECG recording was sampled at 360 Hz per channel with 11-bit resolution over a 10-mV range, ensuring high-fidelity signal representation [10]. The dataset was annotated by at least two independent cardiologists, with disagreements resolved through consensus, resulting in approximately 110,000 annotated heartbeats. These annotations serve as ground-truth labels for arrhythmia classification tasks [11].

Table I summarises the key parameters of the dataset, which include different classes of arrhythmias such as Normal Sinus Rhythm (NSR), Atrial Fibrillation (AFib), Premature Ventricular Contractions (PVC), Ventricular Tachycardia (VTach), and Atrial Flutter. The dataset also contains detailed metadata, including signal amplitude range (10 mV), bandwidth (0.1–40 Hz), sampling frequency (360 Hz per subject), and recording duration (30 Minutes per subject) [12].

TABLE I. RESEARCH DATASET PARAMETERS

No	Parameters	Total
1	Normal Sinus Rhythm (NSR)	18 Subject
2	Atrial Fibrillation (AFib)	1 Subject
3	Premature Ventricular Contraction (PVC)	17 Subject
4	Ventricular Tachycardia (VTach)	3 Subject
5	Atrial Flutter	1 Subject
6	Amplitude Max, min	10 mV
7	Bandwidth	0.1–40 Hz
8	Sampling Frequency per subject	360 Hz
9	Interval Sampling	0.00278 s
10	Recording Time per patient	30 Minutes per recording

B. Signal Preprocessing

Fig. 2 illustrates a signal preprocessing flow in which the signal obtained initially is still in its raw form, rendering the PQRST wave segments difficult to interpret clearly. Therefore, the signal was filtered using a Bandpass Filter to remove noise. The bandpass filter is composed of a high pass filter in series with a low pass filter [13]. This type of filter has been widely applied in ECG signal denoising due to its ability to preserve signal morphology while removing baseline wander and high-frequency noise [14]. This BandPass Filter can pass signals in a particular frequency band or “spread” or between specified frequency limits. The Nyquist frequency, defined as half of the sampling frequency (360 Hz), is therefore 180 Hz. This frequency determines the maximum frequency component that can be accurately captured in the ECG signal. So, the frequency results can filter the frequency at the lower and upper limits [15]. The preprocessing stages on Google Colab were carried out as follows:

- (1) Importing Raw Signal into Google Collab `pd.read_csv()`. The signal is stored in a .csv file, allowing it to be directly read in Google Colab.
- (2) Preprocessing by giving input in the form of upper and lower limit frequencies determined by using this function to receive the signal, with a cutoff frequency of 0.5 Hz, a sampling frequency of 360 Hz (standard MIT-BIH), and a filter order set at 5.

The selection of these parameters follows common standards in biomedical signal filtering, as reported in previous ECG studies [16]. Nyq frequency was calculated as half of the sampling frequency, and the cutoff frequency was normalised by dividing it by the new frequency. Butterworth filters were then used to preserve the integrity of the signal phase [17].

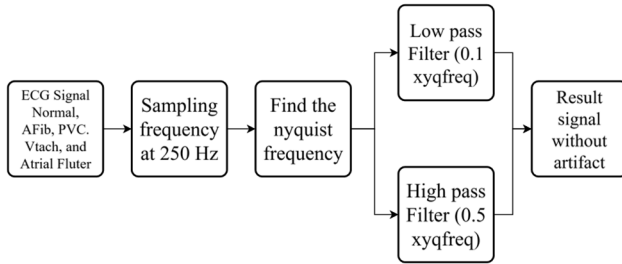


Fig. 2. ECG signal preprocessing flow.

C. Signal Preprocessing

The preprocessing stages on Google Colab were carried out following the stages presented in Fig. 3. The collected dataset was subjected to signal denoising and feature extraction to obtain the P-wave segment.

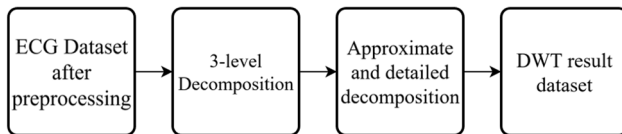


Fig. 3. Feature extraction process using Discrete Wavelet Transform (DWT).

