



ENHANCED ECG-BASED CARDIAC DISORDER DETECTION USING RECURRENT NEURAL NETWORK ENHANCED TEMPORAL TRANSFORMER AND FIRE HAWK OPTIMIZATION

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ABSTRACT

Quick treatment and management of heart disease depend on an accurate and early diagnosis. An Electrocardiogram (ECG) is a vital indicator tool used in medical practice to evaluate cardiovascular illness. In order to tackle the challenges of cardiac classification, this study presents an innovative method based on Deep Learning (DL) approach, namely Recurrent Neural Network Enhanced Temporal Transformer (RETT). The implemented research is initiated with an Adaptive Wavelet Filter based pre-processing that enhances the quality of an ECG signal. Subsequently, the Hilbert Huang Transform (HHT) based feature extraction is exploited for extracting necessary features, which are crucial for detecting abnormalities and diagnosing heart disorders. Then, RETT classification approach is utilized for detecting the cardiac affliction accurately. Finally, the performance of a RETT approach is enhanced with the aid of a Fire Hawk Optimization (FHO) algorithm. The developed approach is executed in python software that shows the performance of DL that is useful for evaluating cardiovascular disease with an accuracy of 99.70%. This research aids in the generation of precise and effective diagnostic tools for dealing with pressing cardiac health issues.



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I. INTRODUCTION

Around the world, heart disease is regarded as one of the most hazardous and life-threatening chronic illnesses. Heart disease often arises when the heart is unable to pump sufficient blood to other body parts for them to function normally [1]. Over 64 million people worldwide endure from Heart Failure (HF), which is a clinical disease that is becoming more common. Heart failure with maintained ejection fraction is more complicated than heart failure with decreasing EF, which results in different diagnostic criteria and probably contributes to "failed" clinical studies [2]. Cardiovascular illnesses are diagnosed and evaluated by doctors using electrocardiography procedures. Experts visually evaluate the ECG signal, which is an established method in cardiology for assessing a patient's heart health is the electrocardiogram (ECG) [3].

Expert cardiologists carefully examine the ECG as part of standard medical procedures in order to diagnose potentially fatal heart arrhythmias. Cardiologists save time and obtain objective diagnostic outcomes by automatically classifying cardiac arrhythmias. The computer-aided classification and detection of ECG signals in hospitals and the health community has attracted significant economic interest due to these benefits [4], [5]. Machine learning (ML) and Artificial Intelligence (AI) have demonstrated substantial promise in automating the diagnosis of heart disease in ECG signals in recent years. By increasing the precision and effectiveness of arrhythmia detection, these technologies lessen the strain on healthcare systems [6]. A crucial step in the classification of ECG signals is feature extraction, which is a part of data representation [7]. Principal component analysis (PCA) based feature extraction, serves to simplify and improve the interpretability of models by reducing the number of features while keeping the majority of the relevant information. It is challenging to comprehend the new features (principal components) produced by PCA in terms of the original variables since they are linear combinations of the original features [8]. Because of its nonlinear character, the Kernel principal component analysis (KPCA) method in [9] is better than the PCA methodology for categorizing heartbeats from ECG signals. But compared to PCA, KPCA generates more intricate algorithms. The wavelet scattering transform, which is developed in [10], produces low variance features of real-valued signals that are usually needed in classification tasks, conserves data in high frequency and is immune to signal deformations. However, the WST employs preset wavelet filters, which isn't ideal for every kind of data or application. To overcome such issues, the Hilbert Huang transform is developed in this work for feature extraction. A method for detecting heart problems is the Support Vector Machine (SVM), which is presented in [11]. Finding the plane that divides the model's data points is challenging since there are many different ways a hyper plane is configured in an N-dimensional environment.

Even when a sizable percentage of record entries are inaccessible, the Random Forest (RF) approach, which is presented in [12], still produce the same results when applied to huge datasets. However, because RF models are ensemble in nature, they are intricate and challenging to understand. The Multilayer Perceptron (MLP), which is developed in [13], is extremely adaptable for handling complicated problems since it can approximate any continuous function. However, MLP over fits the training data in the absence of enough training data or regularization strategies. In primary care settings, CNN helps to reduce missed diagnoses and misdiagnosis while also increasing efficacy and reducing labour expenses. However, CNN necessitates meticulous adjustment of several hyper parameters, which is complicated and time-consuming [14]. The results confirm the idea that data collection is done more accurately when detecting diabetes and heart-related diseases and diagnoses using Artificial Neural Networks (ANN) classifier [15]. However, there are sustainability issues because huge neural networks require a lot of energy to train and operate. As a result, this research develops a RETT classification approach and its performance is enhanced by meta-heuristic algorithm, which includes Particle Swarm Optimization (PSO) [16], firefly optimization [17], Artificial Bee Colony (ABC) [18] and Cuckoo Search (CS) [19] and Harmony Search Optimization algorithm [20]. However, these approaches has some limitations such as, lack of diversity in the search space, expensive, slow convergence, stuck in local optima and highly sensitive. Thus, the Fire Hawk Optimization algorithm is implemented in this research for tuning the hyper parameters of a RETT classifier. The main contributions are,

