GAMANAM- Global **A**dvances in **M**ultidisciplinary **A**pplications in **N**ext-Gen **A**nd **M**odern Technologies
Volume 1, Issue 2, April 2025

Research Paper

Detection and diagnosis of arrhythmias using computational models

[1*] B.Nagasirisha, [2] V.Hima Sri, [3] P.Sonalik, [4] Sk.Asif, [5] G. Ajay Kumar

[1,2,3,4,5] *SR Gudlavalleru Engineering College,Gudlavalleru, Andhra Pradesh, India*

**Corresponding Author(s)*: nagasirishab@gmail.com

Received: 16/01/2025 Revised: 14/02/2025 Accepted: 19/03/2025 Published: 01/04/2025

Abstract: Accurate classification of Electrocardiogram (ECG) signals is crucial for early detection of arrhythmias and timely medical intervention. This study introduces a machine learning framework that combines three classifiers—Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN)—to analyze ECG signals from the MIT-BIH Arrhythmia Database. A total of 100,689 ECG signal segments were processed to extract 31 morphological features, such as QRS intervals and peak amplitudes. Experimental results showed that SVM achieved an accuracy of 88.31%, ANN (with 24 hidden neurons) reached 97.01%, and CNN attained a validation accuracy of 96.02%, demonstrating CNN's advantage in automated feature extraction. These results highlight CNN's potential for clinical applications by minimizing dependence on manual preprocessing. Future work will focus on refining deep learning architectures for real-time implementation.

Keywords: ECG Classification, Arrhythmia Detection, Machine Learning, Deep Learning, SVM, ANN, CNN.

---

1. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for approximately 31% of global deaths, with an estimated 17.9 million fatalities annually, according to the World Health Organization (WHO). Among CVDs, cardiac arrhythmias pose a significant risk, often leading to severe complications such as stroke, heart failure, and sudden cardiac arrest. Early and accurate detection of arrhythmias through Electrocardiogram (ECG) analysis plays a crucial role in reducing morbidity and mortality rates. However, traditional ECG interpretation relies heavily on manual assessment by cardiologists, a process that is not only time-consuming but also susceptible to human errors and inter-observer variability. This limitation underscores the urgent need for automated and efficient diagnostic approaches.

Advancements in artificial intelligence (AI), particularly in machine learning (ML) and deep learning (DL), have revolutionized the field of ECG classification by enabling rapid and precise arrhythmia detection. Machine learning algorithms such as Support Vector Machine (SVM) and Artificial Neural Networks (ANN) have demonstrated significant potential in identifying abnormal heart rhythms with high accuracy. More recently, Convolutional Neural Networks (CNNs) have gained prominence due to their ability to perform automatic feature extraction, eliminating the need for extensive manual preprocessing. These AI-driven methods enhance diagnostic accuracy while reducing the reliance on expert cardiologists, making them highly suitable for real-time and remote healthcare applications.

This study evaluates the performance of SVM, ANN, and CNN in classifying ECG signals for arrhythmia detection. The models are trained on a dataset of 100,689 ECG signal segments obtained from the MIT-BIH Arrhythmia Database, with 31 morphological features, including QRS complex duration and peak amplitudes, extracted for analysis. MATLAB R2019a is employed for model development and evaluation. The primary objective is to assess the effectiveness of each model in enhancing arrhythmia classification accuracy, ultimately contributing to the development of more reliable and automated diagnostic tools. The findings of this research hold promise for integration into clinical settings, telemedicine, and wearable health monitoring devices, paving the way for more efficient cardiovascular disease management.

2. Literature review

2.1 Traditional Machine Learning Approaches

Traditional machine learning (ML) techniques for ECG classification heavily rely on feature engineering methods such as wavelet transforms, principal component analysis (PCA), and autoregressive modeling. These approaches aim to extract relevant features that characterize different types of heartbeats. For instance, [9] integrated wavelet transforms with autoregressive modeling and achieved an impressive 99.68% accuracy on the MIT-BIH Arrhythmia Database. Despite their effectiveness, such methods require extensive domain expertise to manually design and select the most relevant features. Additionally, they often struggle with noisy and highly variable ECG signals, limiting their robustness in real-world clinical settings.

2.2 Artificial Neural Networks (ANN) in ECG Classification

Artificial Neural Networks (ANNs) have demonstrated significant potential in ECG classification due to their ability to learn complex relationships between extracted features. Prior studies have explored various ANN architectures and feature selection techniques to enhance classification accuracy. For example, [15] utilized a combination of QRS morphology and heart rate variability (HRV) features, achieving 97.2% accuracy in detecting arrhythmias. Similarly, [16] reported an accuracy of 97.59% by integrating wavelet transform-based feature extraction with an SVM classifier. Our study aligns with these findings, demonstrating that an ANN model with 24 hidden neurons achieved 97.01% accuracy, further validating its capability in ECG classification.