After preprocessing, DWT was applied to decompose the ECG signal into multi-resolution frequency components. We used the Daubechies-4 (db4) wavelet function, commonly employed in ECG signal analysis due to its compact support and similarity to QRS waveforms. The signal was decomposed up to level 3, generating both approximation and detail coefficients. From these coefficients, statistical features such as energy, entropy, mean, and standard deviation were extracted. These features served as the input to the classifier. They captured relevant frequency-domain characteristics across different time windows, where the signal was divided into sub-band components at various levels of resolution. The signal was split into sub-bands, including four levels, to examine the approximate signal produced. The db4 mother wavelet was then applied to the signal to provide information about the relevant frequency characteristics in the ECG signal [18, 19]. By using db4, the signal will be divided into more minor frequencies [20]. The extracted signal output was then classified.

Furthermore, the windowing process occurred after the feature extraction stage. The windowing technique used was oversampling windowing. The signal extracted in 1 Hour of recording time was divided into several parts, with each block being 2500 samples and the combined distance between blocks being 100 samples 800 ms/window [21, 22].

D. Analysis of System Performance Results

The classification stage was carried out after extracting the signal, as described by the flowchart in Fig. 4. The data were divided into five classes: normal, Atrial Fibrillation, Premature Ventricular Contraction, Ventricular Tachycardia, and Atrial Flutter.

The ECG signal classification began by uploading the data to a Google Drive account. The data was then divided into training and test data in an 80:20 ratio. The training data was used for the classification process using the proposed method, while the test data was used to evaluate the trained model. The data was uploaded in csv format to facilitate processing. Next, the ECG data was categorised into five classes based on the types of arrhythmias in the dataset. Each dataset was labelled accordingly. 100.csv is classified as Normal Sinus Rhythm (NSR), 101.csv as Atrial Fibrillation (AFib), 105.csv as Premature Ventricular Contraction (PVC), 103.csv as Ventricular Tachycardia (VTach), and 106.csv as Atrial Flutter. Although the dataset was limited to five labelled recordings, the application of windowing and segmentation techniques resulted in a large number of training samples. This strategy partially mitigates the data volume limitation, but we acknowledge that the lack of subject variability remains a limitation. Addressing this will be a focus in future work. After labelling, all datasets were merged using the “concat” function from the pandas library in Python, which is used to combine multiple tabular data structures into a single unified dataset. This allows for efficient processing and preparation for model training [23].

The next stage involved defining functions for the Random Forest, SVM, and AdaBoost architectures, which were used to train the model. Once the model training was complete, the classification algorithm was tested on the test data to assess the model’s performance. The evaluation employed an optimiser and loss function, with metrics such as loss, accuracy, validation, and validation loss being recorded. For RF classification, the model was initialised with two key parameters to ensure consistent results: `n_estimators`, set to 10, 50, 100, 200, 300, 400, and 500, and `random_state`, set to 42. The `n_estimators` parameter defined the number of decision trees in the RF, while the RF Classifier was used for model training.

In the SVM model, several key parameters were set, including `kernel = ‘rbf’` to utilise the Radial Basis Function kernel, `random_state = 42` to maintain result consistency, `C = 1.0` to balance classification margin and error, and `gamma = ‘scale’`, to automatically adjust the gamma value based on the number of features. This kernel has been widely used in biomedical signal classification because it handles nonlinear separation efficiently [24]. The training process was accelerated using parallel threading with `joblib.parallel_backend`. After training, the model predicted labels on the validation and test sets, with accuracy and training time recorded for evaluation.

While the classifiers were implemented using commonly accepted default parameters based on previous studies, no exhaustive hyperparameter optimisation (e.g., GridSearchCV or RandomizedSearchCV) was conducted

in this work. Initial tests with selected parameter values (e.g., $n_estimators = 100$, $C = 1.0$) yielded satisfactory results and served the purpose of establishing a performance baseline. Future work may include a more thorough parameter tuning process to maximise performance and reliability.

For the AdaBoost model, the key parameters included $n_estimators$, set to 10, 50, 100, 200, 300, 400, and 500, and $random_state$, set to 42, to ensure consistency. The $n_estimators$ parameter determined the number of decision trees in the model, while the classification algorithm was implemented using the AdaBoostClassifier [25].

Finally, the trained classification models were tested using the test data to evaluate their success rate. At this stage, an optimiser and loss function were used for model evaluation, with the results displayed in terms of loss, accuracy, validation, and validation loss, as shown in Fig. 4.

