ECG-HO-Net: A Hybrid Deep Learning Framework for Automated Arrhythmia Detection Using Hippopotamus Optimization and Liquid Neural Networks

Md. Shamshad Begum
Department of Electronics and Communication Engineering, School of Engineering, Mohan Babu University (erstwhile Sree Vidyanikethan Engineering College), Tirupati, India
shamshad.ncet@gmail.com (corresponding author)

Nimmagadda Padmaja
Department of Electronics and Communication Engineering, School of Engineering, Mohan Babu University (erstwhile Sree Vidyanikethan Engineering College), Tirupati, India
padmaja202@gmail.com

Received: 13 April 2025 | Revised: 1 June 2025, 1 July 2025, and 24 July 2025 | Accepted: 27 July 2025

 DOI: https://doi.org/10.48084/etasr.11464

ABSTRACT

With the increasing incidence of cardiovascular disorders and the limitations of existing ECG classification methods in handling signal variability and feature redundancy, there is a pressing need for a hybrid model that ensures both accuracy and adaptability in arrhythmia detection. The proposed ECG-HO-Net combines adaptive Liquid Neural Networks (LNN) and Hippopotamus Optimization (HO) for feature selection to detect arrhythmia. The process starts with preprocessing: Butterworth filtering removes noise, min-max normalization scales signals between 0 and 1, and Pan-Tompkins detects R-peaks to segment heartbeats. Feature extraction includes time-domain metrics such as Mean Heart Rate (99.82 BPM) and RMS (0.609), along with frequency-domain analysis using FFT to capture spectral components of the ECG. The model was evaluated on the MIT-BIH Arrhythmia dataset, comprising more than 109,000 annotated heartbeats of various types of arrhythmias. The novelty of ECG-HO-Net lies in its unique integration of HO for efficient feature selection and LNNs for adaptive temporal learning. Performance analysis shows that the proposed model outperformed state-of-the-art models, achieving 99.2% accuracy, 99.71% precision, 99.51% recall, 99.73% F1-score, and 99.24% specificity.

Keywords-arrhythmia; CVD; ECG; LNN; accuracy; optimization; heart

I. INTRODUCTION

Accurate and real-time detection of arrhythmias from ECG signals remains a critical challenge due to signal noise, class imbalance, high inter-patient variability, and the computational complexity of existing models. Cardiovascular Disease (CVD) has arrhythmias as a significant contributing cause, which is still the leading cause of death worldwide [1-6]. The early diagnosis of arrhythmias depends on Electrocardiography (ECG), a widely used non-invasive technique to evaluate cardiac electrical activity [5-7]. To improve diagnostic accuracy and efficiency, automated and intelligent ECG classification models are needed, as manual ECG interpretation is time-consuming and prone to errors [8-12]. Conventional machine learning methods have limited generalizability across ECG datasets by depending on handcrafted features and manual selection approaches [13-18]. Deep learning-based models have shown encouraging results, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) [18-21]. However, they often suffer from high computational costs, overfitting, and difficulty capturing both spatial and temporal dependencies in ECG signals [22]. The contributions of this study are as follows:

- Introduces ECG-HO-Net, a novel hybrid deep learning model combining Hippopotamus Optimization (HO) for bio-inspired feature selection and a Liquid Neural Network (LNN) for capturing temporal ECG patterns.
- Preprocessing involves Butterworth filtering, min-max normalization, and Pan-Tompkins R-peak detection to enhance signal quality.
- Extracts and optimizes both time- and frequency-domain features for accurate classification.

II. RELATED WORKS

In [24], the Fourier Decomposition Method (FDM) was combined with a Support Vector Machine (SVM), which detected arrhythmias with an accuracy of 98.03%. Large datasets challenge SVM models, resulting in higher computational costs and trouble in managing non-linear ECG variations. In [25], a shallow Convolutional Neural Network (CNN) achieved 0.974 accuracy, 0.980 specificity, 0.957 precision, and 0.961 recall. However, the limited depth of the CNN model might restrict its capacity to detect deeper hierarchical features from ECG signals. In [26], a Linear Deep Convolutional Neural Network (LDCNN) achieved a remarkable accuracy of 99.38%, along with 99.60% precision, 99.40% recall, and 99.60% F1-score. However, the linearity constraint of this model might restrict feature interactions in extremely nonlinear ECG signals. In [27], a stacked CNN model achieved 94.2% accuracy and F1-score in arrhythmia classification, but this complex model has increased computational cost and possible overfitting on smaller datasets.

In [28], a deep learning model achieved an accuracy of 98.9%. However, the main disadvantage of conventional deep learning methods is their reliance on computationally costly training techniques and big annotated datasets. In [29], a Naïve Bayes (NB) classifier achieved an accuracy of 88.05%, which is a limited performance in ECG classification due to its feature independence assumption, since ECG signals have highly correlated and sequential properties. In [30], a fusion model included Continuous Wavelet Transform (CWT), achieving accuracy, sensitivity, and specificity of 98.5%, 98.5% and 95.6%, respectively. However, a significant drawback of CWT-based models is their high computational demand, making real-time deployment difficult. In [31], a Generative Adversarial Network (GAN) was used for arrhythmia identification. However, GANs are famously challenging to learn and call for computational resources and significant hyperparameter tuning. Recent Transformer-based deep learning models have emerged as powerful tools for ECG analysis. ECGformer [32] leveraged the self-attention mechanism of the Transformer architecture to classify ECG signals.