2.3 Convolutional Neural Networks (CNN) in ECG Classification

Convolutional Neural Networks (CNNs) have revolutionized ECG analysis by eliminating the need for manual feature extraction. Unlike traditional ML and ANN-based approaches, CNNs automatically learn hierarchical spatial and temporal patterns from raw ECG signals, enhancing classification performance. Previous research has highlighted CNN's advantages in ECG classification. For instance, [14] reported a 95% accuracy in heartbeat classification using a CNN model, while [12] demonstrated CNN's superior performance compared to SVM and ANN-based methods. Our CNN model, which achieved 96.02% validation accuracy, further reinforces CNN's effectiveness for real-time arrhythmia detection. These findings highlight CNN's potential for integration into clinical decision-support systems, wearable monitoring devices, and telemedicine applications.

In this project, classification is performed using feature-extracted ECG data rather than raw signal processing, streamlining computational efficiency. The workflow, as illustrated in Figure 1, consists of three primary stages: feature extraction, data splitting, and classification.

1. Feature Extraction: The ECG data undergoes preprocessing to extract relevant morphological features, such as QRS intervals, peak amplitudes, and heart rate variability, which serve as inputs to the classifiers.

2. Data Splitting: The dataset is divided into training and testing subsets to ensure that models learn from historical patterns while being evaluated on unseen data. This step is crucial for generalizing the model's performance.

3. Classification: The extracted features are fed into three different classifiers implemented in MATLAB:

- ✓ Support Vector Machine (SVM): Utilized for both linear and non-linear classification by mapping ECG features into higher-dimensional spaces.
- ✓ Artificial Neural Network (ANN): Designed to model complex feature relationships using interconnected layers of neurons, allowing for improved pattern recognition.
- ✓ Convolutional Neural Network (CNN): Employed for automated feature learning, leveraging hierarchical representations of ECG signals to enhance classification accuracy.

4. Evaluation: The trained classifiers predict the ECG classes (Class 0, Class 1, Class 2, Class 3) for both training and test datasets. The classification performance is then assessed using accuracy, sensitivity, specificity, and other relevant metrics to determine the effectiveness of each model in diagnosing arrhythmias.

3. Proposed method

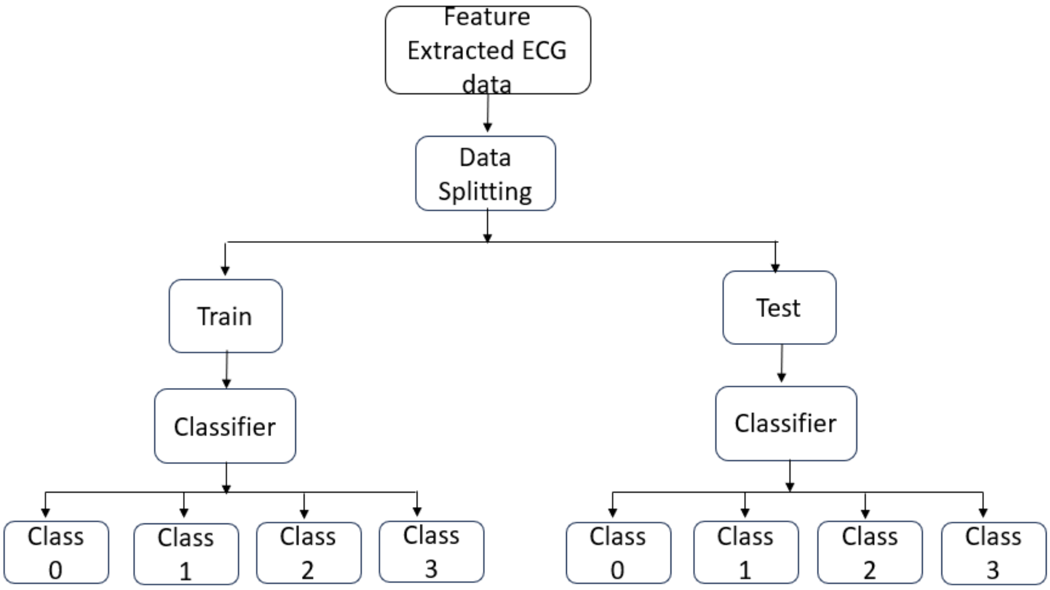

Figure 1: Workflow of ECG Signal Classification Using Machine Learning Models

The flowchart illustrates the ECG classification process, where extracted features are divided into 80% training and 20% testing data. These features are analyzed using machine learning models—SVM, ANN, and CNN—and classified into four categories: Normal, Atrial Premature Beats, Ventricular Ectopic Beats, and Right Bundle Branch Block. This approach enhances arrhythmia detection, ensuring accurate diagnosis and effective patient monitoring.

