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ADVANCED ECG SIGNAL ANALYSIS USING AM-RNN AND OPTIMIZED FEATURE SELECTION FOR IMPROVED CARDIAC DIAGNOSIS

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ABSTRACT

Electrocardiogram (ECG) signals are essential in diagnosis and monitoring of cardiac conditions. However, effective and accurate classification of these signals remain as a challenge, due to noisy nature of data and increased complexity in distinguishing between various cardiac patterns. This work presents novel approach for ECG signal classification through an integrated Deep Learning (DL) framework. Initially, ECG signal pre-processing is performed where normalization is done to mitigate noise and ensure consistency across the dataset. Feature extraction is conducted using Power Spectral Density (PSD) analysis, which identifies the power distribution of signal in frequency domain. To further enhance classification performance, a feature selection process is implemented using the Monarch Butterfly Optimization (MBO) algorithm, which efficiently reduces the dimensionality of feature set via choosing the relevant and discriminative features. Selected features are subsequently fed into an Attention-infused morphological Recurrent Neural Network (AM-RNN) for classification. The AM-RNN incorporates adaptable filters that adjust based on input data resulting in superior performance in classifying numerous cardiac conditions. Proposed system is implemented using Python software, and results demonstrate the superiority of the work in comparison to existing techniques.



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I. INTRODUCTION

Cardiovascular Disease (CD) or generally heart disease are one among the major deathliest diseases that affects heart and blood vessels [1]. According to World Health Organisation (WHO) around over millions of people die per day over the globe due to CD [2]. These diseases are most often difficult to recover and sometimes further causes severe diseases such as cancer, stroke, diabetes and incurable heart failure [3]. The major reason behind this deadliest disease are unhealthy eating habits, smoking, consumption of excessive alcohol and less physical activity. CD is most commonly predicted using the symptoms like chest tightness, pain, discomfort, difficulty in breathing, ankle swelling, dizziness, fatigue, weight loss and increased heartbeat [4], [5]. The intensity of these symptoms depends on the type and severity of the heart disease. Consecutively, ECG devices are utilized for capturing and recording the behaviour of heart through the electrodes, that is sensors, which are placed to the patient specific body parts, enabling to monitor heart conditions [6]. ECG is performed in various types of compositions, to identify and analyse any heart issues by the cardiologist, normally, ECG is divided into three waves as illustrated in Figure 1, the P-wave, QRS Complex and the T wave, where, P-wave describes the atria depolarization, QRS complex indicates the ventricle and prevalent amplitude depolarization at R point and T-wave imitates repolarization of ventricles [7]. However, this approach is very time consuming and cannot be accurate all the time. Therefore, designing an automated solutions for evaluating and analysing the ECG is essential [8].

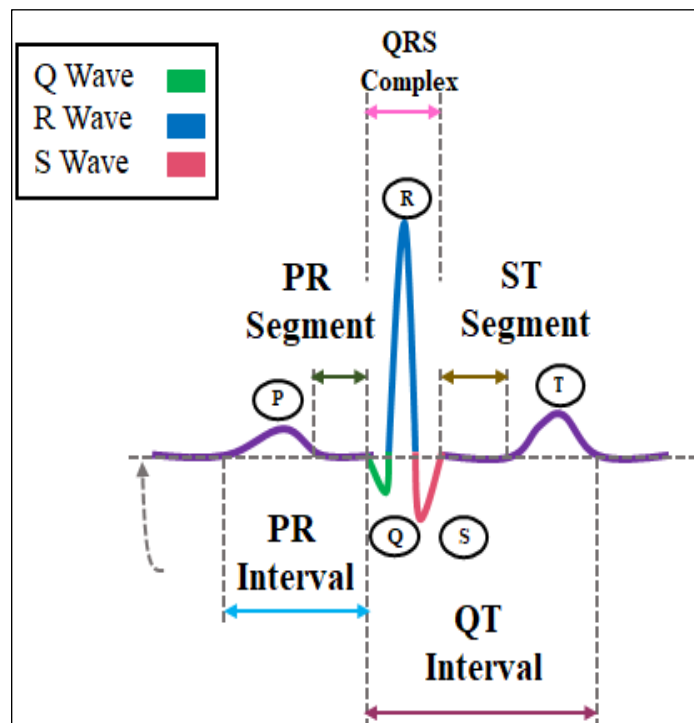


Figure 1: ECG signals.
Source: Authors, (2026).

Thus, Deep Learning (DL) based classification technique for automatic prediction of CD using ECG signals is developed. DL has the capability to analyse the complex signals, thus enabling to determine intricate patterns, extract features with reduced processing time, potentially, enhancing CD predictions [9]. There are different types of DL models available such as Long Short-Term Memory (LSTM) [10], Generative Adversarial Network (GAN) [11], Radial Basis Function Network (RBFN) [12] and Recurrent Neural Network (RNN) [13]. In particular, LSTM is capable of handling large sequential signals, providing early detection of CD including abnormal heart behaviour by analysing the intricate patterns in ECG signals. Nevertheless, LSTM suffers from computational complexity, overfitting and data quality dependencies. Significantly, GAN offers better training using minimal data, improved handling of imbalanced data, and robustness towards noise and sensor errors with more effective detection of complex and complicated CD conditions. Despite this, GAN struggles with training instability and requires large number of datasets, GAN also struggles with overfitting issues and computational intensity. Similarly, in [14] the authors utilized RBFNN based classifier for diagnosis of heart disease in patients using ECG signals. RBFNN is used as they are simple, efficient, and flexible and is capable of determining complicated signal patterns. In spite of these advantages RBFNN still cannot meet the desired performance, because they are highly sensitive towards parameters, larger amount of memory requisite, and reduced interpretability. Consecutively, the authors in [15] used K-Nearest Neighbour (KNN), classifying Phonocardiogram (PCG) signals to diagnose and predict cardiac health conditions. Utilizing KNN enables simple and easy integration with increased adaptability and flexibility. Nonetheless, KNN is not applicable due to its computational expenses and larger memory requirements. Considering these benefits and limitations of the above mentioned DL based classification models, this paper focuses on developing an Advanced ECG diagnosis using AM-RNN which enables to capture both local and global patterns with improved adaptability, flexibility and reliability. To further enhance the system performance and to improve the input signal quality, signal pre-processing, feature extraction and selection techniques are implemented. Therefore, the developed system as a whole assures accurate and effective detection of CD in patients. The major outline and contributions of the proposed system is listed below,