III. PROPOSED SYSTEM

Figure 1 shows the proposed method for detecting and classifying arrhythmias from ECG data. ECG signals are preprocessed with filtering, normalization, and R-peak detection, and then features are selected using the HO algorithm. The MIT-BIH dataset (80:20 split) was used to train and test a lightweight LNN with two hidden layers (64 and 32 neurons), ReLU activation, leak rate of 0.35, and Softmax output. This setup ensures accurate, efficient multi-class arrhythmia detection.

The proposed method, called ECG-HO-Net, is a hybrid framework that integrates HO for feature selection and LNNs for adaptive learning. Each ECG signal can be represented as a time-series function:

$$ECG(t) = A \cdot \sin(2\pi f t + \phi) \quad (1)$$

where A is the amplitude of the signal, f is the heart rate frequency, t is time, and ϕ is the phase shift.

Data preprocessing follows data collection to improve the ECG signal's usability and quality. A Butterworth low-pass filter is applied to remove high-frequency noise:

$$H(f) = \frac{1}{\sqrt{1+\left(\frac{f}{fc}\right)^{2n}}} \quad (2)$$

where f_c is the cutoff frequency, and n is the filter order. Min-max normalization is applied to standardize ECG amplitude across all samples:

$$ECGnorm(t) = ECG(t) - \frac{min(ECG)}{max(ECG)-min(ECG)} \quad (3)$$

This scales values between 0 and 1 for better comparability.

ECG signals are segmented based on R-peaks, identified using the Pan-Tompkins algorithm:

$$Rpeak = argmax_t\left(\frac{d^2ECG(t)}{dt^2}\right) \quad (4)$$

Each segment represents a heartbeat cycle containing P-QRS-T waves.

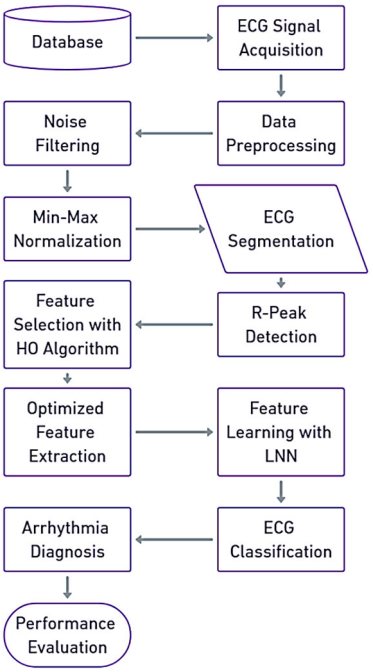

Fig. 1. Block diagram of the proposed system.

Feature selection is optimized using the HO algorithm, which mimics the behavior of hippopotamuses in their habitat. The HO algorithm was configured with a population of 30 and run for 50 iterations. It is a bio-inspired, population-based method used for ECG feature selection. Each agent represents a binary vector indicating selected features. The algorithm alternates between exploration (searching new regions) and exploitation (refining near-optimal solutions). A fitness function evaluates solutions by balancing classification accuracy and feature reduction. The process runs for 50 iterations, selecting the best feature subset for input to the LNN classifier. The fitness function used in HO is based on

maximizing classification accuracy Acc while minimizing the number of features N_f:

$$F = w_1 \cdot Acc - w_2 \cdot N_f / N_{Total} \quad (5)$$

where w_1, w_2 are weight factors, and N_{total} is the total number of features.

HO was chosen for its better balance between exploration and exploitation and faster convergence than PSO, GA, and ACO. Unlike PSO and ACO, which can prematurely converge or get stuck in local minima, HO dynamically adjusts search intensity, making it ideal for precise and efficient ECG feature selection in high-dimensional spaces.

Key time-domain and frequency-domain features are extracted from the optimized feature set. Mean Heart Rate (HR) is given by:

$$HR = \frac{60}{\overline{RR}} \quad (6)$$

where $\overline{RR}$ is the average time interval between R-peaks. RMS is given by:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{n} ECG_i^2} \quad (7)$$

The power spectrum $P(f)$ is extracted using the Fast Fourier Transform (FFT):

$$P(f) = \left| \sum_{t=0}^{T} ECG(t) e^{-j2\pi ft} \right|^2 \quad (8)$$

which helps distinguish between normal and arrhythmic beats.

Model training uses the LNN component of ECG-HO-Net. The LNN architecture includes an input layer, two hidden layers (64 and 32 neurons), a leak rate of 0.35, ReLU activation, and a final Softmax layer for classifying into five arrhythmia types. The LNN neuron state is updated using:

$$h_t = (1 - \alpha) h_{t-1} + \alpha f(W x_t + b) \quad (9)$$

where h_t is the hidden state at time t, α is the leak rate, $f(\cdot)$ is the activation function (ReLU or tanh), W and b are weight parameters, and x_t is the input feature at time t. LNN was chosen over LSTM and GRU for its dynamic and continuous-time neuron states that adapt to changing ECG signals. Unlike the fixed gates and heavier computations of LSTM, LNNs offer lightweight, flexible dynamics that track temporal and morphological ECG variations more effectively. The model classifies ECG signals into different arrhythmia categories using softmax activation, where the probability of a class is given by:

$$P(y_i) = e^{z_j} / \sum_{j=1}^{C} e^{z_j} \quad (10)$$

where z_i is the model output for class i, and C is the total number of arrhythmia classes. The model outputs diagnostic feedback with probability scores and predicted arrhythmia class:

$$ArrhythmiaType = argmax P(y_i) \quad (11)$$

Finally, the proposed model's performance was evaluated using accuracy, sensitivity, and specificity.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (13)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (14)$$

where TP, TN, FP, and FN denote True Positive, True Negative, False Positive, and False Negative counts, respectively.