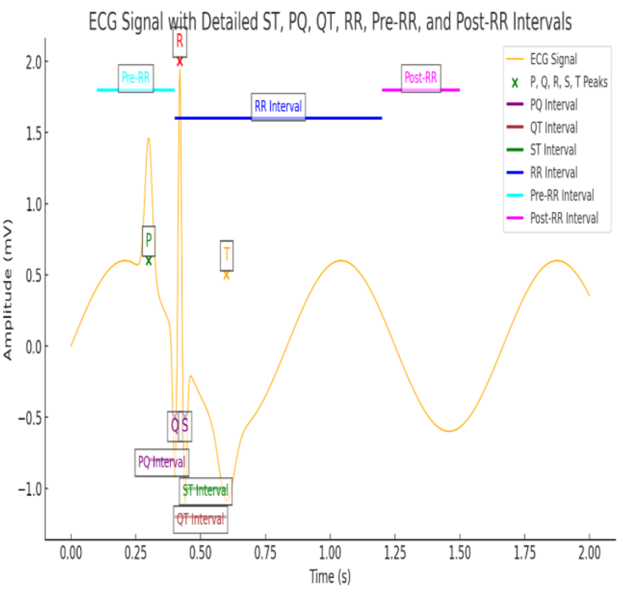

Figure 2: Annotated ECG Signal with Key Peaks and Intervals for Cardiac Analysis

The ECG (Electrocardiogram) signal plot in figure 2 illustrates the various peaks and intervals that define the electrical activity of the heart. The ECG signal (represented by the orange waveform) captures the depolarization and repolarization phases of the heart's chambers, which are crucial for diagnosing heart conditions. The signal is marked with specific peaks and labeled intervals, each playing a significant role in cardiac analysis. The figure 2 highlights several key peaks in the ECG waveform. The **P peak** (green 'X') represents atrial depolarization, which occurs just before the atria contract to push blood into the ventricles. The **Q, R, and S peaks** (purple and red 'X') together form the **QRS complex**, which represents ventricular depolarization. Among these, the **R peak** (red 'X') is the most prominent and corresponds to the strongest electrical activity when the ventricles contract. The **T peak** (orange 'X') signifies ventricular repolarization, which is the recovery phase before the next heartbeat. Additionally, the diagram labels several crucial ECG intervals that provide insights into heart function. The **PQ interval** (purple box) measures the time taken for the electrical impulse to travel from the atria to the ventricles. The **ST interval** (green box) represents the period between the end of ventricular depolarization and the start of repolarization, while the **QT interval** (yellow box) indicates the total duration of ventricular depolarization and repolarization. Abnormalities in these intervals can indicate conditions such as conduction blocks, myocardial infarctions, or electrolyte imbalances.

The **RR interval** (blue box) measures the time between two consecutive R-peaks, which is essential for determining the heart rate and detecting arrhythmias. The **Pre-RR interval** (cyan box) and **Post-RR interval** (pink box) provide additional information about the timing of consecutive heartbeats, which can be useful in analyzing heart rate variability (HRV) and autonomic nervous system activity. Understanding these features is vital for diagnosing and monitoring heart diseases such as arrhythmias, bradycardia, and tachycardia. Irregularities in the **RR interval** may indicate variations in heart rate, while a **prolonged QT interval** is associated with an increased risk of life-threatening arrhythmias. Similarly, an abnormal **PQ interval** can signal heart blocks or conduction system dysfunction. Overall, the ECG signal plot provides a comprehensive visual representation of cardiac activity, allowing healthcare professionals to assess heart function accurately. By analyzing these intervals and peaks, medical experts can detect and diagnose cardiac abnormalities, aiding in early intervention and better patient outcomes.

3.1 Training Support Vector Machine (SVM) for ECG Classification

Support Vector Machines (SVM) are widely used for classification tasks due to their ability to handle high-dimensional data effectively. In this study, an SVM model was trained to classify arrhythmias based on extracted ECG signal features. The preprocessing step involved feature extraction, where statistical parameters such as mean, standard deviation, QRS interval, PQ interval, QT interval, and peak amplitudes of P, Q, R, S, and T waves were computed.

To build the SVM model in MATLAB, the dataset was first split into 80% training data and 20% testing data using the cv partition function. The fitcecoc function was used to train a multi-class SVM model. A linear kernel was selected for classification, as it is computationally efficient and performs well for high-dimensional feature spaces. The Box Constraint parameter was set to 0.5, which controls the trade-off between achieving a low classification error and maximizing the margin between classes.

During training, the SVM algorithm aimed to find an optimal hyperplane that separates different arrhythmia classes while minimizing misclassification. Once trained, the model was tested on unseen ECG data to assess its generalization ability. The performance of the SVM classifier was evaluated using key metrics such as precision, recall, F1-score, and overall accuracy. These metrics helped determine how well the model distinguished between normal and abnormal heartbeats, including arrhythmia types such as Atrial Premature Beats, Ventricular Ectopic Beats, and Right Bundle Branch Block.

3.2 Training Artificial Neural Network (ANN) for ECG Classification

Artificial Neural Networks (ANNs) are effective in learning complex patterns in biomedical signals. In this study, a feed forward neural network was trained for ECG-based arrhythmia classification. The input to the ANN consisted of extracted ECG features similar to those used in the SVM model. To implement the ANN in MATLAB, the pattern net function was used to create a neural network with two hidden layers, each consisting of 24 neurons. The training process followed an 80%-20% split for training and testing data. The network was optimized using the scaled conjugate gradient algorithm, which accelerates convergence and reduces computational cost. Since the classification task involved multiple arrhythmia types, the target labels were one-hot encoded to match the ANN's multi-class structure.