- To implement Signal pre-processing normalization is performed to enhance the signal quality for better classification.
- To utilize a PSD based Feature extraction technique for identifying and analyzing the signal frequencies and characteristics.
- To deploy MBO based Feature selection technique for extracting the most relevant and intricate signal features
- To employ an AM-RNN classifier for acquiring precise and accurate classification, enabling improved detection of CD.

II. PROPOSED MODELLING

Figure 2 illustrates the developed CD prediction model comprising of enhanced classifiers for achieving improved ECG signal analysis. Initially, the original signal is collected from the patient datasets, these raw signals comprises of unwanted interferences and disturbances. Thus, these signals goes through pre-processing state, where normalization is done to reduce noises and redundancies within the ECG signals. Afterwards, pre-processed signals are fed to PSD based feature extraction technique, where ECG undergoes signal analysis for identifying the domain frequencies and characteristics of signal energy distribution.

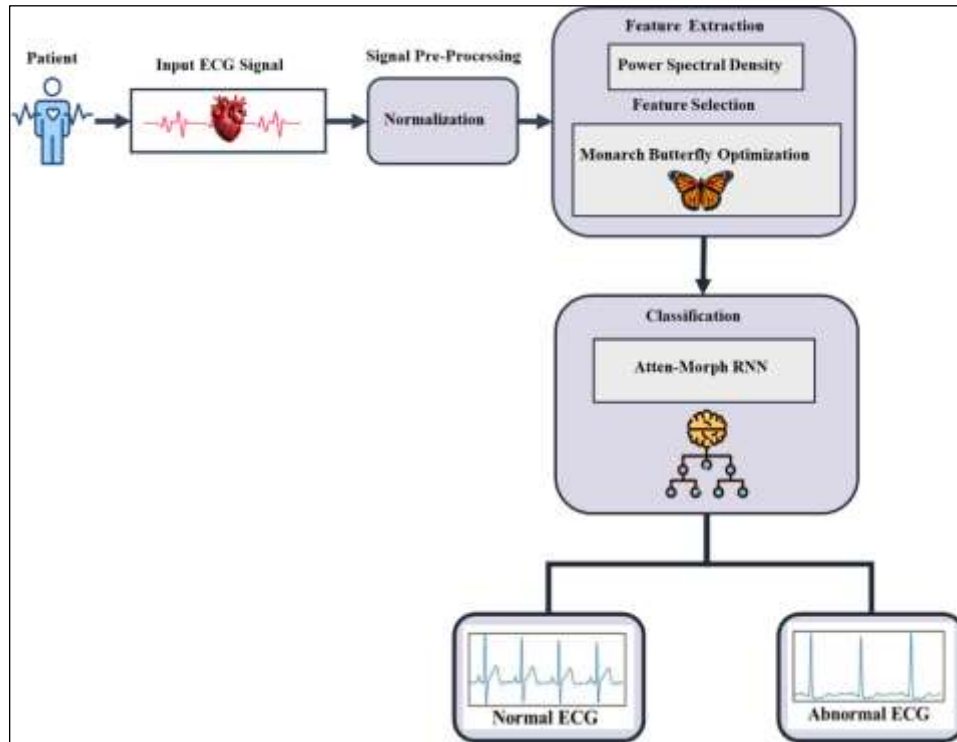


Figure 2: Proposed System Block Diagram.
Source: Authors, (2026).

Later, Feature selection using MBO is performed for selecting the more relevant and suitable feature for determining the intricate features of the ECG signals. Finally, the signal is fed to the AM-RNN based classifier for further classification process, which enables to detect or diagnose CD in patients. Therefore, the developed system as a whole ensures optimum and improved performance with accurate ECG analysis for the prediction of CD.

II.1 MODELLING OF PRE-PROCESSING STAGE (NORMALIZATION)

Pre-processing is the one among the essential stage, as noises and unwanted interference increase waves which affects the diagnosis accuracy. Significantly, ECG's comprises of certain amount of interferences, which makes pre-processing an essential stage. ECG's normally contain different types of interferences, hence, normalization is performed for enhancing the input signal quality. Normalization is the process that analyse the ECG signals and remove any unwanted noises and interferences.

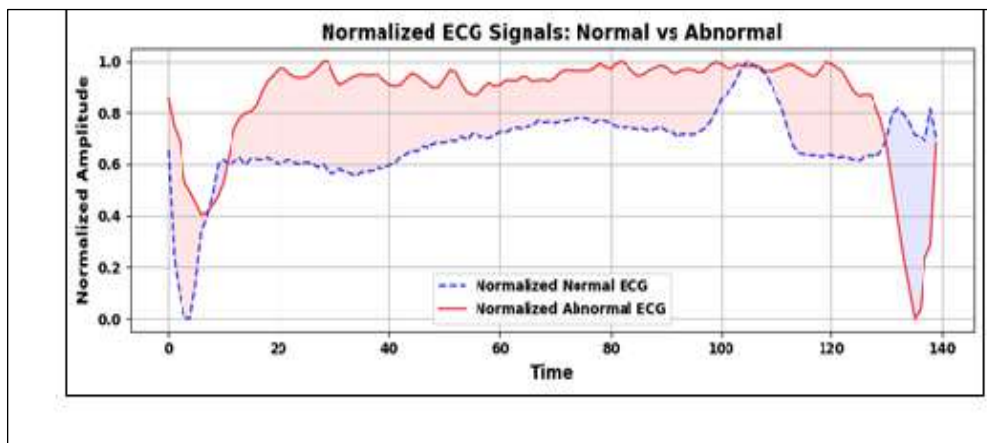


Figure 3: Normalized ECG signals.
Source: Authors, (2026).