IV. PROPOSED MODEL

The proposed ECG-HO-Net is a hybrid deep learning framework combining the strengths of LNNs for adaptive learning and the HO algorithm for optimal feature selection, which is potent in arrhythmia detection from ECG signals. ECG-HO-Net's architecture ensures an adequate selection of the most informative features for classification while handling the intrinsic variability in ECG signals. Using HO for feature selection, the first stage of the network searches the feature space to find the most pertinent characteristics that help to classify arrhythmia. Search agents, or hippopotamuses, simplify the model by eliminating less important and redundant elements, thus improving its generalizing capacity. Then, LNN, a dynamic neural network that detects both short-term and long-term dependencies in ECG waveforms, receives the ideal feature set. Unlike conventional deep learning architectures, LNN uses a time-continuous state representation, which qualifies for processing sequential physiological signals.

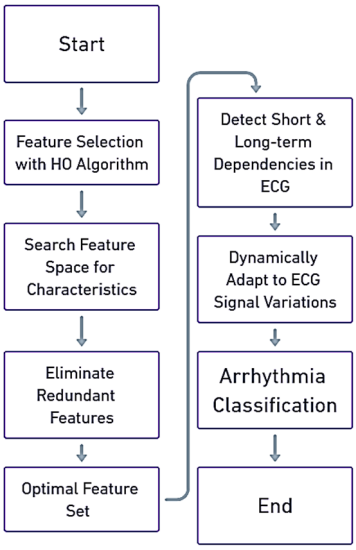

Fig. 2. Architecture of the proposed model.

A. Algorithm of the Proposed Model

The algorithm below describes the key components of ECG-HO-Net, focusing on feature selection with HO, feature extraction, adaptive learning with LNN, and arrhythmia classification.

```
Algorithm: ECG-HO-Net
1: Input ECG Signal
   Collect raw ECG signals from datasets.
```

```
   Preprocess by filtering noise and
   normalizing data.
   Segment signals based on detected R-
   peaks.
2: Feature Selection using HO
   Initialize a population of hippopotamus
   agents with random positions
   (features).
   Evaluate fitness based on
   classification accuracy.
   Update hippopotamus positions.
   Select the optimal feature subset for
   classification.
3: Feature Extraction
   Extract time-domain features
   Extract frequency-domain features using
   FFT.
4: Train Liquid Neural Network (LNN)
5: Classification
   Apply the softmax function to classify
   arrhythmia types.
6: Diagnostic feedback
   Generate a report with the detected
   arrhythmias
   Provide real-time predictions
```

V. RESULTS AND DISCUSSION

The MIT-BIH Arrhythmia Database, developed by the MIT Division of Health Sciences and Technology, is a benchmark dataset in cardiac electrophysiology [23]. It contains 48 half-hour two-channel ambulatory ECG recordings from 47 subjects (60% inpatient, 40% outpatient), sampled at 360 Hz with 11-bit resolution. Designed to cover a wide range of arrhythmic patterns, it includes 109,443 annotated heartbeats classified into five AAMI-standard classes: normal (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). The dataset reflects real-world class imbalance, with 89,694 normal beats and fewer arrhythmic beats (e.g., 7,266 supraventricular ectopic, 7,135 ventricular ectopic).

TABLE I. DATASET DISTRIBUTION

Class	Heartbeat count
Normal (N)	89,694
Supraventricular (S)	7,266
Ventricular (V)	7,135
Fusion (F)	802
Unknown (Q)	4,546

Figure 3 shows ECG data taken from the BIT MIH database, with a small amount of noise to replicate a typical ECG trace and a basic sinusoidal waveform including harmonics. Figure 4 shows ECG data before and after a Butterworth low-pass filter. While the filtered signal (red) is smoother, the original data in light opacity showcases some high-frequency noise.

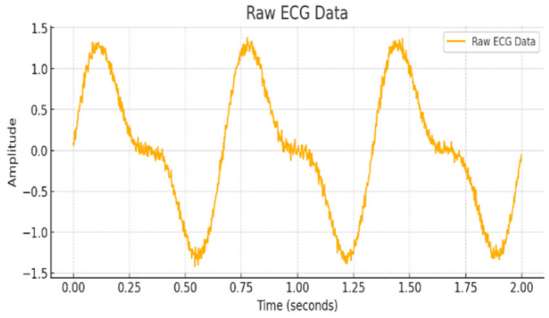

Fig. 3. Raw ECG signal.

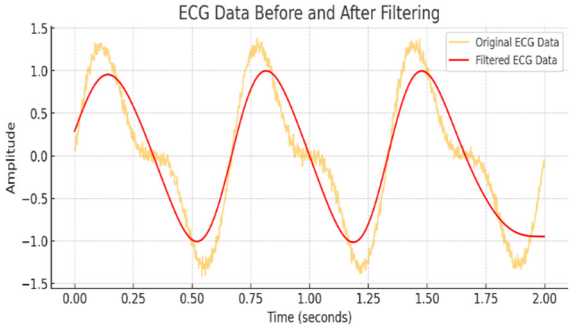

Fig. 4. Filtered ECG data.

Figure 5 displays ECG data both before and after min-max normalization. The filtered data, shown in semi-transparent yellow, was converted to the normalized data shown in green, with the amplitude normalized in the range of 0 to 1.