- The Adaptive Wavelet Filter based pre-processing is filtering out high-frequency noise, such as interference and muscle artifacts, without affecting the important features of the ECG signal.
- Integrates the HHT based feature extraction that extracts the relevant features, which are essential for detecting abnormalities and diagnosing heart conditions.
- Implements RETT classification method for accurately predicting the cardiac affliction in an early stage.
- The Fire Hawk Optimization algorithm is exploited for fine-tuning the hyper parameters of a RETT classifier.

II. PROPOSED METHODOLOGY

The developed block diagram for predicting cardiac affliction is depicted in Figure 1. The process is initiated with capturing the ECG signal that contains the valuable data about electrical activity of heart. Nevertheless, ECG signals are contaminated with noise and artifacts, which requires a preprocessing stage. It is performed by utilizing an Adaptive Wavelet Filter that efficiently removes noise and enhances signal quality by decomposing it into distinct frequency components while conserving critical cardiac data. The next stage contains HHT based feature extraction, which is a decomposition approach that aids to analyze ECG signals by decomposing it into Intrinsic Mode Functions (IMFs). It is exploited to extract the features like instantaneous frequency and amplitude that is crucial for detecting the abnormalities in the electrical activity of heart.

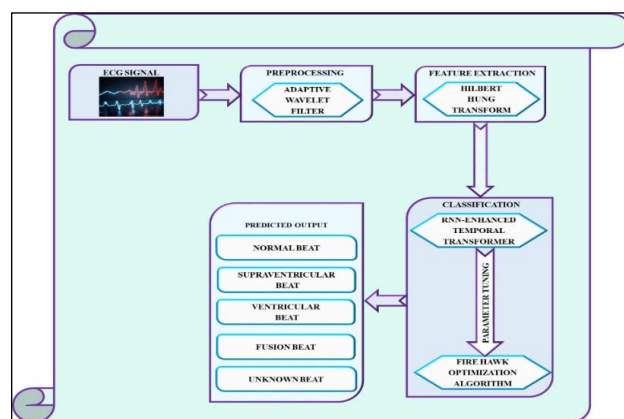


Figure 1: Proposed block diagram.
Source: Authors, (2026).

Then, the signal is fed into a RETT for classification, which is a combination of RNN and transformer based architecture, exploited to acquire temporal dependencies in ECG data. It enhances the learning efficacy by integrating attention mechanisms to concentrate on important time dependent patterns in ECG signal, making it highly effective for detecting cardiac affliction. To further enhance the performance of classifier, the Fire Hawk Optimization algorithm is utilized that fine tunes the hyperparameter of developed classifier. By optimizing parameters, ensures that the DL model attains optimal accuracy and robustness, ensures it is the reliable tool for automated diagnosis of cardiac affliction.

II.1 ADAPTIVE WAVELET FILTER

Pre-processing process is necessary in the developed system in order to enhance the signal quality. In the preprocessing phase, the ECG signal is treated to eliminate unwanted and noisy signals, improving the accuracy. Traditional FIR or IIR filters are used for filtering when the target signals and the noise's frequencies are not overlapped.

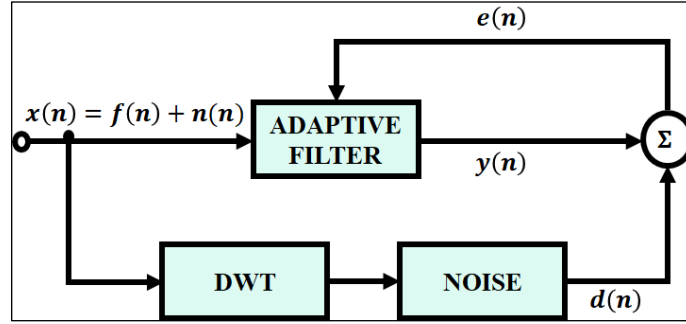


Figure 2: Structure of Adaptive Wavelet Filter Traditional wavelet transform are used to de-noise them when they partially overlap. Source: Authors, (2026).

However, for the target signal, the filtered signal is not the best estimate. There is link between the original noise and the decomposed noise of DWT that is the optimum reference signal for an adaptive filter. As illustrated in Figure 2, the input signal is,

$$x(n) = f(n) + n(n) \quad (1)$$

Where, the noise is indicated by $n(n)$, target signal is $f(n)$ and reference signal decayed form input signal in DWT is $d(n)$. Based on LMS algorithm, the adaptive rule is,

$$E[e^2(n)] = \min \quad (2)$$

The output signal is impending to target signal and filter's weight factor following this rule,

$$w(n+1) = w(n) + 2\mu e(n) \quad (3)$$

After preprocessing, the Hilbert Huang Transform is utilized for extracting the relevant feature from an ECG signal.