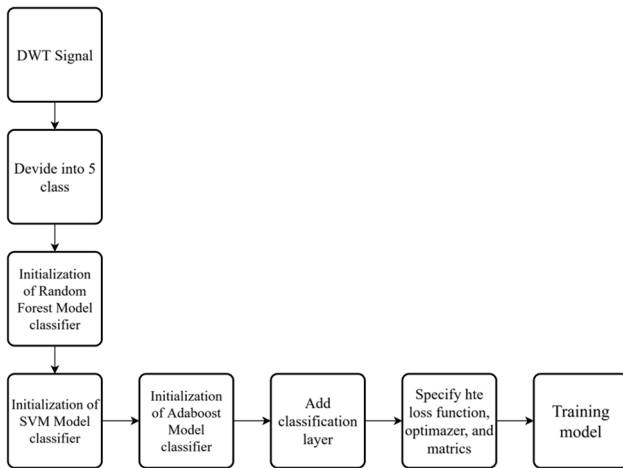


Fig. 4. Flowchart using RF, SVM, AdaBoost.

E. Model Classification

After completing all stages, from signal preprocessing to classification, the final step was the system performance analysis to evaluate the model's accuracy in classifying ECG signals using various evaluation metrics. Fig. 5 illustrates the workflow of this analysis.

In this study, 40 patient samples were used, categorised into Normal Sinus Rhythm (NSR), Atrial Fibrillation (AFib), Premature Ventricular Contraction (PVC), Ventricular Tachycardia (VTach), and Atrial Flutter. The analysis was conducted through several stages. The first stage was signal preprocessing, where noise was removed using a denoising method to ensure cleaner signals for feature extraction. This preprocessing step is essential, as high-quality signal input significantly influences the accuracy and reliability of classification in ECG analysis [26]. Next, feature extraction was performed using the DWT, which captures frequency variations in the ECG signal and extracts essential features for classification.

After extracting the features, the next step was to classify the signals using three main machine-learning algorithms: RF, SVM, and AdaBoost. The trained models were then evaluated using several performance metrics, including accuracy, precision, sensitivity (recall), and F1-Score. Accuracy measures the overall frequency of correct predictions made by the model, while precision identifies how well the model avoids errors in classifying specific arrhythmia conditions. Sensitivity assesses the model's ability to detect arrhythmias correctly, and the F1-Score is a combined metric of precision and sensitivity that evaluates the balance between positive and negative class detection. These evaluation metrics are widely adopted in ECG-based arrhythmia detection studies for their effectiveness in assessing classifier robustness and reliability [27]. The steps are illustrated in Fig. 5.

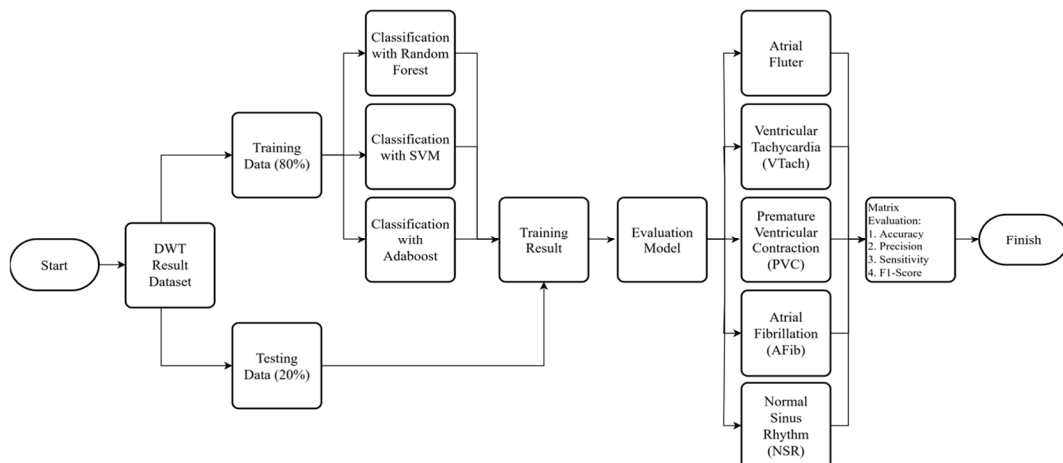


Fig. 5. Flowchart of performance analysis.