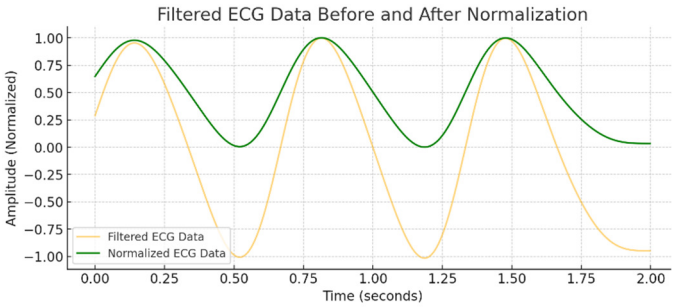

Fig. 5. Normalized ECG signal.

Figure 6 shows the normalized ECG data with red 'R'-marked R-peaks. A basic thresholding technique can be used to find the R-peaks, highlighting the sites where the ECG signal achieves maximum amplitude in every cardiac cycle. The frequency components of the ECG signal shown in Figure 7 help identify frequency-domain features relevant for arrhythmia classification through the FFT plot. Figures 6 and 7 show the time-domain and frequency-domain aspects of the ECG signal, respectively. Based on R-peak intervals, the mean Heart Rate (HR) is approximately 89.82 BPM, and the Root Mean Square (RMS) value of the ECG signal is 0.609, indicating the general strength of the signal.

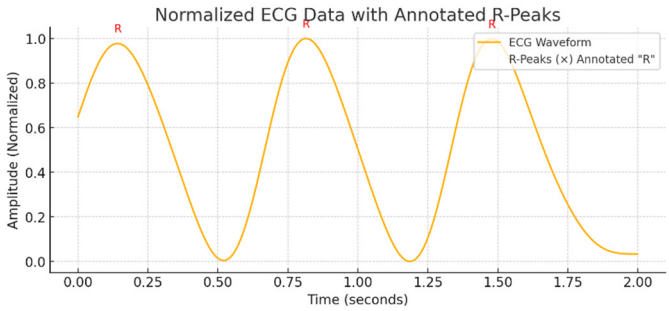

Fig. 6. Normalized ECG with R-Peaks.

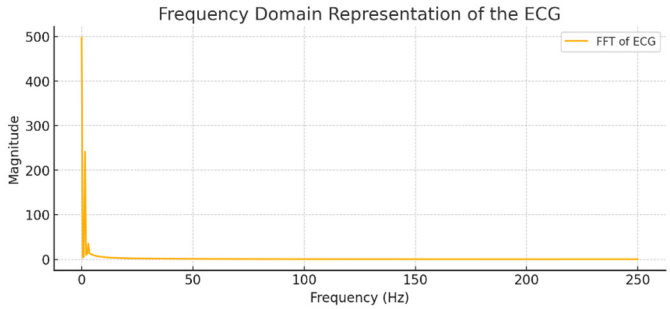

Fig. 7. FFT of ECG.

Plotting the RR intervals, Figure 8 emphasizes the variation in time between consecutive R-peaks. The red dashed line shows the mean RR interval, which approximates the overall heart rate variability. Examining the two features, Figure 9 shows a scatter plot of RR intervals against RMS values.

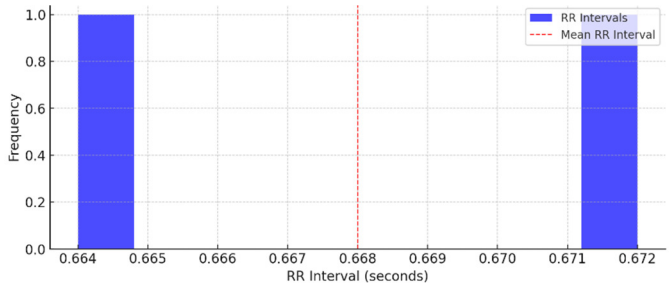

Fig. 8. Distribution of RR intervals

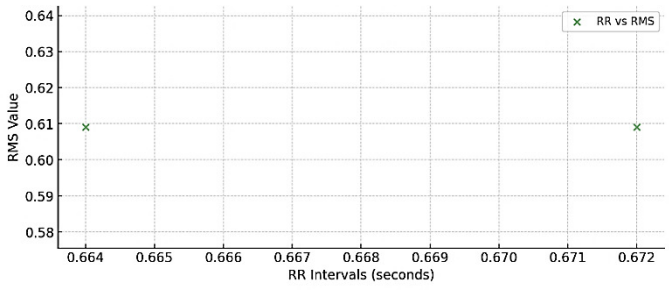

Fig. 9. Scatter plot.

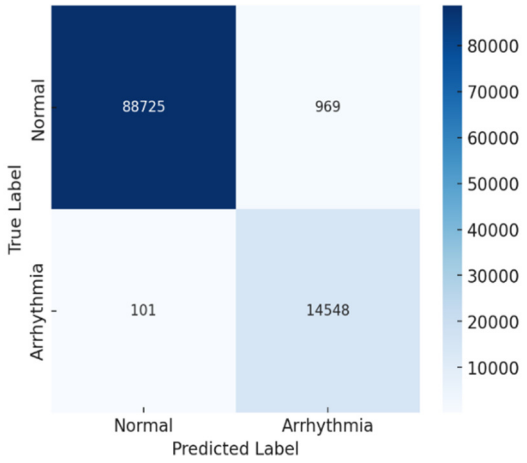

Fig. 10. Confusion matrix.