II.2 HILBERT HUANG TRANSFORM BASED FEATURE EXTRACTION

Hilbert spectrum analysis and EMD are 2 components of the HHT based feature extraction. A signal is broken down into a finite number of band-limited IMFs using the EMD approach. There are two fundamental restrictions on each IMF:

- (1) The number of extreme points and zero crossings in the complete data series are need to be equal or differ by no more than one.
- (2) The mean value of the envelopes produced by local minima and maxima is zero at any given time point.

A signal $x(t)$ is broken down by the EMD into n IMFs, such as $c_1(t), c_2(t), \dots, c_n(t)$ and a residue signal $r_n(t)$. The original signal $x(t)$ is,

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (4)$$

Where, i^{th} IMF is denoted by $c_i(t)$ and number of intrinsic modes is n . The Hilbert transform $c_H(t)$ for any real IMF $c(t)$ is,

$$c_H(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{c(\tau)}{t-\tau} d\tau \quad (5)$$

Where, singular integral's Cauchy principal value is P and the analytic function is,

$$z(t) = c(t) + jc_H(t) = a(t)e^{j\phi(t)} \quad (6)$$

The instantaneous amplitude $a(t)$ and phase $\phi(t)$ is,

$$a(t) = \sqrt{c(t)^2 + c_H(t)^2} \quad (7)$$

$$\phi(t) = \arctan \frac{c_H(t)}{c(t)} \quad (8)$$

The instantaneous frequency is,

$$\omega(t) = \frac{d\phi(t)}{dt} \quad (9)$$

Subsequently, the RETT classifier is utilized to accurately detect the cardiac affliction and its performance is enhanced by FHO algorithm.

II.3 FIRE HAWK OPTIMIZED RNN ENHANCED TEMPORAL TRANSFORMER

The FHO is a metaheuristic algorithm inspired by hunting strategy of hawks in nature. To move toward better positions to force prey, it spreads fire in distinct locations. In detection of cardiac affliction, the FHO is exploited to optimize the hyper parameters of the RETT classifier. Each candidate solution indicates a distinct combination of hyper parameters of the RETT classifier that are: Number of Transformer heads, Number of RNN layer, learning rate, batch size, dropout rate and hidden state rate. Each solution X_i is denoted as vector in search space,

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_j^1 & \cdots & x_d^1 \\ x_1^2 & x_2^2 & \cdots & x_j^2 & \cdots & x_d^2 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_1^i & x_2^i & \cdots & x_j^i & \cdots & x_d^i \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_1^N & x_2^N & \cdots & x_j^N & \cdots & x_d^N \end{bmatrix} \quad (10)$$

Where, number of candidate solution is represented by N , hyper parameter's initial value is $x_j^i(0)$, j th hyper parameter in the i th configuration is x_j^i , number of optimized parameter is d and i^{th} RETT hyper parameter configuration is X_i . Each hyper parameter is randomly initialized by,

$$x_j^i(0) = x_j^{i,min} + rand \times (x_j^{i,max} - x_j^{i,min}) \quad (11)$$

Where, j th hyper parameter's upper and lower bound is indicated by $x_j^{i,max}$ and $x_j^{i,min}$ and random number between 0 and 1 for diversity is $rand$.

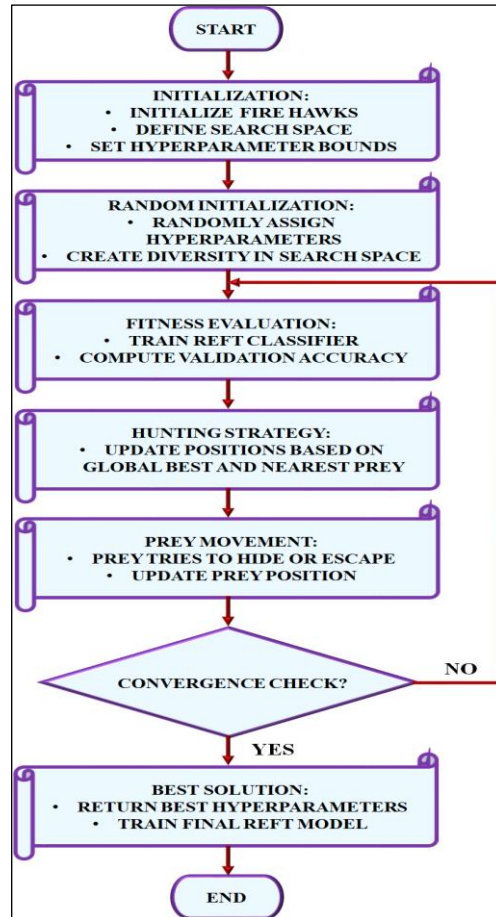


Figure 3: Flowchart of Fire Hawk Optimized RETT.
Source: Authors, (2026).