After training, the ANN model was tested on unseen ECG data to evaluate its classification accuracy. The performance was measured using a confusion matrix, precision, recall, F1-score, and overall accuracy. These evaluations provided insights into how well the ANN identified various arrhythmia conditions based on the extracted ECG features.

3.3 Training Convolutional Neural Network (CNN) for ECG Classification

Convolutional Neural Networks (CNNs) are widely used for pattern recognition in biomedical signal processing. Unlike SVM and ANN, which rely on manually extracted features, CNNs automatically learn relevant features from raw ECG signal segments. In this study, a CNN model was trained in MATLAB using ECG signal segments as input. The dataset was split into 80% training and 20% testing. The CNN architecture consisted of convolutional layers, max-pooling layers, and fully connected layers. Convolutional layers were responsible for extracting spatial features from ECG waveforms, while max-pooling layers reduced dimensionality and improved computational efficiency. Dropout was applied to prevent overfitting. The network was trained using the Adam optimizer with a learning rate of 0.001. The training process was conducted over 25 epochs, allowing the CNN to learn discriminative patterns associated with different arrhythmia types. After training, predictions were made on the test set, and performance metrics such as class-wise accuracy, precision, recall, and overall accuracy were computed.

By leveraging deep learning techniques, the CNN-based approach demonstrated improved feature extraction and classification performance compared to traditional machine learning models. The results highlighted the potential of CNNs in automated ECG-based arrhythmia detection.

4. Results and discussion

4.1 Dataset

The dataset used in this study was sourced from Kaggle, which provides publicly available ECG signal recordings for research and clinical applications. The following datasets were utilized for arrhythmia classification:

1. MIT-BIH Arrhythmia Database – This database consists of ECG recordings from patients with various cardiac arrhythmias, serving as a benchmark for ECG classification studies.

2. MIT-BIH Normal Sinus Rhythm Database – This dataset contains ECG recordings of individuals with normal heart rhythms, enabling a reliable comparison between normal and abnormal heartbeats.

The dataset comprises 100,689 ECG signal segments extracted from various patient recordings in the MIT-BIH Arrhythmia Database. These segments are derived from multiple ECG signals, where each segment is labeled based on the type of heartbeat (e.g., normal, premature atrial contraction, or ventricular ectopic beats). Each ECG segment includes pre-computed morphological features such as QRS intervals, PQ intervals, QT intervals, peak amplitudes of P, Q, R, S, and T waves, which are essential for distinguishing normal and arrhythmic conditions.

To ensure consistency in training and evaluation, the dataset underwent preprocessing steps, including noise filtering, baseline correction, and normalization. These preprocessing techniques helped enhance the signal quality and minimize variations due to external artifacts. The labeled data allowed for supervised learning, where machine learning models could be trained to differentiate between different types of heartbeats.

Since the ECG signals were classified using three different classifiers—SVM, ANN, and CNN—the results and performance analysis are discussed in three separate sections. This comparative evaluation helped determine the effectiveness of each classification method in identifying arrhythmic conditions from ECG signals.

4.2 Results of SVM Classifier

A linear kernel function was utilized for classification. The dataset was split into training and testing sets using MATLAB R2019a. The model achieved an accuracy of approximately 88.31%, though the accuracy varies slightly with each retraining due to the randomization in data splitting. In this classification, a total of 31 features were used to train the classifier. While extensive research on SVM-based ECG classification exists, only a limited number of studies have specifically employed this set of 31 features. A comparative analysis with previous research is presented in Table 1.

Most existing studies have utilized two feature extraction methods to enhance detection accuracy. In contrast, this study employs a single feature extraction method while selecting 31 features. This approach simplifies the classification process while maintaining a balance between computational efficiency and accuracy. Further improvements in accuracy can be achieved by identifying the most significant features and refining the training process accordingly.