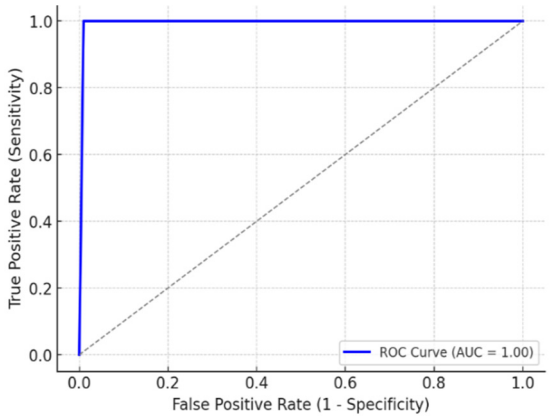

Fig. 11. ROC curve.

In the ECG-HO-Net model, the confusion matrix in Figure 10 shows its classification performance in differentiating regular and arrhythmic beats. Of 89,694 normal beats, the matrix shows that 969 were misclassified as arrhythmic beats, while 88,725 were correctly classified as normal. Likewise, of the 14,649 arrhythmic beats, 14,548 were correctly identified and 101 were incorrectly labeled as normal beats. The low number of misclassifications ensures that the model reduces false alarms and missed arrhythmia detections. For the ECG-HO-Net model, the ROC curve in Figure 11 stays much above the diagonal baseline, suggesting that the model beats random guessing dramatically. Approaching 1.0, the Area Under the Curve (AUC) value confirms even more the strong discriminative power of the model, ensuring the reliability of arrhythmia detection.

The error distribution plot in Figure 12 exposes the misclassification patterns in the ECG-HO-Net model, especially the FP and FN. The model noted 101 FN, where arrhythmic beats were misclassified as normal, and 969 FP, where normal beats were falsely identified as arrhythmias.

Fig. 12. Error distribution.

Table II compares several arrhythmia detection models, traditional and DL-based. The outstanding accuracy of 99.2% makes the proposed model the second best among all current models. The results in Table II are directly taken from the respective studies cited in the Related Works section [24-31]. These models were primarily evaluated using the MIT-BIH Arrhythmia dataset or other standard ECG datasets. The comparison shows that while existing models such as LDCNN [26] achieved high accuracy (99.38%), the proposed ECG-HO-Net achieved 99.2% accuracy with a lightweight and computationally efficient framework. Figure 13 shows the visual trend of accuracy.

TABLE II. ACCURACY COMPARISON

Model	Accuracy (%)
Fourier +SVM [24]	98.03
Shallow CNN [25]	97.4
LDCNN [26]	99.38
Stacked CNN [27]	94.2
Traditional Deep Model [28]	98.9
Naïve Bayes [29]	88.05
Fusion Model with CWT [30]	98.5
GAN Model [31]	98.22
ECG-HO-Net (proposed)	**99.2**

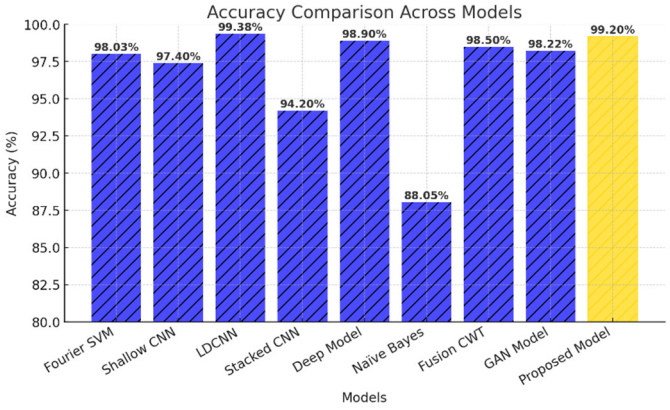

Fig. 13. Accuracy comparison plot.

A comprehensive review of recent studies on ECG-based arrhythmia detection reveals that the MIT-BIH Arrhythmia Database is the most widely utilized dataset across the literature. Specifically, the studies in [24-31] employed the MIT-BIH dataset to train and evaluate their machine or deep learning models. The study in [28] stands out by incorporating multiple publicly available datasets, including MIT-BIH, PTB-XL, and INCART, to facilitate a more robust comparative analysis among diverse ECG sources. Additionally, the study in [31] used a combination of MIT-BIH and private clinical ECG recordings, enhancing the generalizability of their deep learning framework (ElectrApp) using real-world hospital data. This consistent reliance on the MIT-BIH dataset reflects its widespread acceptance and standardization in the field of arrhythmia classification research.

Table III shows the precision values for some chosen models. With a precision of 99.71%, the proposed model beats earlier works. Figure 14 graphically shows the precision comparison, stressing the model's effectiveness in lowering false alarms.

TABLE III. PRECISION COMPARISON

Model	Precision (%)
Shallow CNN [25]	95.7
LDCNN [26]	99.60
Fusion Model with CWT [30]	98.5
GAN Model [31]	97.07
ECG-HO-Net (proposed)	**99.71**

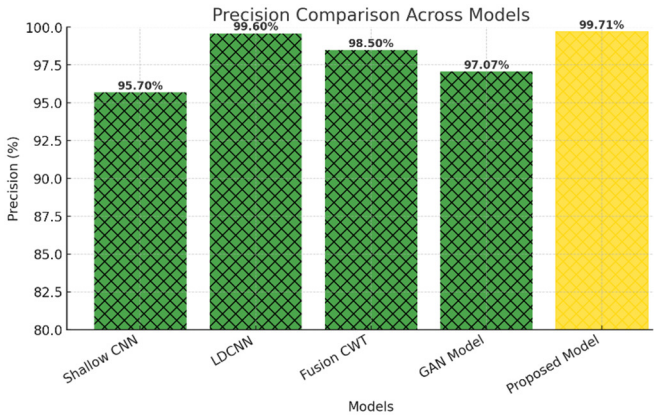

Fig. 14. Precision comparison plot.