Moreover, the main fire that the Fire Hawks use first to disperse fires throughout the search space (nature) is thought to be the global best solution. These aspects are expressed mathematically as follows:

$$PR = \begin{bmatrix} PR_1 \\ PR_2 \\ \vdots \\ PR_K \\ \vdots \\ PR_m \end{bmatrix}, \quad k = 1, 2, \dots, m \quad (12)$$

$$FH = \begin{bmatrix} FH_1 \\ FH_2 \\ \vdots \\ FH_l \\ \vdots \\ FH_m \end{bmatrix}, \quad l = 1, 2, \dots, n \quad (13)$$

Where, number of prey is denoted by m , number of fire hawk is n , the k^{th} prey is PR_K and l^{th} fire hawk is FH_l . The algorithm's subsequent step determines the Fire Hawks' overall distance from the prey. Consequently, each bird's effective area is identified by identifying the prey that is closest to it. The first Fire Hawk with the best objective function value determines which prey is closest to it, while the remaining prey is used to decide the other birds' territory. By assigning stronger fire hawks to better prey, the best hyper parameters of RETT classifier are refined for detection of cardiac affliction. Each fire hawk estimates its distance to the nearest prey,

$$D_k^l = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (14)$$

Where, hyperparameter values are (x_1, y_1) and (x_2, y_2) , distance between l^{th} fire hawk and k^{th} prey is D_k^l . The algorithm's search procedure is set up by categorizing the Fire Hawks and prey. The Fire Hawk with the higher objective function value selects the closest prey inside its designated zone. The succeeding closest prey in the search space is then captured by the other Fire Hawks, proving that the strongest Fire Hawks hunt more successfully than the weaker ones. To start a fire in the chosen location, the Fire Hawks gather burning sticks from the main fire in the next phase of algorithm. In order to make the prey quickly run, each bird in this level chooses a burning stick and drops it in its designated area. In order to make the prey quickly run, each bird in this level picks up a burning stick and drops it in its designated area. Some birds are excited to use the burning sticks from the areas occupied by other Fire Hawks. Fire hawks updates the hyper parameter by,

$$FH_{new}^l = FH^l + (r_1 \times (GB - FH^l) - r_2 \times (FH_{near} - FH^l)) \quad (15)$$

Where, random value among 0 and 1 is indicated by r_1, r_2 , , global best solution is GB , hyperparameter set of l^{th} fire hawk is FH_{new}^l and nearby fire hawk is FH_{near} . The movement of prey within each Fire Hawk's territory is regarded as a vital component of animal behavior for the location updating process in the algorithm's succeeding phase. The prey are either choose to hide, flee or unintentionally run in the direction of the Fire Hawk when it drops a burning stick. Prey move toward safer zones,

$$PR_{new}^q = PR^q + (r_3 \times (FH^l - PR^q) - r_4 \times (SP^l - PR^q)) \quad (16)$$

Where, prey q 's updated hyper parameters are PR_{new}^q , random values are r_3 and r_4 and prey q 's current hyper parameters are PR^q . Inside the territory of fire hawk, the safe place is,

$$SP^l = \frac{\sum_{q=1}^r PR^q}{r}, \quad q = 1, 2, \dots, r, \quad l = 1, 2, \dots, n. \quad (17)$$

Where, safe zone is SP^l and number of preys are r . When prey escapes its original region, the hyper parameters are updated as,

$$PR_{new}^q = PR^q + (r_5 \times (FH_{Alter} - PR^q) - r_6 \times (SP - PR^q)) \quad (18)$$

Where, new fire hawk from distinct region is FH_{Alter} , random numbers are r_5 and r_6 . The new safe place outside any territory of fire hawk is,

$$SP = \frac{\sum_{k=1}^m PR^k}{m}, \quad k = 1, 2, \dots, m, \quad (19)$$

Where, total number of prey in the search space are m . The flowchart of Fire Hawk Optimized RETT is revealed in Figure 3.

Table 1: Pseudo code for Fire Hawk optimized RETT classifier.

Procedure Fire Hawk optimized RETT classifier
Step 1: Initialize Fire Hawk Optimizer (FHO) Initialize population of Fire Hawk (FH) as candidate hyperparameter sets Define search space for hyper parameters – Learning Rate (LR) $\in [0.0001, 0.01]$ – Dropout Rate (DR) $\in [0.1, 0.5]$ – Number of RNN Hidden units (HU) $\in [64, 512]$ – Number of Transformer Attention Heads (AH) $\in [2, 8]$ Set maximum number of iterations (max_Iter) Evaluate fitness for initial Fire Hawks using validation accuracy # Step 2: Main FHO search loop While Iteration < Max_Iter do: Generate n as a random integer for number of Fire Hawks Determine Fire Hawks and preys in the hyperparameter search space Calculate total distance between Fire Hawks and preys Assign Fire Hawk's territories by dispersing preys For each Fire Hawk i in n: Update Fire Hawk position For each prey q in Fire Hawk territory Compute safe place inside the Fire Hawk territory Update prey position based on SP^l Update prey position based on PR_{new}^q Compute safe place outside the Fire Hawk territory Update prey position based on PR_{new}^q End for End for # Step 3: Evaluate new solutions Train RETT with updated hyperparameters Compute fitness Update Global Best (GB) if a better solution is found End while # Step 4: Return Best Hyperparameters Return Global Best (GB) hyperparameter set for final model training End procedure

Source: Authors, (2026).