Normalization is performed for attaining amplitude of ECG signals ranging between zero and one respectively, which expressed using,

$$\text{Normalized ECG} = \frac{x_n - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

Where, x_n denotes the ECG signals samples, $x_{\max}$ and $x_{\min}$ are the maximum and the minimum amplitude of the ECG signals. After the pre-processing state, the ECG signals undergo feature extraction using PSD which enables enhanced analysis of ECG signals making it suitable for detecting various heart conditions.

II.2 MODELLING OF POWER SPECTRAL DENSITY

The utilization of PSD based feature extraction enables to attain frequency domains form original input ECG signals, making is easier to train classifier models for accurate and precise prediction of CD. PSD or commonly power spectrum characterizes distribution of energy into frequency components consisting of energy, where energy is generally termed as area under the squared magnitude of signal regarded. Henceforth, PSD identifies frequencies, enabling to extract patterns and frequencies of signal. PSD is identified as Fourier transform of the auto-correlation function, which is the signal with slowed copy of itself as the function of delay that depends on the distribution of data points in the series.

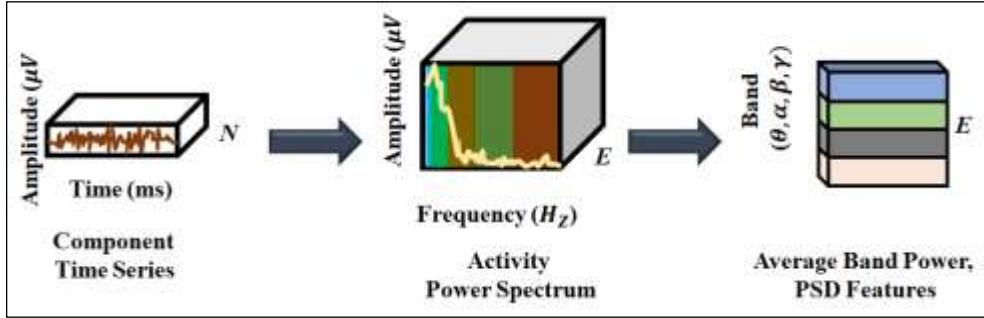


Figure 4: PSD Features.
Source: Authors, (2026).

The PSD is evaluated using Fourier transform is determined using,

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft} dt \quad (2)$$

Where, $X(f)$ indicates frequency domain, f stands frequency, t refers to time and j stands imaginary unit. Significantly, the Discrete Fourier Transform (DFT) of the signals is given by,

$$X(k) = \sum_{n=0}^{N-1} x[n]e^{-j2\pi \frac{k}{N}n} \quad (3)$$

Here, N stands number of samples and k represents frequency index respectively. After the feature extraction process, feature selection is carried out utilizing MBO algorithm, which attains optimum extraction of most relevant feature form the ECG signals.

II.3 MODELLING OF MBO BASED FEATURE SELECTION

MBO is developed based on monarch butterfly migration behaviour. MBO is significantly a population based intelligent optimization algorithm that impersonates the seasonal migration habits of monarch butterflies. The entire butterfly population is divided into two subpopulations namely subpopulation-1 and subpopulations-2 respectively, according to this, MBO comprises of two operators. The information is exchanged between both the subpopulations using the migration operator. The butterfly operator adjusts and passes only the finest information to the upcoming generations. In this approach, every monarch butterfly position determines the ECG features, hence each extracted feature is divided into subpopulations and each butterfly possess its own optimum feature with finest accuracy. Their fitness function is expressed using,

$$Fitness = \max(accuracy) \quad (4)$$

Butterfly is further update its position in two dissimilar ways such as (a) Migration and (b) Butterfly Adjusting stage.

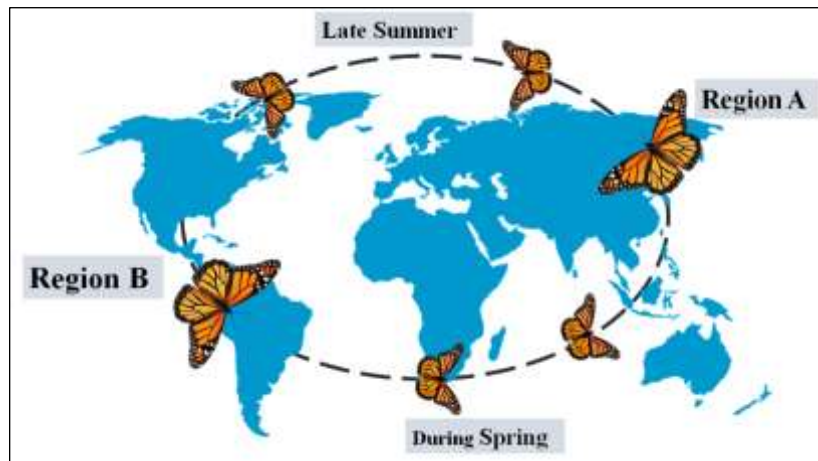


Figure 5: MBO process.
Source: Authors, (2026).