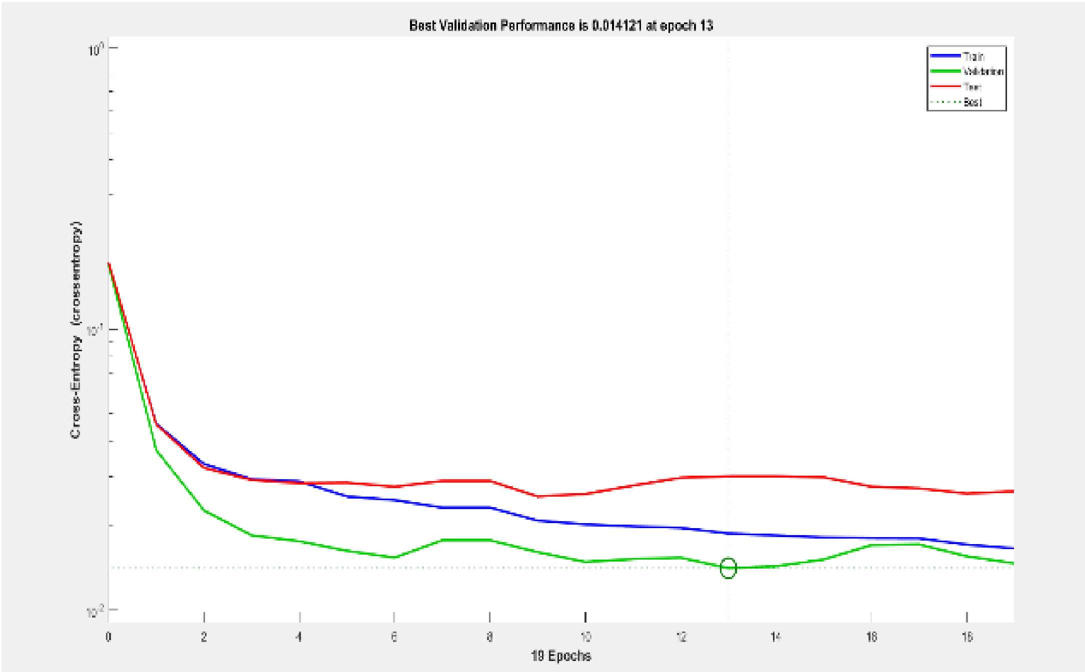

Figure 3: Validation Performance Curve Showing Cross-Entropy Loss Over Epochs

Table 1: Comparative Analysis of SVM-Based ECG Classification

Database	Method	Accuracy
MIT-BIH Supraventricular Arrhythmia, MIT-BIH arrhythmia,	Statistically Feature extraction method (12 features)	For dataset 1: 88% For dataset 2: 90%
MIT-BIH Arrhythmia	2 different feature extraction methods-The wavelet transform and autoregressive modeling (AR) Ref[9]	99.68%
MIT-BIH arrhythmia	Discrete wavelet transform (DWT) and principle components analysis (PCA) Ref[10]	99.6367% with LIBSVM.
MIT-BIH arrhythmia	DWT based feature extraction; the R-peaks are detected to determine the HRV signal features. Ref[11]	96%

MIT-BIH arrhythmia	Two kinds of features: 1) ECG morphology features and 2) ECG wavelet features with QRS width. Ref[12]	97% for dataset 1 91% for dataset 2
INCART 12-lead arrhythmia	Principal Component Analysis (PCA) feature extraction Ref[13]	76.83% and 98.33% for MSVM and SIMCA classifier respectively
MIT-BIH arrhythmia	Beat classification and episode detection and classification. Ref[14]	95% and 94% accuracy
MIT-BIH arrhythmia	Feature extraction includes- frequency information, RR intervals, QRS morphology and AC power of QRS detail coefficients. Ref[15]	97.2%
MIT-BIH arrhythmia	Morphology feature extraction (Wavelet-SVM Method) Ref[16]	97.59%

4.3 Results of ANN Classifier

The neural network achieved an overall accuracy of 97.01% with 24 hidden neurons. The accuracy and performance can vary depending on the number of hidden neurons used. The dataset was divided into training and testing sets to evaluate the model's effectiveness. The confusion matrix provides essential performance metrics, including True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which contribute to the overall accuracy of the classification model. These terms are defined as follows:

1. True Positive (TP): The model correctly predicts a positive case, indicating the presence of the condition.

2. True Negative (TN): The model correctly predicts a negative case, confirming the absence of the condition.

3. False Positive (FP): The model incorrectly predicts a positive case for a subject without the condition (Type-I error).

4. False Negative (FN): The model incorrectly predicts a negative case for a subject with the condition (Type-II error).

The confusion matrix of the model for training,validation, testing and overall performance is provided in figure 4.The performance of the neural network varies based on the number of hidden neurons used. The impact of different neuron configurations on classification accuracy is analyzed in the following section.