III. RESULT AND DISCUSSIONS

This section analyzes the outcomes of developed Fire hawk optimized RETT classifier for the prediction of cardiac disease. The developed research is implemented in Python software and comparative analysis is made with conventional approaches.

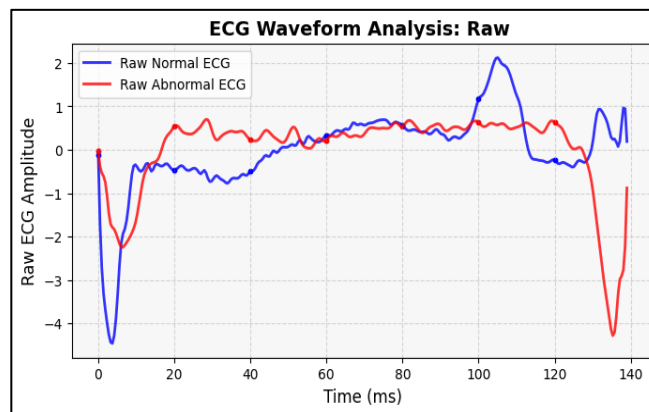


Figure 4: Analysis of ECG waveform.

Source: Authors, (2026).

The ECG waveform for identifying the cardiac disorder is represented in Figure 4 that highlights the differences among normal and abnormal heart activity patterns, which are significant in detecting cardiac disorders. The normal waveform has a constant pattern with predictable peaks whereas the abnormal waveform denotes the irregularities, representing possible disruptions in the electrical activity of heart. This analysis serves as a fundamental step in ECG-based cardiac disorder detection, enabling the identification of early signs of heart disease.

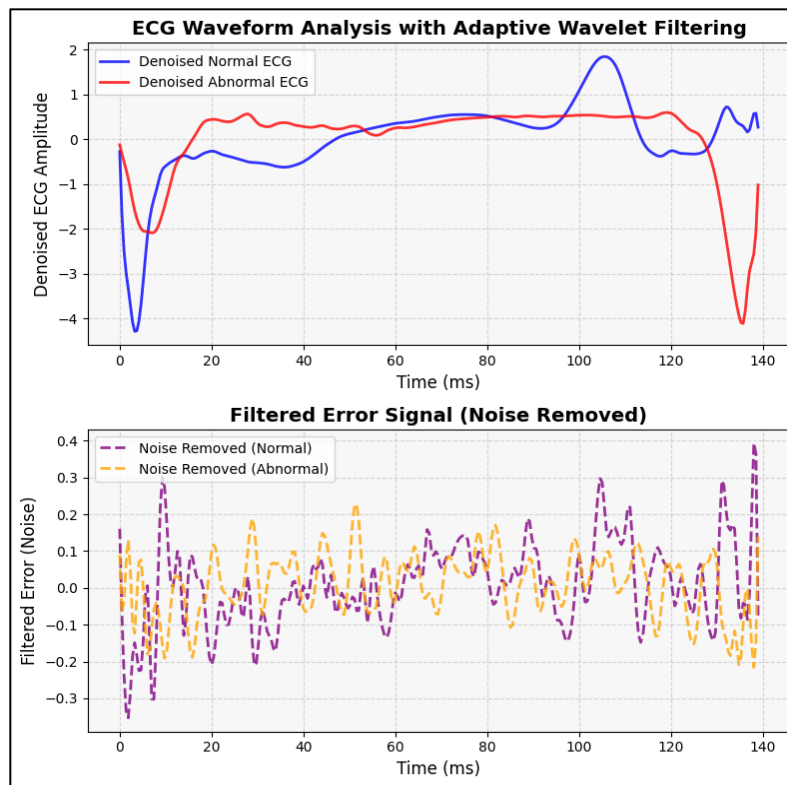


Figure 5: Pre-processed signal.
Source: Authors, (2026).

The Pre-processed signal with Adaptive wavelet filter is displayed in Figure 5. Compared to ECG signals, the denoised waveform has smoother patterns, which is easier to detect the cardiac conditions. The second graph indicates the filtered error signal, representing the noise removed from the ECG signal. The diminished amplitude and smoother denoised waveform assure the efficacy of Adaptive wavelet filter in improving ECG signal clarity. It is significant for accurately identifying cardiac disorders, as it allows better interpretation of heart's electrical activity.