III. RESULTS AND DISCUSSION

The expected research output is to be able to analyse ECG signals for patients with cardiovascular disease, especially Atrial Fibrillation, Premature Ventricular Contraction, Ventricular Tachycardia, and Atrial Flutter,

using the DWT method. Next, it can group or classify patients with normal conditions, AFib, PVC, VTach, and Atrial Flutter with RF, SVM, and AdaBoost methods. Ultimately, it achieves good system performance, as evidenced by its accuracy, precision, sensitivity, and F1-Score.

A. Data Reading Results on Google Colab

ECG signal data reading was done in Google Colaboratory by downloading the .csv files on the ATM PhysioBank page (physionet.org). Then, the files were imported into Google Colab. The signal was displayed in 3600 Seconds or 1 Hour from 23 Hours of sampling on the patient, with an annotation of N or Normal and in the amplitude range of ± 6 mV. The 04015m.info file displayed information related to signal recordings, such as the number of samples and as many as 900,000 samples/signal with a sampling interval of 0.004 s. Fig. 6 shows the raw signal extracted from the file, illustrating the recorded ECG waveform. The signal displayed in the image consists of only one channel (Lead II), which records the atrial activity of the heart, allowing for the diagnosis of common conditions, such as AFib, PVC, VTach, and Atrial Flutter.

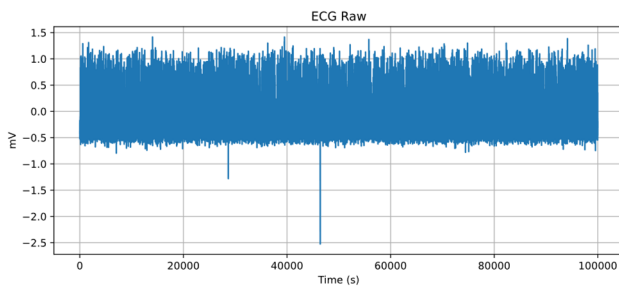


Fig. 6. Raw ECG signal loaded from PhysioNet MIT-BIH dataset (single channel).

B. Signal Preprocessing Result

The signal was displayed in 3600 Seconds or 1 Hour from 23 Hours of sampling on the patient, with an annotation of N or Normal. The signal preprocessing stage was also conducted on Google collaboration by specifying the upper and lower frequency limits, ensuring that the signal was filtered only within a predetermined range. The bandpass filter was configured with a lower cutoff of 0.5 Hz and an upper cutoff of 40 Hz, in line with typical ECG preprocessing standards. The Nyquist frequency for the 360 Hz sampling rate was 180 Hz, ensuring the preservation of relevant cardiac signal components.

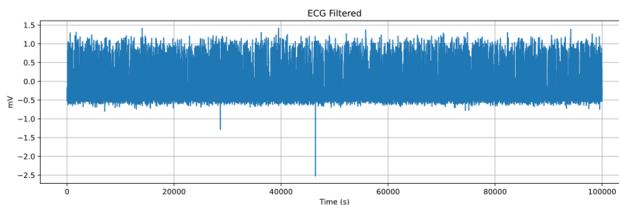


Fig. 7. Signal after preprocessing.

Fig. 7 shows the signal display after filtering using Bandpass filtering. After preprocessing, the resulting signal exhibited significantly reduced noise, with the amplitude range shrinking to ± 3 mV. This noise was filtered by applying a bandpass filter, which removed waves outside the designated frequency range. In addition to denoising the noise in the signal, the bandpass filter was also helpful in adjusting the signal's shape, facilitating more efficient computation during the feature extraction

process. Although filtering did not remove 100% of the noise, it substantially minimised the distortion in the signal caused by measurement artefacts or errors in ECG recording. Fig. 8 compares the raw and preprocessed signals, clearly illustrating the effectiveness of the filtering process in reducing noise and refining the waveform.

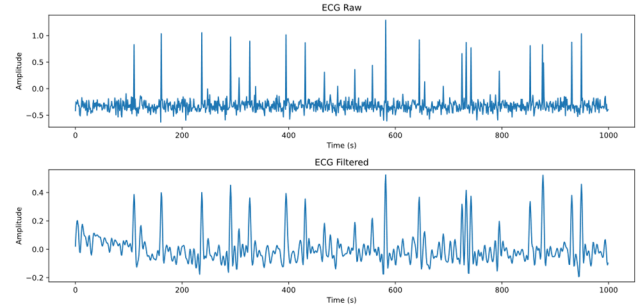


Fig. 8. Signal comparison before and after preprocessing.