(a) **Migration:** In order to maintain butterfly population, migration process interchanges the parent butterfly position with that of next generations butterfly which is obtained using,

$$M_{i,k}^{t+1} = \begin{cases} M_{r_1,k}^t & \text{if } r \leq p \\ M_{r_2,k}^t & \text{otherwise} \end{cases} \quad (5)$$

Where, $M_{i,k}^{t+1}$ indicates k th element of M_i at $t + 1$ generation, similarly, $M_{r_1,k}^t$ stands k th element of M_{r_1} at t generation. Significantly, r_1 and r_2 stands randomly chosen from the subpopulation 1 and 2. Value of r is termed as,

$$r = rand * pari \quad (6)$$

Here, $rand$ value is assumed between $[0,1]$ and $pari$ stands migration duration set to 1.2.

(b) **Butterfly adjusting Operator:** In this state, location of butterflies in subpopulation 2 is determined and their positions relies on these points. The butterfly position is updated using,

$$M_i^{t+1} = \begin{cases} M_{best,k}^t & \text{if } rand \leq t \\ M_{r_3}^t & \text{if } rand > h \wedge rand \leq BAR \\ M_{i,k}^t + \gamma (dM_k - 0.5) & \text{if } rand > h \wedge rand > BAR \end{cases} \quad (7)$$

Here, $M_{best,k}^t$ refers k th element of present fittest butterfly in the entire population in t generation and BAR denotes the butterfly changing rate, γ value is represents as,

$$\gamma = \frac{W_{max}}{t^2} \quad (8)$$

Where, W_{max} implies the maximum distance a single butterfly can cover in the current generation. dM defines the maximum distance covered by i butterfly which is calculated using levy flight,

$$dM = levy(x_i^t) \quad (9)$$

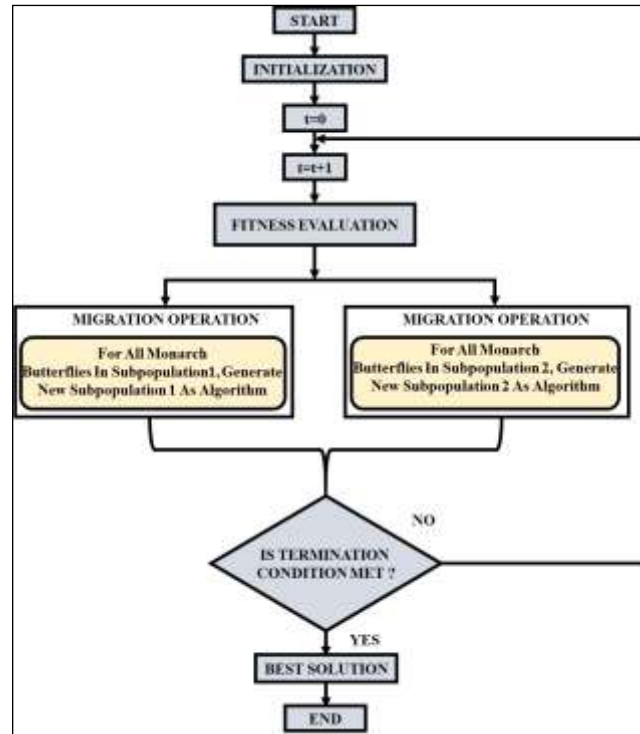


Figure 6: Flowchart for MBO algorithm.

Source: Authors, (2026).

Further, for the accurate and precise detection of CD using ECG signals, Classifier is deployed, which enables to organize ECG signals into normal and abnormal, and various heart conditions precisely. For achieving this, AM-RNN is utilized, which discussed in detail below.

II.4 MODELLING OF AM-RNN

The AM-RNN is the integration of Attention Mechanism, Morphological Operations combined with the RNN for performing classification on ECG signals. A RNN is a class of NN which connects nodes of each layer to form directed graph of temporal sequence. These recurrent connections are normally relationships between present and previous state.

RNN based classifier is widely considered due to its capability of handling sequential data for achieving enhanced predictions. Significantly, attention mechanism is incorporated with RNN to effectively analyse the signals to further augment the model prediction accuracy. The attention mechanism is utilized for modelling the relative combination between each signal of the T distinct feature maps. Particularly, it focuses on the specific extra step in the interpretation process, by determining the salient regions, designating distinct features. The ECG signals goes through Morphological layer, RNN layer, Attention layer and output layer for attaining the classification outcomes. The developed model comprises of Input layer, morphological layer, RNN layer and attention layer.

- (i) **Input Layer:** Input of the model are ECG's signals containing heartbeat characteristics. Each signal undergoes pre-processing stage, for improving the input signal quality.
- (ii) **Morphological layer:** This layer is most commonly used in signal pre-processing for extracting the signal features on the basis of their morphology or shape. Morphological process is capable of analyzing the signal characteristics such as noise and local minima. The two major operations of dilation and erosion.

Dilation: This process improves peaks and highlights substantial features of the ECG signals. The dilation process is expressed using,

$$D(X)[t] = \max_{s \in S} (X[t + s]) \quad (10)$$

Where, $D(X)[t]$ indicates the dilated signal during time t , S refers to the structuring element, $X[t + s]$ denotes the neighboring values defined by S .