Table IV provides a detailed recall comparison showing every model's degree of actual arrhythmic beat identification. With a recall of 99.51%, the proposed model can capture actual positive cases with minimum false negatives.

TABLE IV. RECALL COMPARISON

Model	Recall (%)
Shallow CNN [25]	96.1
LDCNN [26]	99.40
Fusion Model with CWT [30]	98.5
GAN Model [31]	96.95
ECG-HO-Net (proposed)	**99.51**

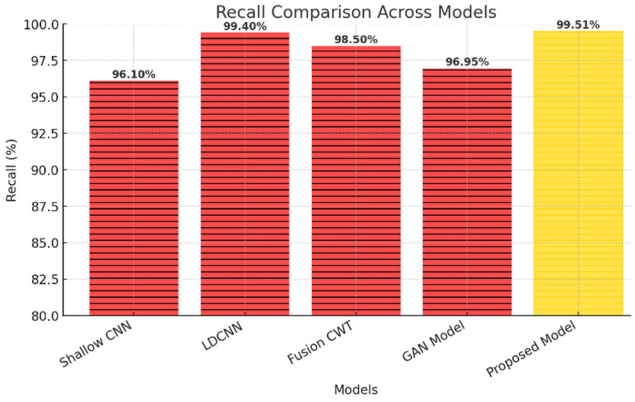

Fig. 15. Recall comparison plot.

Table V shows the F1-score comparison, which balances recall and accuracy, guaranteeing a model performs well over FP and FN. The higher F1-score of the proposed model indicates a reduction in misclassification.

TABLE V. F1-SCORE COMPARISON

Model	F1-Score (%)
LDCNN [26]	99.60
Stacked CNN [27]	94.2
ECG-HO-Net (proposed)	**99.73**

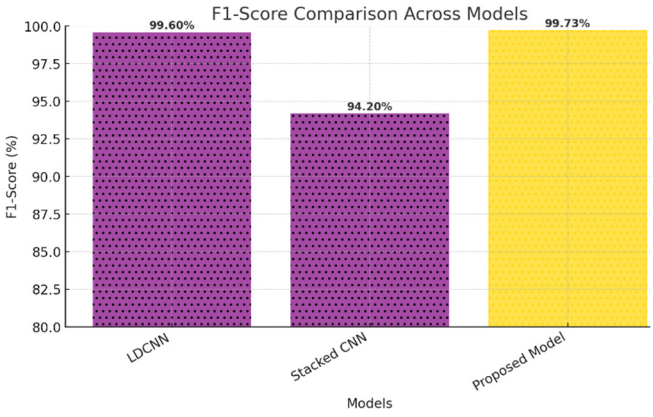

Fig. 16. F1-score comparison plot.

Table VI shows a specificity comparison, which tests every model's capacity to correctly classify normal heartbeats without misidentifying them. Recording a specificity of 99.24%, the proposed model greatly exceeds existing works. Figure 17 depicts the specificity comparison. High recall ensures arrhythmias are accurately detected without being missed. High specificity prevents normal beats from being misclassified. Collectively, they make ECG-HO-Net a reliable tool for real-time monitoring and improved patient care.

TABLE VI. SPECIFICITY COMPARISON

Model	Specificity (%)
Shallow CNN [25]	98.0
Fusion Model with CWT [30]	95.6
ECG-HO-Net (proposed)	**99.24**

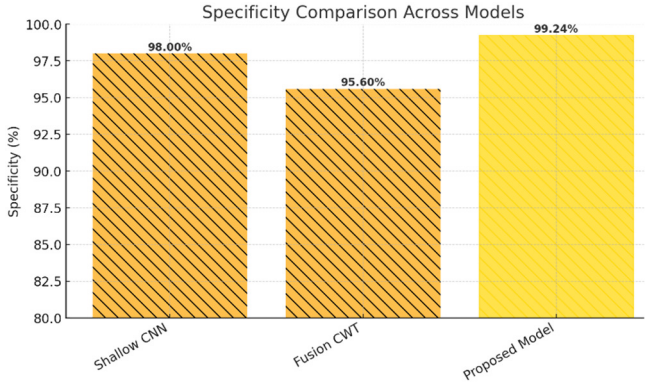

Fig. 17. Specificity comparison plot.

The results of the proposed model were compared with Transformer-based models such as ECGformer [32], which achieves high accuracy using deep encoder stacks but suffers from high computational cost, limiting real-time use. In contrast, ECG-HO-Net offers a lightweight and efficient alternative, combining HO and LNN to balance accuracy and computational efficiency.

The results in Table VII confirm that ECG-HO-Net not only exceeds traditional classifiers in standard metrics but also maintains superior performance in class-balanced metrics, such as MCC and balanced accuracy, which are critical for clinical dependability. The computational efficiency of ECG-HO-Net suits real-time healthcare settings. Trained on an Intel i7 system with a GTX 1650 GPU, it completed 50 epochs on the MIT-BIH dataset in 5.3 minutes. Inference took just 12.4 ms per ECG segment, enabling near-instant arrhythmia detection.