C. Discrete Wavelet Transform Feature Extraction

The feature extraction stage aims to reconstruct the signal into a new form according to the selected mother wavelet and examine the energy distribution closest to the initial signal. The resulting signal was clearer, allowing the difference in the PQRS wave to be seen, and the pattern was more easily recognised by machine learning.

Fig. 9 shows that the signal was decomposed using the db4 mother wavelet at level 3, enabling a good balance between time and frequency localisation. The resulting signal preserved important morphological features while reducing noise and redundant information. The resulting signal shape has a minor frequency and amplitude but still represents each wave without addition or subtraction. The reconstructed signal facilitates the input process for machine learning models, as it has been standardised into a uniform pattern suitable for pattern comparison. This uniformity simplifies the classification task, allowing the signal to be more effectively categorised into five distinct classes. Statistical features such as energy, entropy, mean, and standard deviation were derived from the detail coefficients to serve as inputs to the classification models.

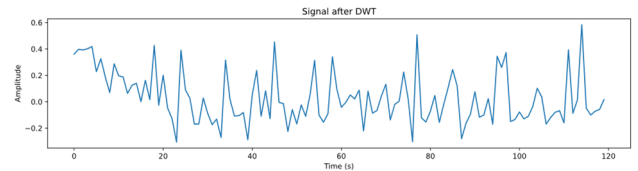


Fig. 9. Signal after extraction.

In addition, the selection of the decomposition level was also based on the relativity of the resulting energy, as shown in Fig. 10. This energy relativity aims to examine how similar the signal reconstruction is to the initial signal. Using the db4 mother wavelet, 3-level decomposition produced the best energy relativity among several other levels of 66.64%. However, the 100% energy relativity also did not determine how well the signal was reconstructed. Each mother wavelet had different characteristics in displaying energy relativity. For

example, Sym4, with five levels, produces an energy relativity of 94%. Still, the resulting signal reconstruction showed a similar pattern to the initial signal so that no new patterns could be used as variations in machine learning processing. Therefore, selecting db4 with three decomposition levels is an appropriate choice for extracting new signal patterns.

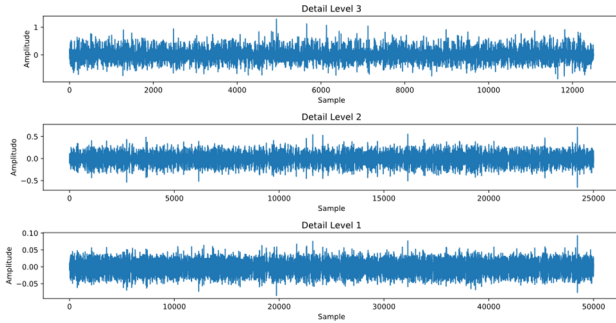


Fig. 10. Signal after extraction.

D. Signal Windowing

The signal windowing technique was applied after the feature extraction process to augment the data and increase the amount of training data. The overlapping method avoids missing information in the signal and produces a variety of patterns in the training data. The windowing process was done in Python software by exporting the signal in .csv format. The difference resulting from this file export lies in the X axis label, which changed from ‘time (s)’ to ‘samples’, indicating that the signal reading graph now represents the number of samples and amplitude of the reconstructed signal.

Fig. 11 illustrates the overlapping windowing technique applied to the signals. The windowing process involved cutting the signal into pieces that overlap 50%. Fig. 11 shows the two initial cuts of the variable ‘filtered_signal’, where the signal in the second cut starts halfway at the end of the signal in the first cut. This process is called overlapping.

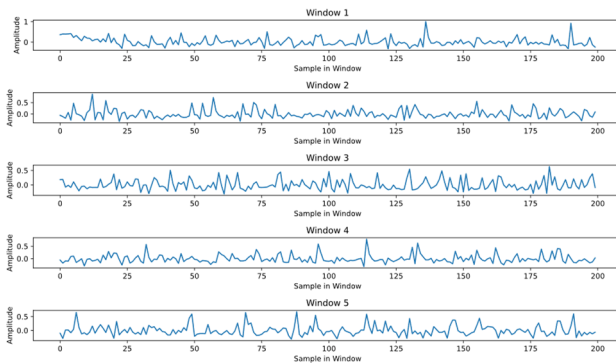


Fig. 11. Windowing overlapping signals.