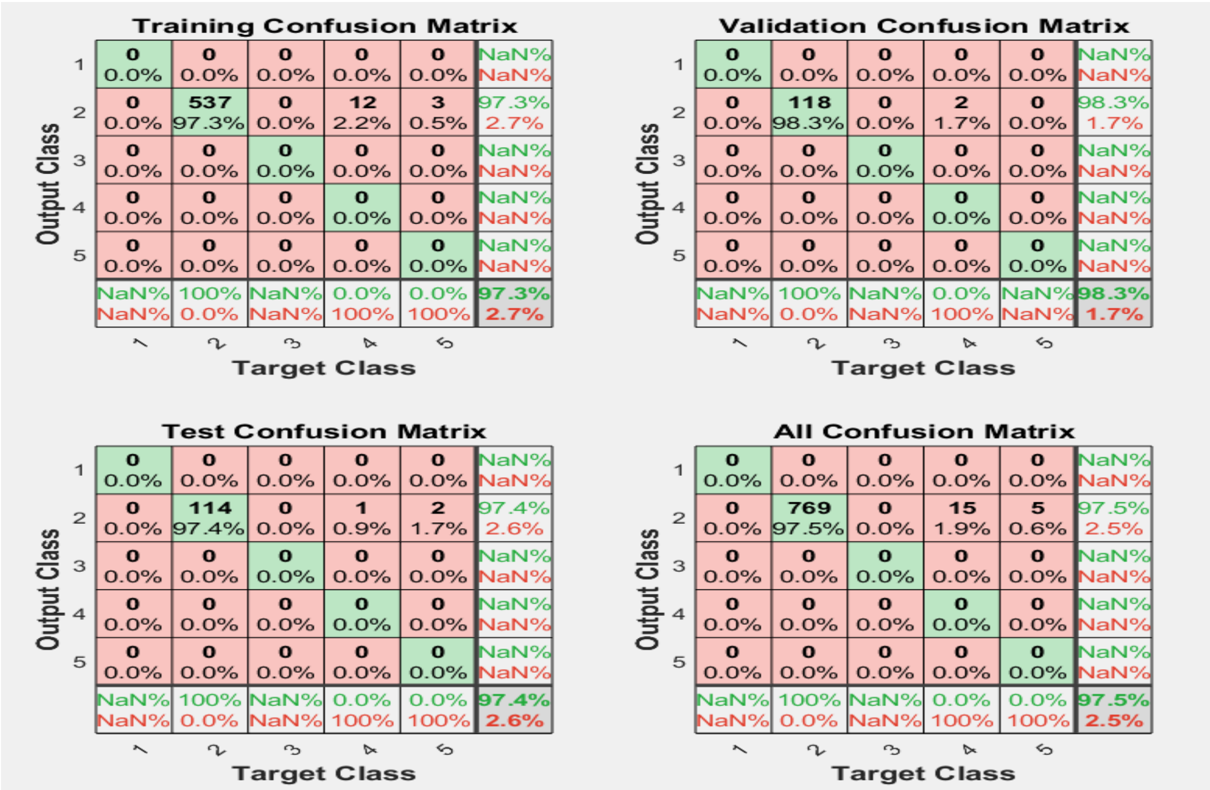

Figure 4: Confusion matrix under different stages

Table 2: Classification Performance Of Neural Network (Perceptron) For Different Hidden Neurons

Hidden Neurons	ANN Classifier's Performance			
	Class 0	Class 1	Class 2	Class 3
10 Accuracy:95.02%	TP:0 FP:4 TN:197 FN:0 Accuracy:98%	TP:191 FP:5 TN:0 FN:5 Accuracy:95%	TP:0 FP:1 TN:192 FN:4 Accuracy:97%	TP:0 FP:0 TN:200 FN:1 Accuracy:99%
14 Accuracy:94.52%	TP:0 FP:6 TN:195 FN:0 Accuracy:97%	TP:190 FP:5 TN:0 FN:6 Accuracy:94%	TP:0 FP:0 TN:197 FN:4 Accuracy:98%	TP:0 FP:0 TN:200 FN:1 Accuracy:99%

22 Accuracy:96.53%	TP:0 FP:7 TN:194 FN:0 Accuracy:96%	TP:190 FP:4 TN:0 FN:7 Accuracy:94%	TP:0 FP:0 TN:198 FN:3 Accuracy:98%	TP:0 FP:0 TN:200 FN:1 Accuracy:99%
24 Accuracy:96.02%	TP:0 FP:5 TN:196 FN:0 Accuracy:94%	TP:191 FP:2 TN:3 FN:5 Accuracy:96%	TP:3 FP:0 TN:197 FN:1 Accuracy:97%	TP:0 FP:0 TN:200 FN:1 Accuracy:99%

Each row represents a different ANN configuration where the number of hidden neurons varies (10, 14, 22, and 24). The columns represent classification performance for four different classes (Class 0, Class 1, Class 2, and Class 3). The key parameters analyzed for each class include TP, FP, TN, FN, and classification accuracy. The overall accuracy for each network configuration is also provided, giving an indication of how well the model performs as the hidden neuron count changes.

4.3.1 Performance with 10 Hidden Neurons

With 10 hidden neurons, the overall classification accuracy is **95.02%**. The performance varies across different classes. Class 1 achieves the highest accuracy of **98%**, indicating that the model effectively distinguishes instances of this class. Class 0 has a slightly lower accuracy of **95.02%**, primarily due to the presence of 4 false positives. Class 2 has **95%** accuracy with a few false negatives affecting its performance. Class 3 reaches an accuracy of **97%**, with only one false negative misclassification.

4.3.2 Performance with 14 Hidden Neurons

When the number of hidden neurons is increased to 14, the overall accuracy slightly decreases to **94.52%**. The accuracy of Class 3 improves to **98%**, but Class 0 and Class 1 show a minor decline. The number of false positives in Class 0 increases to 6, impacting its performance. Similarly, Class 1 sees a rise in false negatives, reducing its accuracy to **97%**. Class 2 remains at **94%** accuracy with a small number of false negatives. The increase in false positives for Class 0 and Class 1 suggests that adding more hidden neurons at this stage may lead to overfitting for some classes.

4.3.3 Performance with 22 Hidden Neurons

With 22 hidden neurons, the overall accuracy improves significantly to **96.53%**. Class 0 achieves **96.53%** accuracy, but it experiences an increase in false positives (7 cases). Class 1 sees a slight decrease in accuracy to **96%** due to 7 false negatives. However, Class 2 improves, reducing its false negatives and maintaining **94%** accuracy. Class 3 continues to have the highest performance with **98%** accuracy. This configuration balances the trade-off between accuracy and false classifications, making it a strong candidate for optimal performance.