TABLE VII. COMPARISON WITH BASELINE MODELS

Model Used	MCC	Balanced accuracy (%)
SVM	0.845	92.14
LSTM	0.910	95.82
Random Forest	0.876	93.65
Decision Tree	0.852	92.88
PSO-based Model	0.893	94.27
ACO-based Model	0.901	94.95
ECG-HO-Net (proposed)	**0.984**	**99.38**

VI. CONCLUSION

The proposed ECG-HO-Net model efficiently combines LNNs for adaptive learning with HO for feature selection, ensuring accurate and efficient detection of arrhythmias from ECG signals. The model improves signal quality and feature extraction using systematic preprocessing, comprising Butterworth filtering, min-max normalization, and R-peak detection by employing the Pan-Tompkins algorithm. With 99.2% accuracy, 99.71% precision, 99.51% recall, 99.73% F1-score, and 99.24% specificity, ECG-HO-Net achieves better results than current approaches, significantly lowering misclassification errors. The model was validated using the MIT-BIH Arrhythmia Dataset, which ensures clinical relevance. Unlike existing deep learning models, ECG-HO-Net ensures dynamic feature optimization, lightweight architecture, and improved real-time performance for arrhythmia detection.

Further proving its dependability in differentiating between normal and arrhythmic beats, the AUC-ROC (0.99) makes ECG-HO-Net a strong and scalable solution for real-time cardiac monitoring and automated diagnosis.

Expanding ECG-HO-Net to classify several types of arrhythmia, including Atrial Fibrillation, Ventricular Tachycardia, and Premature Ventricular Contractions, will be the main focus of future developments, allowing granular and disease-specific diagnostics. Furthermore, combining Explainable AI (XAI) methods will improve interpretability, giving physicians more understanding of the model's inferences.

REFERENCES

[1] M. Alfaras, M. C. Soriano, and S. Ortín, "A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection," *Frontiers in Physics*, vol. 7, Jul. 2019, https://doi.org/10.3389/fphy.2019.00103.

[2] A. Leenhardt, I. Denjoy, and P. Guicheney, "Catecholaminergic Polymorphic Ventricular Tachycardia," *Circulation: Arrhythmia and Electrophysiology*, vol. 5, no. 5, pp. 1044–1052, Oct. 2012, https://doi.org/10.1161/CIRCEP.111.962027.

[3] N. Sureja *et al.*, "Enhancing Arrhythmia Prediction using the Naked Mole Rat Algorithm and Machine Learning," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 17170–17176, Oct. 2024, https://doi.org/10.48084/etasr.8274.

[4] N. Singh, V. K. Gunjan, F. Shaik, and S. Roy, "Detection of Cardio Vascular abnormalities using gradient descent optimization and CNN," *Health and Technology*, vol. 14, no. 1, pp. 155–168, Jan. 2024, https://doi.org/10.1007/s12553-023-00807-6.

[5] H. Lee and M. Shin, "Learning Explainable Time-Morphology Patterns for Automatic Arrhythmia Classification from Short Single-Lead ECGs," *Sensors*, vol. 21, no. 13, Jun. 2021, Art. no. 4331, https://doi.org/10.3390/s21134331.

[6] "The top 10 causes of death," *World Health Organization*. https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death.

[7] K. P. Nandini and G. Seshikala, "Efficient ECG Arrhythmia Detection on FPGA using Machine Learning and Fiducial Windowing," *Engineering, Technology & Applied Science Research*, vol. 15, no. 2, pp. 21100–21105, Apr. 2025, https://doi.org/10.48084/etasr.9589.

[8] I. Saini, D. Singh, and A. Khosla, "Delineation of ECG Wave Components Using K-Nearest Neighbor (KNN) Algorithm: ECG Wave Delineation Using KNN," in *2013 10th International Conference on Information Technology: New Generations*, Las Vegas, NV, USA, Apr. 2013, pp. 712–717, https://doi.org/10.1109/ITNG.2013.76.

[9] R. Saini, N. Bindal, and P. Bansal, "Classification of heart diseases from ECG signals using wavelet transform and kNN classifier," in *International Conference on Computing, Communication & Automation*, Greater Noida, India, May 2015, pp. 1208–1215, https://doi.org/10.1109/CCAA.2015.7148561.

[10] M. A. Adam and A. Mukhtar, "Heartfelt insights: AI and machine learning applications for cardiac wellness," *International Journal of Advanced Engineering Technologies and Innovations*, vol. 1, no. 4, pp. 231–247, 2024.

[11] T. Behl *et al.*, "Pleotropic Effects of Polyphenols in Cardiovascular System," *Biomedicine & Pharmacotherapy*, vol. 130, Oct. 2020, Art. no. 110714, https://doi.org/10.1016/j.biopha.2020.110714.

[12] A. Anusha, N. Padmaja, D.V.S. Manaswi, and B. S. Kumar, "IOT Based Stress Detection and Health Monitoring System," *HELIX*, vol. 10, no. 2, pp. 161–167, Mar. 2020, https://doi.org/10.29042/2020-10-2-161-167.

[13] S. Nurmaini *et al.*, "Robust detection of atrial fibrillation from short-term electrocardiogram using convolutional neural networks," *Future Generation Computer Systems*, vol. 113, pp. 304–317, Dec. 2020, https://doi.org/10.1016/j.future.2020.07.021.

[14] I. Silva, G. B. Moody, and L. A. Celi, "Challenges and pitfalls of multimodal data fusion: a case study in physiological stress detection," *Frontiers in neurology*, vol. 3, 2012.