In this study, windowing divided a single signal into multiple chunks or samples. From a total of 900,000 samples (1 Hour), a windowing technique with a size of 200 samples (800 ms) and overlapping of 100 samples (400 ms) per window slice was performed. From the

windowing process, 89 chunks, or equal to 71.2 Seconds (1.18 Minutes) for each signal labelled ‘NSR’, 50 chunks or equal to 40 Seconds (0.67 Minutes) for the signal labelled ‘AFib’, 62 chunks or equal to 49.6 Seconds (0.83 Minutes) for each signal labelled ‘PVC’, 77 chunks or equal to 61.6 Seconds (1.03 Minutes) for each signal labelled ‘VTach’, and 30 chunks or equal to 24 Seconds (0.4 Minutes) for each signal labelled ‘Atrial Flutter’. The results of this windowing technique were stored in the ‘window’ variable for the classification process, resulting in 12,854 total signal data points.

E. Classification Results

The expected outcomes of the research are to analyse ECG signals in patients with cardiovascular diseases, specifically AFib, PVC, VTach, and Atrial Flutter, using the DWT method. The research also aims to classify patients based on these conditions using RF, SVM, and AdaBoost methods and to achieve optimal system performance, measured by accuracy, precision, sensitivity, and F1-Score.

1) Classification parameters using Random Forest (RF)

Model training aims to train the SVM to learn several various signal types and distinguish the specific details associated with each of the five classes. Fig. 12(a) shows the accuracy graph with a C value of 100. It can be seen that the accuracy has increased to 97.3%. The training performed shows an accuracy of 97.3% and a validation accuracy of 97.20%. The resulting loss from Fig. 12(b) shows a significant decrease in log loss as the C value increases. Initially, both the train loss and validation loss were around 0.25 for low C values, and both continued to drop significantly, reaching a log loss value of around 0.1 (C = 100). This consistent decrease indicates that the SVM model improves its ability to learn the data as the value of C increases, providing greater flexibility in separating the classes.

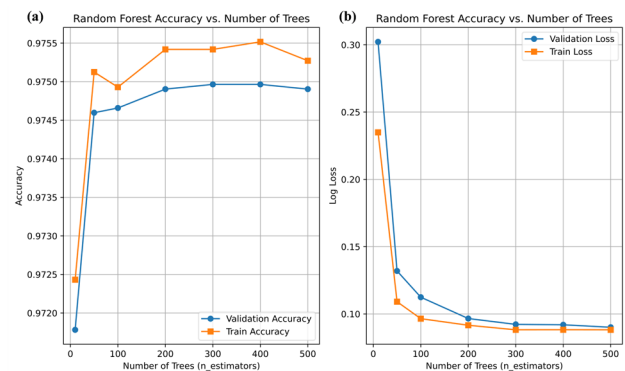


Fig. 12. Performance of RF with varying number of trees: (a) Accuracy vs. n_estimators, (b) Log Loss vs. n_estimators.

2) Classification parameters using Support Vector Machine (SVM)

The aim of model training is similar to that of the Random Forest (RF) method. Fig. 13(a) shows the accuracy graph with a C value of 100, indicating that the accuracy has increased to 97.3%. The training performed

shows an accuracy of 97.3% and a validation accuracy of 97.20%. The resulting loss from Fig. 13(b) shows a significant decrease in log loss as the C value increases. Initially, both the train loss and validation loss were around 0.25 for low C values, and both continued to drop significantly, reaching a log loss value of around 0.1 (C = 100). This consistent decrease also indicates that the SVM model improves its ability to learn the data as the value of C increases, allowing for greater flexibility in separating the classes.

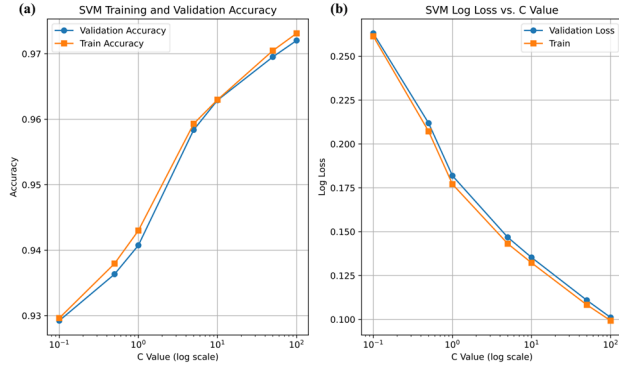


Fig. 13. Performance of the SVM model with different C values: (a) Accuracy vs. C, (b) Log Loss vs. C.