Erosion: This process reduces the peaks and removes the unwanted fluctuations or noises.

$$E(X)[t] = \min_{s \in S} (X[t + s]) \quad (11)$$

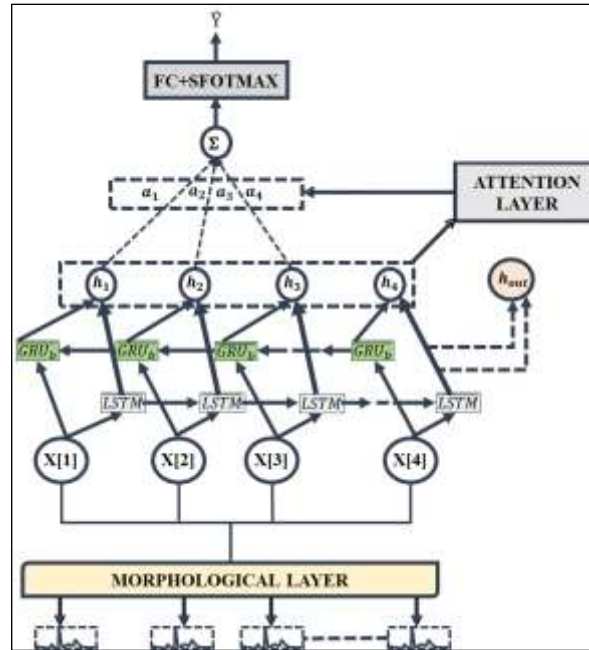


Figure 7: AM-RNN architecture diagram.

Source: Authors, (2026).

- (iii) **RNN layer:** RNN is developed for the classification and the detection of CD using ECG signals. Performance efficiency of RNN is determined using the percentage of accuracy, specificity and sensitivity. RNN is generally learning based model which follows a sequential approach. RNN's particularity is due to the connections between its hidden layers. RNN creates similar hidden layers with same weights and biases which are given as input for each step. RNN runs the process in loops, later alters its hidden state, update and store in its memory.

Gated Recurrent Unit (GRU): GRU comprises of two gates namely, reset gate and an update gate. Preceding gates define on ways to integrate new input with previous memory and other one determines amount of requisite memory needed.

LSTM: LSTM established to model temporal sequence and long-range dependencies. Its major role is memory back-up of RNN, thus, making it more accurate and precise.

- (iv) **Attention layer:** Attention mechanism in NN is inspired by the human brain behavior while dealing with problems. Consecutively, Doctors concentrate on the ECG heartbeats for CD diagnosis, rather than paying attention to the minute and intricate parts while diagnosing for CD. Therefore, the integration of attention mechanism is to allocate different weights to different parts. That is, model allocates higher weights for the present input for achieving improved diagnosis outcomes. Conversely, it allocates smaller weights when the relationship among the present and diagnosis result is un-related. The feature extracted by RNN in the hidden state $\vec{h}_1$ and $\overleftarrow{h}_1$ is given by,

$$h_{out} = [\vec{h_1}^T; \overleftarrow{h_1}^T]^T \quad (12)$$

Similarly, e_i between h_{out} and h_1 at time t is expressed as,

$$e_i = V_e^T \tan h (W_e h_i + U_e h_{out}) \quad (13)$$

The soft max function is calculated for attaining weight a_i in time i using,

$$a_i = \frac{\exp(e_i)}{\sum_{k=1}^r \exp(e_k)} \quad (14)$$

The output attained from the attention layer is the weighted average of the hidden states. Therefore, the proposed system as a whole assures ensures enhanced performance in terms of accurate and precise CD prediction.

III. RESULTS AND DISCUSSION

This section illustrates results attained by the implementation process using Python software for validating the proposed system. In addition to this, comparative analysis are also discussed to determine the efficiency and prediction accuracy.

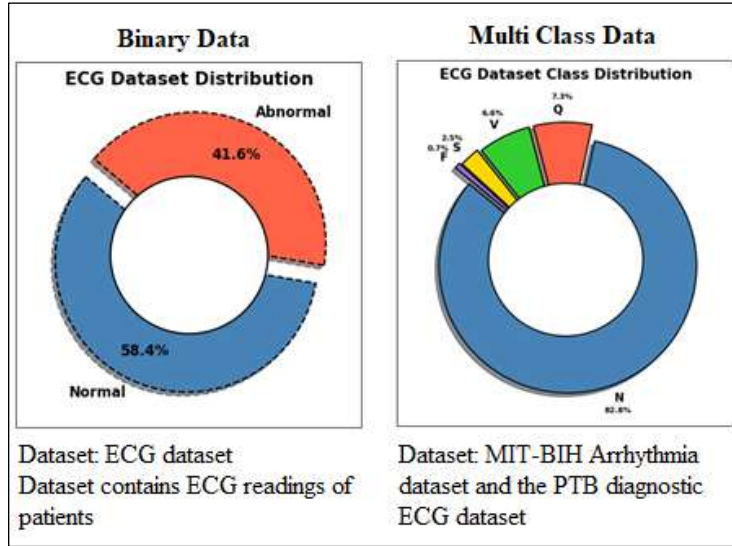


Figure 8: Input Dataset.
Source: Authors, (2026).

Figure 8 represents the two types of input dataset namely, Binary dataset comprising the ECG dataset containing ECG readings of the patients and Multi-class dataset set containing of MIT-BIH arrhythmia dataset and PTB diagnostic ECG data. According to above figure, binary dataset consists of 58.4% of normal dataset and 41.6% abnormal dataset. Significantly, the multi-class dataset is divided into Normal (N) of 82.8%, Unclassified beat (Q) of 7.3%, Ventricular ectopic beat (V) of 6.6%, Supraventricular ectopic beat (S) of 2.5% and Fusion beat (F) of 0.7% respectively.