[15] A. Brenyo and M. K. Aktas, "Review of Complementary and Alternative Medical Treatment of Arrhythmias," *The American Journal of Cardiology*, vol. 113, no. 5, pp. 897–903, Mar. 2014, https://doi.org/10.1016/j.amjcard.2013.11.044.

[16] K. A. Swamy, S. Prathima, N. Padmaja, and C. Sushma, "Dual Threshold Log Spectral Distance Voice Activity Detector based Effective Statistical Speech Enhancement," *International Journal of Advanced Science and Technology*, vol. 29, no. 03, pp. 5640–5653, 2019.

[17] Y. Hagiwara *et al.*, "Computer-aided diagnosis of atrial fibrillation based on ECG Signals: A review," *Information Sciences*, vol. 467, pp. 99–114, Oct. 2018, https://doi.org/10.1016/j.ins.2018.07.063.

[18] A. Kumar and F. Shaik, "Importance of Image Processing," in *Image Processing in Diabetic Related Causes*, Springer Singapore, 2016, pp. 5–7.

[19] T. Tsutsumi, N. Takano, N. Matsuyama, Y. Higashi, K. Iwasawa, and T. Nakajima, "High-frequency powers hidden within QRS complex as an additional predictor of lethal ventricular arrhythmias to ventricular late potential in post–myocardial infarction patients," *Heart Rhythm*, vol. 8, no. 10, pp. 1509–1515, Oct. 2011, https://doi.org/10.1016/j.hrthm.2011.06.027.

[20] S. Kumar, A. Mallik, A. Kumar, J. D. Ser, and G. Yang, "Fuzz-ClustNet: Coupled fuzzy clustering and deep neural networks for Arrhythmia detection from ECG signals," *Computers in Biology and Medicine*, vol. 153, Feb. 2023, Art. no. 106511, https://doi.org/10.1016/j.compbiomed.2022.106511.

[21] X. Liu, H. Wang, Z. Li, and L. Qin, "Deep learning in ECG diagnosis: A review," *Knowledge-Based Systems*, vol. 227, Sep. 2021, Art. no. 107187, https://doi.org/10.1016/j.knosys.2021.107187.

[22] A. A. Ahmed, W. Ali, T. A. A. Abdullah, and S. J. Malebary, "Classifying Cardiac Arrhythmia from ECG Signal Using 1D CNN Deep Learning Model," *Mathematics*, vol. 11, no. 3, Jan. 2023, Art. no. 562, https://doi.org/10.3390/math11030562.

[23] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, Feb. 2001, https://doi.org/10.1109/51.932724.

[24] B. Fatimah, A. Singhal, and P. Singh, "ECG arrhythmia detection in an inter-patient setting using Fourier decomposition and machine learning," *Medical Engineering & Physics*, vol. 124, Feb. 2024, Art. no. 104102, https://doi.org/10.1016/j.medengphy.2024.104102.

[25] T. Rasti and Q. Zhu, "ECG-Based Arrhythmia Detection by A Shallow CNN Model," *Series of Cardiology Research*, vol. 6, no. 1, Oct. 2023, https://doi.org/10.21203/rs.3.rs-3407809/v1.

[26] A. Bayani and M. Kargar, "LDCNN : A new arrhythmia detection technique with ECG signals using a linear deep convolutional neural network," *Physiological Reports*, vol. 12, no. 17, Sep. 2024, Art. no. e16182, https://doi.org/10.14814/phy2.16182.

[27] S. Sattar *et al.*, "Cardiac Arrhythmia Classification Using Advanced Deep Learning Techniques on Digitized ECG Datasets," *Sensors*, vol. 24, no. 8, Apr. 2024, Art. no. 2484, https://doi.org/10.3390/s24082484.

[28] A. M. L. Echeverry, S. Lopez Flórez, J. B. Guapacha, J. Gutiérrez, and F. De La Prieta, "ElectrApp: Deep learning framework to enhance cardiac arrhythmia detection," *Logic Journal of the IGPL*, vol. 33, no. 4, Jul. 2025, Art. no. jzae102, https://doi.org/10.1093/jigpal/jzae102.

[29] K. Vinutha and U. Thirunavukkarasu, "Prediction of arrhythmia from MIT-BIH database using support vector machine (SVM) and naive bayes (NB) classifiers," *AIP Conference Proceedings*, vol. 2853, no. 1, May 2024, Art. no. 020198, https://doi.org/10.1063/5.0197452.

[30] M. Scarpiniti, "Arrhythmia Detection by Data Fusion of ECG Scalograms and Phasograms," *Sensors*, vol. 24, no. 24, Dec. 2024, Art. no. 8043, https://doi.org/10.3390/s24248043.

[31] A. K. P. Gladis, A. Ahilan, N. Muthukumaran, and L. Jenifer, "ECG Arrhythmia Measurement and Classification for Portable Monitoring," *Measurement Science Review*, vol. 24, no. 4, pp. 118–128, Aug. 2024, https://doi.org/10.2478/msr-2024-0017.

[32] T. Akan, S. Alp, and M. A. Nobel Bhuiyan, "ECGformer: Leveraging Transformer for ECG Heartbeat Arrhythmia Classification," in *2023 International Conference on Computational Science and Computational Intelligence (CSCI)*, Las Vegas, NV, USA, Dec. 2023, pp. 1412–1417, https://doi.org/10.1109/CSCI62032.2023.00231.