3) Classification parameters using AdaBoost

Model training for Adaboost follows a similar objective as in the RF and SVM methods. Fig. 14(a) shows the accuracy graph with 10 $n_estimators$, achieving an accuracy of 0.902 for both training and validation. The resulting loss from Fig. 14(b) shows a significant increase in 0 to 500, with train loss reaching around 1.57 and validation loss around 1.59. Increasing $n_estimators$ to 50 slightly raised training accuracy to 0.907, while validation accuracy stayed at 0.902. At 100 $n_estimators$, the validation accuracy dropped to 0.891, and the training accuracy to 0.892. Further increases caused overfitting, with both accuracies falling to 0.556 at 500 $n_estimators$. The graph indicates that increasing the number of trees beyond a certain point decreases accuracy and increases log loss in the validation set.

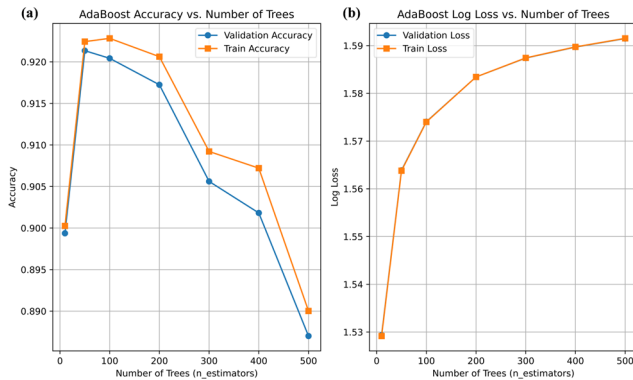


Fig. 14. Performance of the AdaBoost model with varying numbers of estimators: (a) Accuracy vs. $n_estimators$, (b) Log Loss vs. $n_estimators$.

4) Evaluation of classification results using confusion matrix

Recent research has demonstrated the effectiveness of machine learning techniques in classifying ECG signals. Nasim *et al.* [6] proposed an evolutionary-neural mechanism for arrhythmia classification using single-lead ECG, achieving high accuracy by optimising feature selection. Li *et al.* [7] introduced a biased dropout strategy combined with morphology-rhythm features, demonstrating improved model generalisation. Alinsaif [8] performed a comprehensive graph-based analysis of the MIT-BIH dataset, emphasising the significance of data representation in ECG classification.

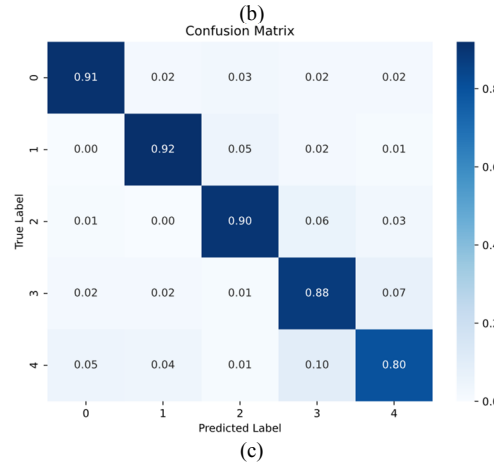
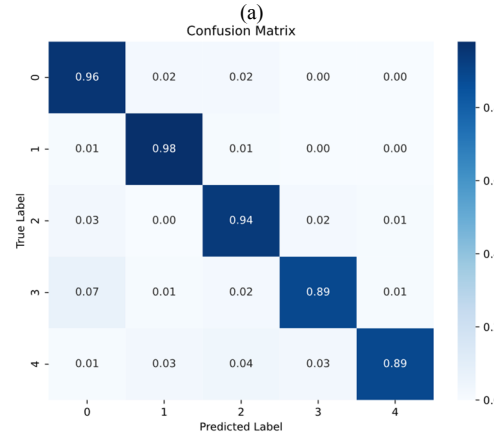
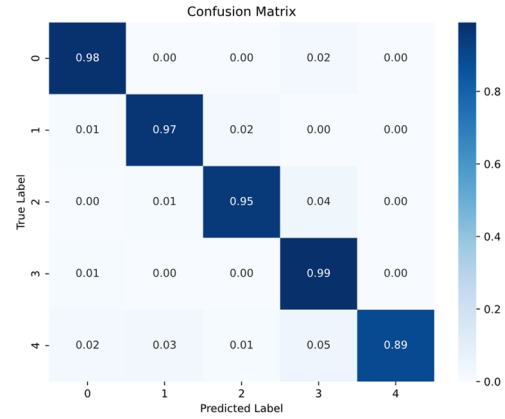