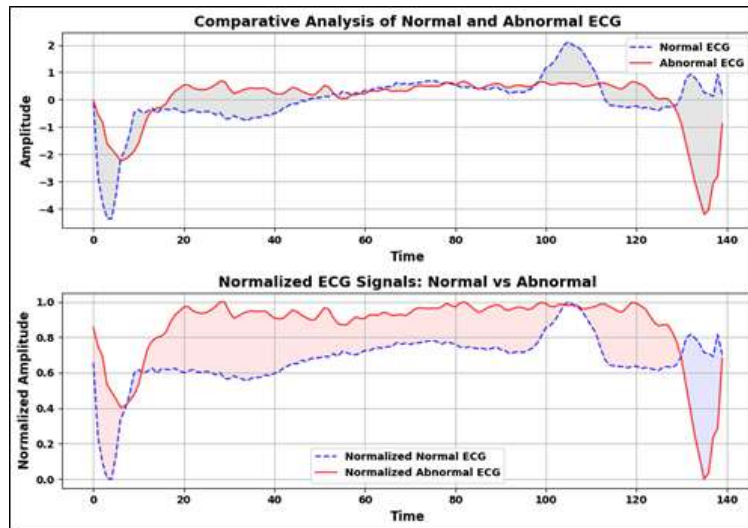


Figure 9: Normal Vs Abnormal ECG.
Source: Authors, (2026).

Figure 9 indicates the comparative analysis of normal vs abnormal dataset along with normalized ECG signals, where x-axis represents time and y-axis indicates, amplitude in first plot and normalized amplitude in the second plot. In the first graph, blue line representing normal ECG and red line representing abnormal ECG exhibits different performance in different time. Significantly, in second graph, the shaded part between both lines indicates the difference between them.

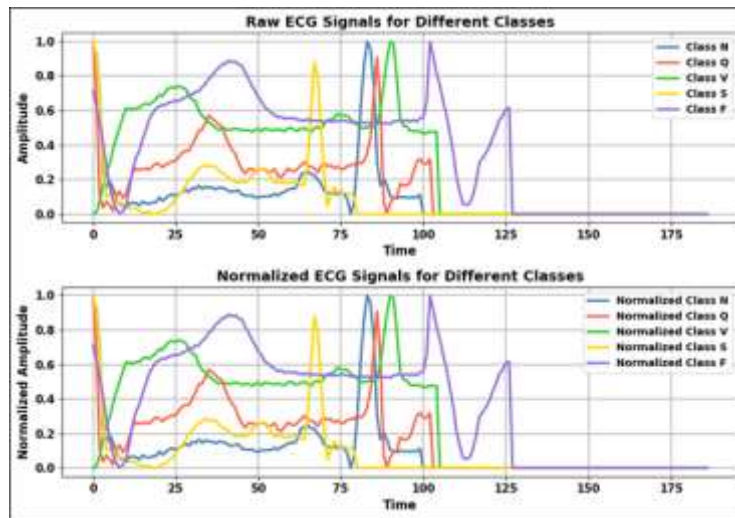


Figure 10: Raw and Normalized ECG signals for different classes.
Source: Authors, (2026).

Figure 10 implies the raw ECG signals and normalized ECG signal for various classes including N, Q, V, S and F which are differentiated using distinct coloured lines. Here, x-axis indicates the amplitude in first graph and normalized amplitude in the second graph for various classes. From the above graph it is visible that, each class exhibit different performance under varying time series, representing variations between raw and normalized ECG signals.

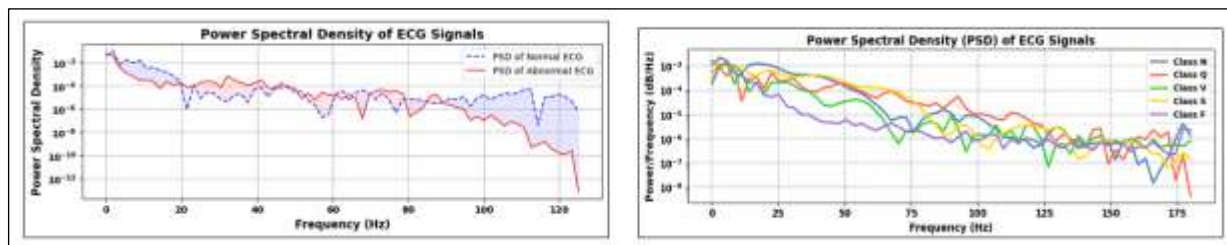


Figure 11: PSD of ECG signals.
Source: Authors, (2026).

Figure 11 refers to PSD graph for both datasets that is binary and multi-class datasets, where the first plot showcases the PSD graph for binary dataset, in which x-axis represents PSD and y-axis indicates Frequency in (Hz), here dashed blue line implies normal ECG signals and red line implies abnormal ECG signals. Similarly, second graph represents PSD for multi-class dataset comprising of various classes.

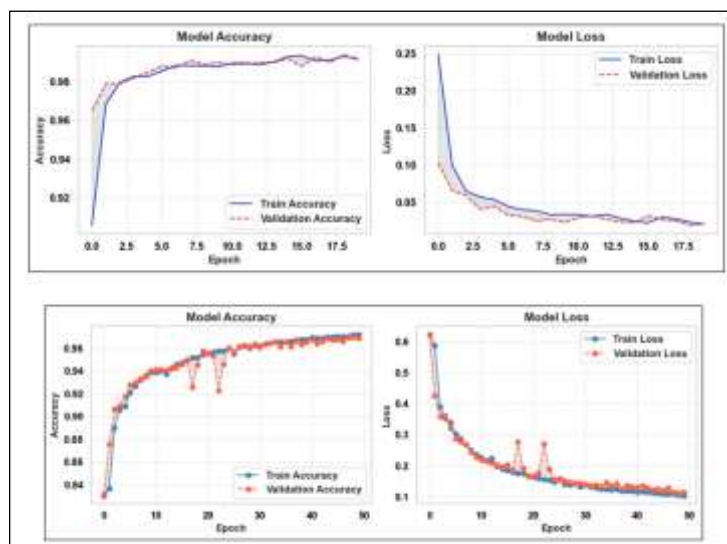


Figure 12: Model Accuracy and Loss.
Source: Authors, (2026).