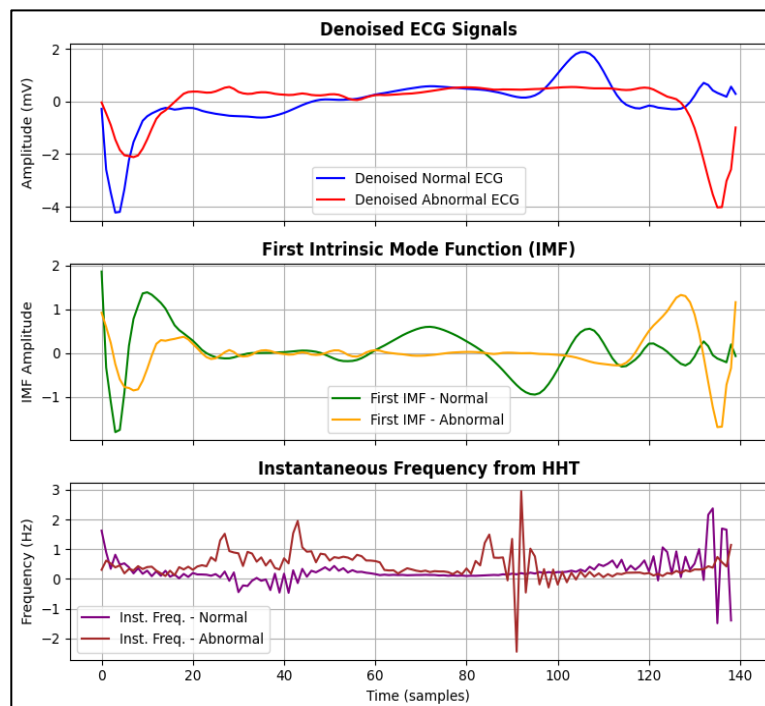


Figure 6: HHT based feature extraction.
Source: Authors, (2026).

The HHT based feature extraction for the detection of cardiac disorder is illustrated in Figure 6. The denoised signals are smoother and more distinguishable, allowing better identification of cardiac irregularities. The middle graph represents the First Intrinsic Mode Function extracted from the ECG signals. The IMF helps decompose the complex ECG signal into simpler components, aiding in better diagnosis of cardiac anomalies. Then, the instantaneous frequency from HHT provide insights into cardiac rhythm disturbances and other heart conditions. This comprehensive analysis using denoising, IMF extraction and HHT-based frequency analysis enhances the accuracy of cardiac disorder detection by capturing both frequency and time domain features.

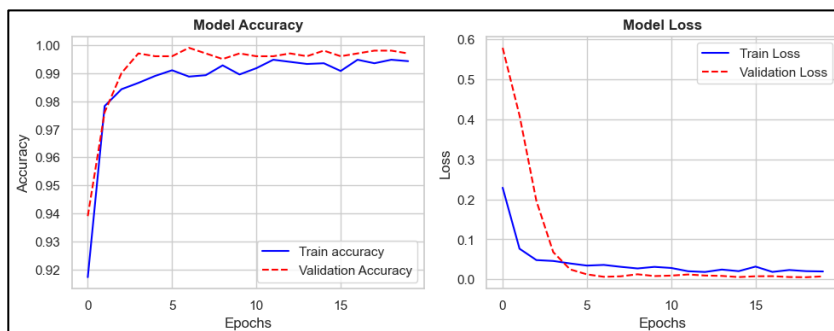


Figure 7: Training and validation results.

Source: Authors, (2026).

Figure 7 illustrates the training and validation outcomes for the detection of cardiac disorder. The validation accuracy is 99.70%, indicating that the model is efficient in learning the patterns in ECG signals. Also, it has reduced loss, denoting that model has the minimal overfitting. The high accuracy and low loss indicate that the model is well-trained and capable of distinguishing between normal and abnormal ECG signals, making it effective for detecting cardiac disorders such as arrhythmias, myocardial infarction, and other heart-related anomalies.

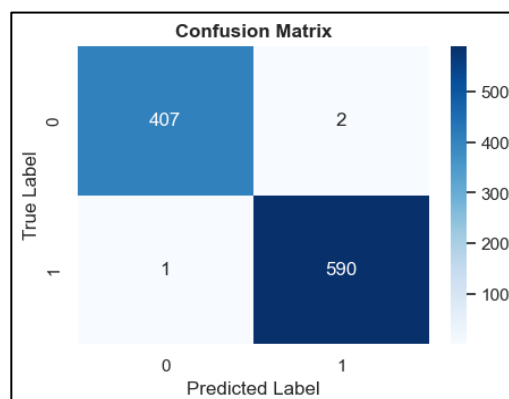


Figure 8: Confusion matrix.