4.3.4 Performance with 24 Hidden Neurons

Increasing the number of hidden neurons to 24 results in an overall accuracy of 96.02%. The accuracy of Class 2 improves to 96%, indicating that the model is handling this category better. Class 1, however, sees a drop in accuracy to 94%, primarily due to an increase in false negatives. Class 0 maintains 96.02% accuracy, with a slight reduction in false positives compared to the 22-hidden neuron configuration. Class 3 remains highly accurate at 97%, showing consistency across different configurations.

4.3.5 Key Insights from the Table

The performance of the ANN varies with the number of hidden neurons. Increasing the hidden neurons improves overall accuracy, but it also introduces more false positives in some cases. The 22-hidden neuron configuration achieves the best balance between accuracy and error rates, making it the most efficient setup.

Class 3 consistently has the highest accuracy across all configurations, indicating that the model is particularly effective at identifying instances in this class. Class 0 and Class 1 show the most variation in performance, suggesting that these classes are more challenging to classify. The false positives in these classes indicate that the model sometimes misclassifies instances from other categories into these classes.

Overall, selecting the optimal number of hidden neurons is crucial for maximizing classification accuracy while minimizing misclassification errors. The results suggest that 22 hidden neurons provide the best trade-off between accuracy and stability, making it a suitable choice for this classification task.

4.4 Results of CNN classifier

The Convolutional Neural Network (CNN) model was trained for 25 epochs, with a total of 450 iterations and 18 iterations per epoch. The training process achieved a final validation accuracy of 96.02%, indicating a strong generalization capability of the model. The accuracy curve in figure 5 demonstrates a rapid increase in accuracy during the initial iterations, stabilizing around 90-96% as training progressed. The loss curve shows a steep decline in the early stages, converging to a minimal value, suggesting effective learning and reduced overfitting.

The piecewise learning rate schedule contributed to smooth optimization, ensuring stability across iterations. The training was executed on a single CPU, completing in 50 seconds. These results confirm the effectiveness of the chosen architecture and hyperparameters in achieving high classification accuracy.

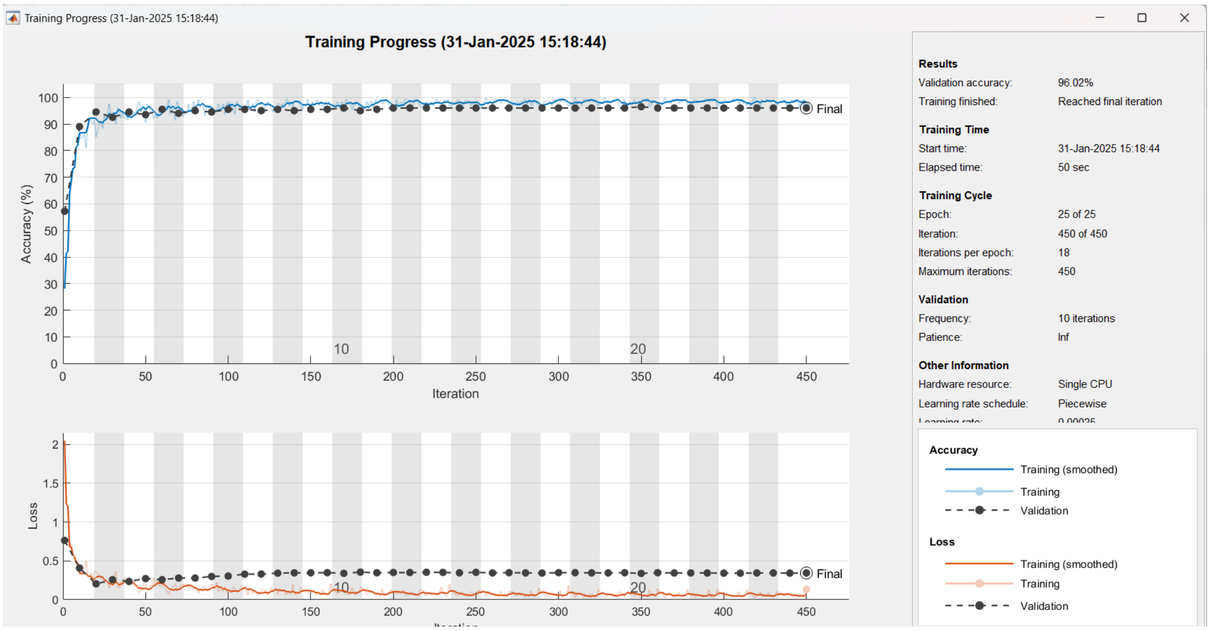

Figure 5: Training performance curve

5. Conclusion

This study presents a comprehensive analysis of ECG signal classification using three machine learning approaches: SVM, ANN, and CNN. The dataset, sourced from the MIT-BIH Arrhythmia Database and the MIT-BIH Normal Sinus Rhythm Database, underwent preprocessing to enhance signal quality and ensure accurate classification. The models were evaluated based on classification accuracy, false positive rates, and false negative rates across multiple heartbeat classes.