Figure 12 demonstrates model accuracy and class for both datasets, where first two graph showcases model accuracy and loss for binary dataset. Here, blue line indicates the training accuracy of 99% and red line implies the validation accuracy of 99.10% with model training and validation loss below 0.05, indicating the higher prediction accuracy using binary dataset. Consecutively, the second two graphs showcases the model accuracy and loss on the basis of multi-class dataset, which depicts training accuracy of 96 % and validation accuracy of 96.69% , with training and testing losses below 0.2 respectively.

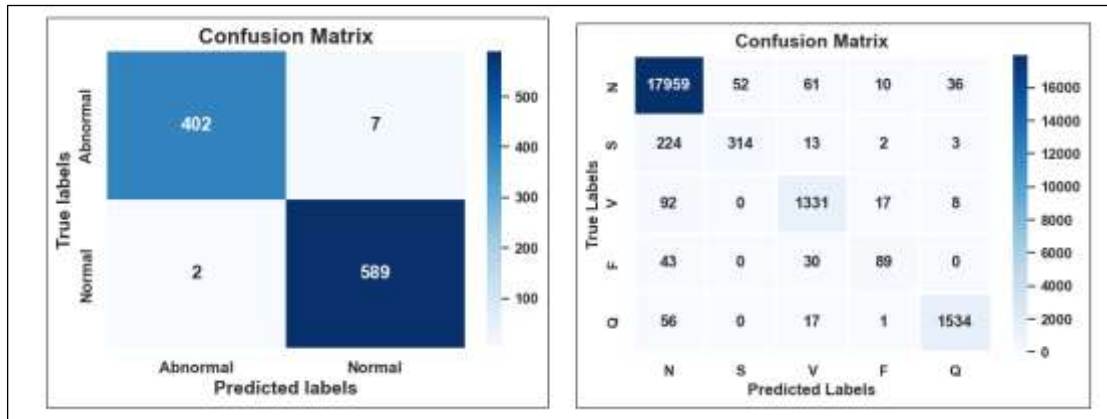


Figure 13: Confusion Matrix.

Source: Authors, (2026).

Figure 13 denotes confusion matrix for both datasets, first confusion matrix comprising of two classes namely normal and abnormal classes. Around 402 data are classified as normal, 7 abnormal data are classified as normal similarly 2 normal data are falsely classified as abnormal and around 589 data are correctly classified as normal, where the dark blue colour implies higher value prediction. Significantly, the second confusion matrix comprises of the multi-class dataset, in which around 17959 are correctly classified. Thus, both confusion matrix showcases the classification performance consisting of true and false predictions.

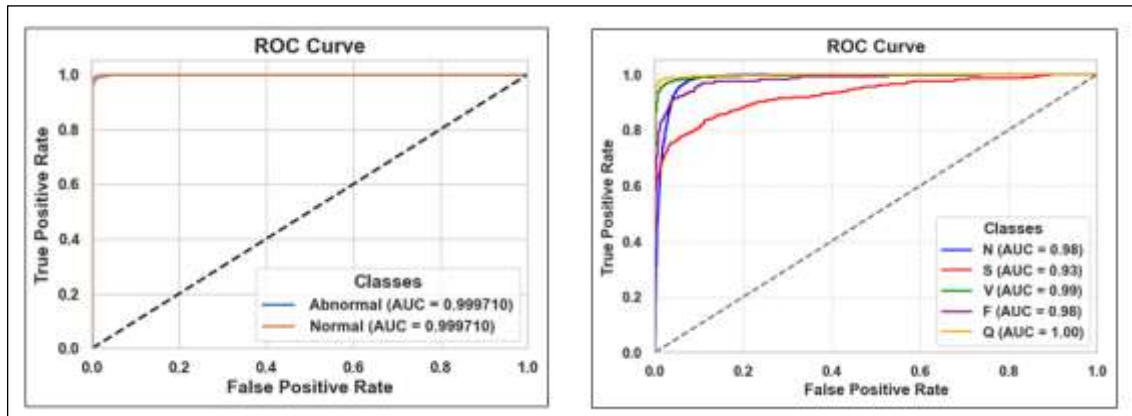


Figure 14: ROC curve.

Source: Authors, (2026).

Figure 14 represents the ROC curve for two different datasets, indicates the abnormal AUC of 0.9997, likewise normal AUC of 0.9997, the curve refers to the higher classification performance. Furthermore, the second graph showcases the ROC curve for five different classes where each class is represented using different colour, in which each class showcases distinct AUC such as N depicts AUC of 0.98, S shows AUC of 0.93, V 0.99, F 0.98 and Q 1.00 respectively. Table 1 denotes the performance metrics depicted by two different datasets in terms of performance metrics.

Table 1: Performance Metrics.

Performance Metrics (Binary Dataset)		Performance Metrics(Multi-class Dataset)	
Accuracy	0.9910	Accuracy	0.9696
Precision	0.9910	Precision	0.9681
Recall	0.9910	Recall	0.9696
F1-Score	0.9910	F1-Score	0.9680
ROC-AUC	0.9997	ROC-AUC	0.9774
Matthews Corr. Coefficient	0.9814	Matthews Corr. Coefficient	0.8979
Cohen's Kappa	0.9813	Cohen's Kappa	0.8971
Log Loss	0.0213	Log Loss	0.1141
Hamming Loss	0.0090	Hamming Loss	0.0304
Jaccard Score	0.9821	Jaccard Score	0.9427

Source: Authors, (2026).