Source: Authors, (2026).

The confusion matrix indicating the performance of a ML model for the detection of cardiac disorder is seen in Figure 8. The matrix compares the model's predicted labels against the true labels to estimate classification accuracy. It indicates that the model has 407 normal cases while it misclassifies 2 normal cases as abnormal. Also, it has only 1 abnormal case that is misclassified as normal and it correctly predicts 590 abnormal cases. The greater number of correct forecasts and the low number of misclassifications reflect the model's high sensitivity and specificity. It indicates that the model is highly effective in distinguishing between normal and abnormal ECG signals, which is essential for detecting cardiac disorders. The small number of false positives and negatives specifies that the model is well-trained and proficient of generalizing well to unseen data.

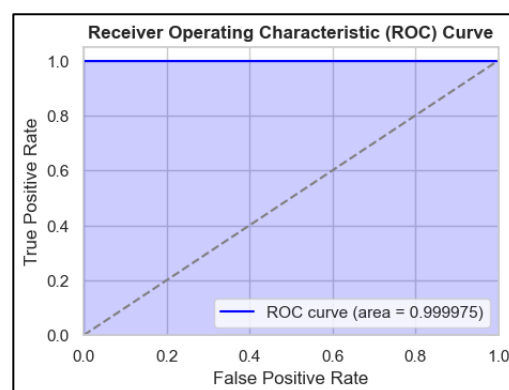


Figure 9: ROC curve.

Source: Authors, (2026).

Figure 9 reveals the Receiver Operating Characteristic (ROC) curve for ECG-based cardiac disorder detection. The ROC value is 0.999975, denotes the model has perfect capability to differentiate among normal and abnormal ECG signals. It demonstrates the model's high sensitivity and specificity, ensuring its reliability in real-world diagnostic scenarios.

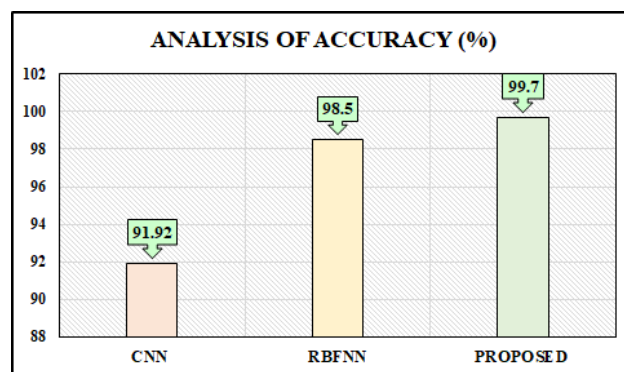


Figure 10: Analysis of accuracy.

Source: Authors, (2026).

Figure 10 represents the analysis of accuracy for Convolutional Neural Network (CNN) [21], Radial Basis Function Neural Network (RBFNN) [22] and developed approach. The developed approach outperforms both CNN and RBFNN, attaining an accuracy of 99.7%, emphasising its superior predictive capability. The results denote that the developed approach is highly effective in accurately diagnosing cardiac diseases. This analysis underscores the potential of the developed approach as a more reliable and precise tool for cardiac disease prediction.

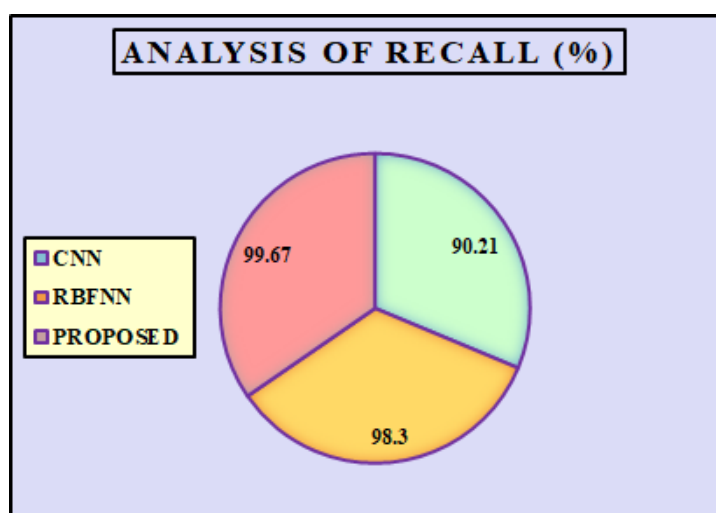


Figure 11: Analysis of Recall.

Source: Authors, (2026).

The analysis of Recall for developed approach with CNN [21] and RBFNN [22] classifier is shown in Figure 11. The developed approach surpasses both CNN and RBFNN, achieving a recall of 99.67%, indicating which is highly capable of minimizing false negatives and correctly identifying the presence of cardiac disease. The higher recall value of the developed approach indicates its superior sensitivity and improved performance in capturing true positive cases, making it more reliable for accurate cardiac disease diagnosis.