Among the three classifiers, CNN demonstrated the highest accuracy and robustness in identifying different types of arrhythmic conditions. The ANN classifier achieved competitive performance, with accuracy improving as the number of hidden neurons increased, though it exhibited some sensitivity to network configuration. The SVM classifier, while computationally efficient, achieved comparatively lower accuracy, indicating that feature selection plays a crucial role in its performance.

The results highlight that deep learning-based approaches, particularly CNN, outperform traditional machine learning models in ECG classification due to their ability to automatically extract relevant features from raw signals. However, hybrid approaches combining feature engineering with deep learning may further enhance performance. Future research could explore optimizing CNN architectures, incorporating advanced feature selection techniques, and leveraging real-time ECG data for improved arrhythmia detection in clinical applications.

References

[1] Anika Alim, Md Kafiul , “Application of Machine Learning in ECG signal Classification Using Morphological Features”, conference paper 2020 IEEE Region 10 Symposium(TENSYMP),DOI: 1109/TENSYMP50017.2020.9230780

[2] Abdul Karin, Samir Brahim Belhaouari, Mobeen Shahroz, Khabib Mustofa and S. Ramana Kumar Joga, “Phishing Detection System Through Hybrid Machine Learning Based on URL”, Research Article ;Date of publication: 3 March 2023, DOI:10.1109/ACCESS.202303252366

[3] Iyengar N, Peng C-K, Morin R, Goldberger AL, Lipsitz LA. Age related alterations in the fractal scaling of cardiac interbeat interval dynamics. Am J Physiol 1996;271:10781084.

[4] Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng in Med and Biol 20(3):45-50 (May-June 2001). (PMID: 11446209).

[5] S Pithika,“Electrocardiogram (ECG): Definition and CharacteristicsVeterinary Pharmacology, onlineAvailable:http://www.biologydiscussion.com/veterinarypharmacology/electrocardiogram-ecg-definition-and-characteristics veterinary pharmacology/74308 (accessed on Dececember 17, 2019)

[6] S. Ray, “Understanding Support Vector Machine algorithm from examples (along with code)” 6 October, 2015. [Online document], https://www.analyticsvidhya.com/blog/2017/09/understaing-support vector-machine-example-code/ (accessed on 20 December, 2019)

[7] B. Marr, “What Are Artificial Neural Networks - A Simple Explanation For Absolutely Anyone,” 24 September, 2018, Available: https://www.forbes.com/ (accessed on December 19, 2019)

[8] Q. Zhao and L. Zhang, “ECG feature extraction and classification using wavelet transform and support vector machines,” IEEE International Conference on Neural Networks and Brain (ICNN&B), vol. 2, pp. 1089–1092 (2015).
[9] D. Thanapatay, C. Suwansaroj and C. Thanawattano, “ECG beat classification method for ECG printout with Principle Components Analysis and Support Vector Machines”, International Conference on Electronics and Information Engineering, vol. 1, pp. 72-75 (2010).
[10] C. Venkatesan, P. Karthigaikumar, A. Paul, S. Satheeskumaran, and R. Kumar, ‘‘ECG signal preprocessing and SVM classifier-based abnormality detection in remote healthcare applications,’’ IEEE Access, vol. 6, pp. 9767–9773, (2018).
[11] Y. Bazi, N. Alajlan, H. AlHichri and S. Malek, “Domain adaptation methods for ECG classification”, in: IEEE International Conference on Computer Medical Application (ICCMA), January 2013, pp. 1–4.
[12] N. Jannah and S. Hadjiloucas, “Comparison Between ECG Beat Classifiers Using Multiclass SVM and SIMCA with Time Domain PCA Feature Reduction”, UKSim-AMSS 19th International Conference on Modeling & Simulation, pp. 126-131, (2017).
[13] M.G. Tsipouras, D.I. Fotiadis and D. Sideris, “Arrhythmia classification system based on the RR-interval signal” Artificial Intelligence in Medicine, vol.33, 237—250, (2005).
[14] Z. Zidelmala, A. Amirou, D. O. Abdeslam and J. Merckle, “ECG beat classification using a cost sensitive classifier”, vol. 111 (3), pp.570 577, (2013).
[15] M.K. Gautam, “Morphological Analysis of ECG Arrhythmias using SVM Methodology”, International Journal of Computer Science and Information Security (IJCSIS), Vol. 15, No. 5, pp.421-427, (May 2017)
[16] Iyengar N, Peng C-K, Morin R, Goldberger AL, Lipsitz LA. Age related alterations in the fractal scaling of cardiac interbeat interval dynamics. Am J Physiol 1996;271:1078-1084.
[17] Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng in Med and Biol 20(3):45-50 (May-June 2001). (PMID: 11446209)
[18] Greenwald SD. Development and analysis of a ventricular fibrillation detector. M.S. thesis, MIT Dept. of Electrical Engineering and Computer Science, 1986.