Fig. 15. Comparison of classification results using three methods: (a) Random Forest, (b) SVM, and (c) AdaBoost.

After the testing stage, the models were saved and evaluated using test data. Table II presents a comparative

summary of performance metrics for the RF, SVM, and AdaBoost classifiers, including accuracy, precision, sensitivity, and F1-Score. The evaluation of the RF model showed an accuracy of 97.50%, recall of 97.47%, F1-Score of 97.38%, and precision of 97.50%, with accuracy for NSR data at 98%, AFib at 97%, PVC at 95%, VTach at 99%, and Atrial Flutter at 89%. The SVM model achieved an accuracy of 97.20%, recall of 97.20%, F1-Score of 97.20%, and precision of 97.10%, with accuracy for NSR data at 96%, AFib at 98%, PVC at 94%, VTach at 89%, and Atrial Flutter at 89%. The AdaBoost model generated an accuracy of 90.20%, recall of 90.24%, F1-Score of 88.22%, and precision of 88.95%, with accuracy for NSR data at 91%, AFib at 92%, PVC at 90%, VTach at 88%, and Atrial Flutter at 80%. These results are further supported by the confusion matrix calculations, as shown in Fig. 15.

TABLE II. COMPARISON OF EVALUATION MATRIX PARAMETERS

Parameter	Random Forest	SVM	Adaboost
Accuracy	97.50%	97.20%	90.20%
Precision	97.50%	97.20%	88.95%
Sensitivity (Recall)	97.47%	97.2%	90.24%
F1-Score	97.38%	97.10%	89.22%

Benchmarking with previous studies reveals that deep learning models consistently achieve higher accuracy in ECG classification tasks. For example, Li *et al.* [28] utilised a deep learning approach incorporating Convolutional Neural Networks (CNN) and achieved an accuracy of 98.5% on a multi-class arrhythmia classification task. Similarly, Wang *et al.* [29] proposed a deep multi-scale fusion neural network for arrhythmia detection, reaching an accuracy of 98.2%. Moreover, Zou *et al.* [30] implemented an RF model with novel context features, achieving an accuracy of 98.0%.

Compared to these models, the RF model in this study demonstrated competitive performance, reaching 97.50% accuracy while maintaining interpretability and lower computational complexity. Although deep learning methods often outperform classical models in terms of raw accuracy, they typically require complex training pipelines, large annotated datasets, and high computational resources. In contrast, classical machine learning models such as RF and SVM offer lower computational demands and better transparency in decision-making, which is critical in clinical applications where explainability is essential. Therefore, while deep learning continues to push performance boundaries, interpretable models still provide practical and efficient solutions, especially in resource-constrained environments.

IV. CONCLUSION

Based on the results and discussion presented, the DWT method, combined with an RF architecture, can improve the efficiency of reading and analysing ECG signals. This method performs best at a $n_{estimator}$ of 100, achieving 97.50% accuracy, 97.50% precision, 97.47% sensitivity, and 97.38% F1-Score. Additionally, the resulting performance yields a training accuracy of 97.6% and a

validation accuracy of 97.50%. Compared to other methods, RF produced the highest accuracy (97.6%), followed by SVM (97.20%) and AdaBoost (90.20%). The results indicate that RF and SVM outperform AdaBoost in terms of accuracy and robustness for ECG arrhythmia classification.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

AUTHOR CONTRIBUTIONS

Melinda Melinda designed and supervised the research while providing suggestions and recommendations, including revising the manuscript; Muhammad Raja visualisation, investigation, reviewing and editing; Junidar Junidar helped interpret the results; Rizka Miftahujannah wrote the paper and analysed the data; Siti Rusdiana visualisation, investigation; Muhammad Irhamsyah Supervision, Validation, and reviewing. All authors had approved the final version.

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