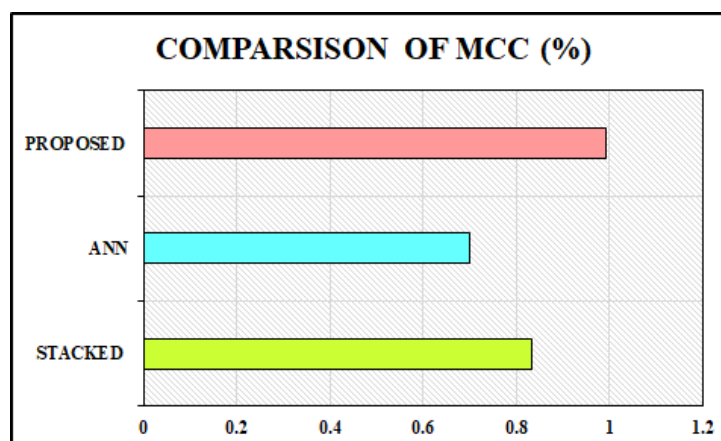


Figure 12: Comparison of MCC.

Source: Authors, (2026).

Figure 12 illustrates the comparison of Matthews Correlation Coefficient (MCC) for distinct classifier used in cardiac disease prediction. The Artificial Neural Network (ANN) [23] model demonstrates a MCC value of 0.70, reflecting a reasonable predictive capability. The Stacked model [24] attains a MCC of 0.835, presenting improved performance in handling classification challenges. However, the developed approach exhibits the highest MCC value of 0.9938, indicating stable classification of both positive and negative cases. It ensures the effectiveness of the developed approach in improving classification accuracy and overall reliability in cardiac disease prediction.

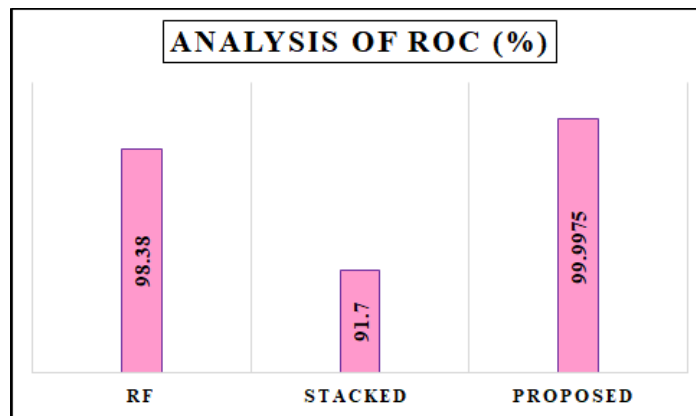


Figure 13: Comparison of ROC.
Source: Authors, (2026).

The comparison of Receiver Operating Characteristic (ROC) for stacked [24], Random Forest (RF) [25] and developed approach is displayed in Figure 13. The developed model has a higher ROC of 99.9975% than other approaches, representing it provides more accurate and reliable predictions. This superior performance indicates that the developed model is highly effective in identifying cardiac diseases with minimal misclassification, making it a valuable tool in clinical diagnosis.

IV. CONCLUSION

By classifying patient ECGs into appropriate cardiac diseases, this research develops an effective transferable DL based ECG classification system that performs autonomous ECG cardiac diagnostics. The Adaptive Wavelet Filter based pre-processing is effective in removing noise and enhancing the quality of ECG signals, which is vital for accurate diagnosis. Then, the HHT based feature extraction method improves the non-invasive diagnosis and early detection of cardiac affliction. Subsequently, the Fire Hawk optimized RETT classifier enhances the accuracy of detecting cardiac diseases by capturing both temporal dependencies and complex patterns in the data. The developed research is implemented in Python software to show the proficiency of developed cardiac affliction detection approach. The outcomes demonstrate that the developed approach performs better than other results in accurately classifying ECGs as either normal or arrhythmia with an accuracy of 99.70%.

V. AUTHOR'S CONTRIBUTION

Conceptualization: S. Dinakar Raj, Kavitha Veerappan, Jeya Bright Pankiraj, K. Sangeetha, Sumesh Joe Cherian and S. Rajeswari.

Methodology: Jeya Bright Pankiraj, K. Sangeetha, Sumesh Joe Cherian and S. Rajeswari.

Investigation: Kavitha Veerappan, Jeya Bright Pankiraj, K. Sangeetha, Sumesh Joe Cherian and S. Rajeswari.

Discussion of results: S. Dinakar Raj, Kavitha Veerappan, Jeya Bright Pankiraj, K. Sangeetha, Sumesh Joe Cherian and S. Rajeswari.

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Approval of the final text: S. Dinakar Raj, Kavitha Veerappan, Jeya Bright Pankiraj, K. Sangeetha, Sumesh Joe Cherian and S. Rajeswari.

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