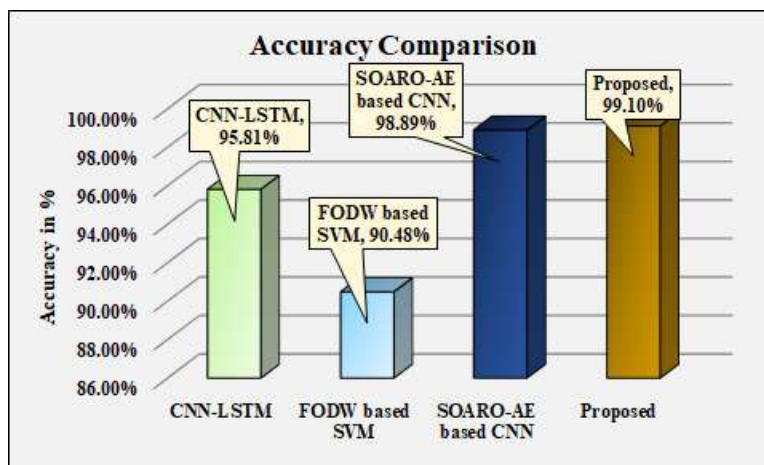


Figure 15: Accuracy Comparison.
Source: Authors, (2026).

Figure 15 indicates accuracy comparison of proposed classifier with other conventional classifiers including CNN-LSTM [16], FODW-SVM [17], and SOARO-AE [18] to evaluate performance efficacy of developed model. From above chart, it is notable that, proposed classifier achieved higher prediction accuracy of 99.10% which is slightly higher than other depicted classifiers, indicating that developed classifier provides accurate and precise detection of CD from the given two datasets.

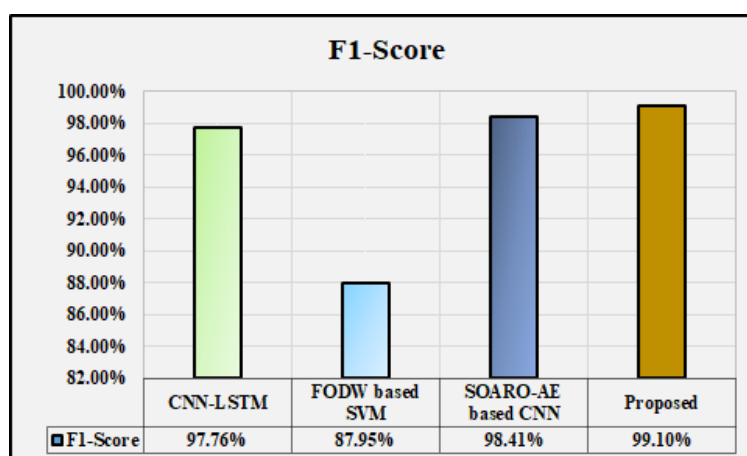


Figure 16: F1 Score Comparison.
Source: Authors, (2026).

Figure 16 represents the F1 Score Comparison in which proposed classifier showcases higher classification performance by attaining increased F1 score when compared to the other traditional approaches like CNN-LSTM depicted 97.76% F1 score, FODW based SVM of 87.95%, and SOARO-AE based CNN attained 98.41%, whereas, the proposed Atten-Morph RNN classifier showcases slightly higher F1 score of 99.10% respectively, referring to improve model performance.

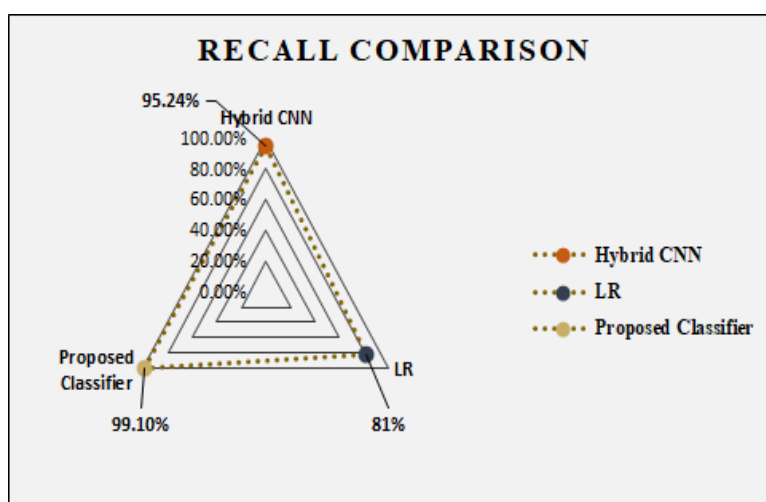


Figure 17: Recall Comparison.
Source: Authors, (2026).

Figure 17 denotes the Recall comparison between proposed AM-RNN based classifier and Hybrid CNN [19] and LR [20], where proposed model depicts increased recall score of 99.10%, while, hybrid CNN and LR attained 95.24% and 81%, indicating that, proposed model depicts improved performance in identifying the relevant positive insights within the given datasets.

IV. CONCLUSION

The proposed system using AM-RNN based classifier for ECG signal classification effectively performance well in terms of identifying various heart conditions with higher accuracy. The pre-processing done by normalization shows better performance in increasing the quality of the input signals. Significantly, implementation of PSD based feature extraction depicts well-defined analysis of signal frequencies and characteristics, enabling to identify intricate features for determining heart conditions. Likewise, the integration of MBO based feature selection ensures optimum selection of most relevant features, thereby, improving classification accuracy by removing irrelevant features. Moreover, the utilization of AM-RNN for classification assures accurate and precise detection of CD, improving the reliability and dependability of the proposed model. The developed system is validates using Python software, and the obtained results showcases the proposed techniques and approaches assures enhanced performance in terms of accuracy (99.10%). Therefore, this work contributes towards effective diagnosis of CD in patients and monitoring of patient heart conditions precisely.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

Methodology: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

Investigation: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

Discussion of results: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

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Resources: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

Supervision: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

Approval of the final text: Laid Gasmi, Nabil Laiche, Salheddine Kabou, Chikr El Mezouar Zouaoui and Abu Hammad Mamoune.

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