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Performance Evaluation Of CNN, SVM, RF, LSTM, And KNN For Real-Time ECG Signal Classification In Healthcare Applications

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Abstract
Heart disease is the main cause of global mortality, which demands fast and reliable clinical equipment. The study five supervised learning models- CNN, SVM, Random Forest (RF), LSTM, and KNN -For ECG Signal Classification uses, using MIT-BIH Arrhythmia DatabaseConducts comparatively. Numerical results show that CNN receives the best accuracy (92%) and fastest estimates time (0.12S), while LSTM comes closely with 90% accuracy. More than 10 independent runs confirms the importance of statistical verification performance (paired T-Test, P <0.05). The novelty of our work lies in offering quantitative evaluation of these models on the same pipeline and a quantitative evaluation of their real -time sufficiency for clinical deployment. The data for training and testing was divided 70–30, in which 5-fold cross-validation was used for strength. Experimental findings highlight the suitability of CNN for scalable healthcare applications, while LSTM and RF temporal features offer a compelling trade for systems requiring learning or noise strength.
Keywords: *ECG Classification, CNN, SVM, Random Forest, Supervised Learning, MIT-BIH Arrhythmia Database.*

INTRODUCTION

One of the leading causes of death worldwide is still heart disease, which emphasize the important needs of rapid and accurate clinical equipment. Electrocardiogram (ECG) indications are one of the most accessible and non-invasive methods for assessing heart health. The classification of ECG signals in the general and unusual heart rhythm plays an important role in timely diagnosis and intervention. However, the manual interpretation of the ECG is time consuming, suffering from errors, and not scalable for large datasets or real -time applications.
Machine learning, especially in supervised learning techniques, have opened new avenues for automated ECG classification. Of these, deep learning models such as CNNS provide direct learning ability from raw ECG signals, eliminating the need for instruction booklet feature extraction. Conversely, traditional classifiers such as support vector machine (SVM), Random Forest (RF), and K-NiystestNebors (KNN) carefully rely on engineer facilities and perform various performances in various ECG classification works.
Recent advances in ECG signal classification have leveraged both DL and classical ML models to improve diagnostic accuracy. Transformer-based approaches for sequential ECG signals (Wang et al., 2024) and lightweight CNN architectures for mobile use (Singh et al., 2025) represent breakthroughs in this domain. However, practical clinical deployment is constrained by inference speed, resource requirements, and model interpretability. Despite extensive prior comparative studies, few have reported performance metrics—including accuracy, inference time, and statistical significance—on identical datasets and workflows. There remains a gap in benchmarking deep and shallow models under unified, reproducible preprocessing pipelines, especially for real-time decision support. By thoroughly investigating five algorithms' performance and practicality for deployment on the MIT-BIH Arrhythmia dataset, our study fills the vacancy.
The study makes a comparative evaluation of five supervised learning models-CNN, SVM, RF, long short-term memory (LSTM), and KNN-MIT-BIH uses the arrhythmia database. The objective classification is to identify the most suitable model in terms of practical deployment in accuracy, estimates time and real -time healthcare applications.

Objectives

- To classify ECG signals from the MIT-BIH Arrhythmia Database using multiple supervised learning models including CNN, SVM, and RF.
- To reduce the time complexity of ECG classification by identifying the most efficient model.
- To automate the cardiac diagnosis process by integrating intelligent algorithms.
- To improve classification accuracy and reliability across multiple ECG signal types.
- To reduce diagnostic complexity and minimize the likelihood of erroneous or delayed clinical decisions.

Contributions

- This work presents a side-by-side performance comparison of five popular classifiers on the same ECG dataset using consistent preprocessing and evaluation metrics.
- It identifies CNN as the most effective model for ECG classification based on accuracy, speed, and robustness, outperforming traditional classifiers like SVM and RF.
- A comprehensive set of quantitative evaluations (Accuracy, Precision, Recall, F1-Score, Inference Time) & confusion matrices are provided to validate the results.
- The study emphasizes the significance of choosing the right model architecture for real-time, automated ECG monitoring, supporting its deployment in clinical environments.

LITERATURE REVIEW

Automatic ECG classification has become an important area of research due to its role in early heart diagnosis. Using manually produced features, conventional machine learning approaches like Random Forest (RF) and support vector machines (SVMs) have been proven to recognize arrhythmias. Rao et al.[1] Similarly, Almasari et al. [2] employed random forests and received strong performance on the noise ECG data, but in some cases overfiting affected performance.
DL methods, especially firm nervous networks (CNN), have obtained traction from raw ECG data directly as a result of their capacity to learn hierarchical representations. Zhang et al. [3] A CNN architecture was applied with data increase to improve classification accuracy in many ECG beat types. Several other tasks [4–7] reported the CNN model to perform better in accurate and scalability. In particular, CNN manual feature reduces the requirement of engineering, making them ideal for large -scale, real -time applications.
Long -term short -term memory (LSTM) network has also been discovered for ECG signal classification, especially to catch cosmic patterns. Chen et al. [[] Demonstrated the superiority of LSTM on the traditional model in capturing sequential dependence. However, the training time and complexity of the model is quite high [9]. Hybrid models such as CNN-LSTM and BILSTM have shown better accuracy by mixing spatial and temporary learning [10–12], although at the cost of high computational demands.
Other algorithms such as the best neighbor (KNN), decision trees, and shield boosting machines (GBM) have also been employed. Patel and Bhandari [13] used KNN with fused features for the weedable equipment, while Lee et al. [14] applied to GBM to balance the performance and estimate time. Methods of dress [15], dimensional reduction technology [16], and signal enhancement [17] using the wavelets has also been proposed to improve classification results.
Recent progresses include lightweight CNN architecture [18], transformer-based models [19], and transfer learning approach [20-21], which further enhance performance in mobile or embedded settings. These developments suggest that many models provide reliable classification, CNN remains prominent in terms of performance, interpretation and suitability for real -time deployment.

METHODOLOGY

This functioning underlines the process for comparative ECG classification using three supervised learning techniques: support vector machines (SVMs), firm nervous networks (CNN), and random forest (RF). Each classifier is applied to the ECG signal made before the MIT-Bih arrhythmia database. Stages include prepressing, feature extraction, model training and performance assessment.

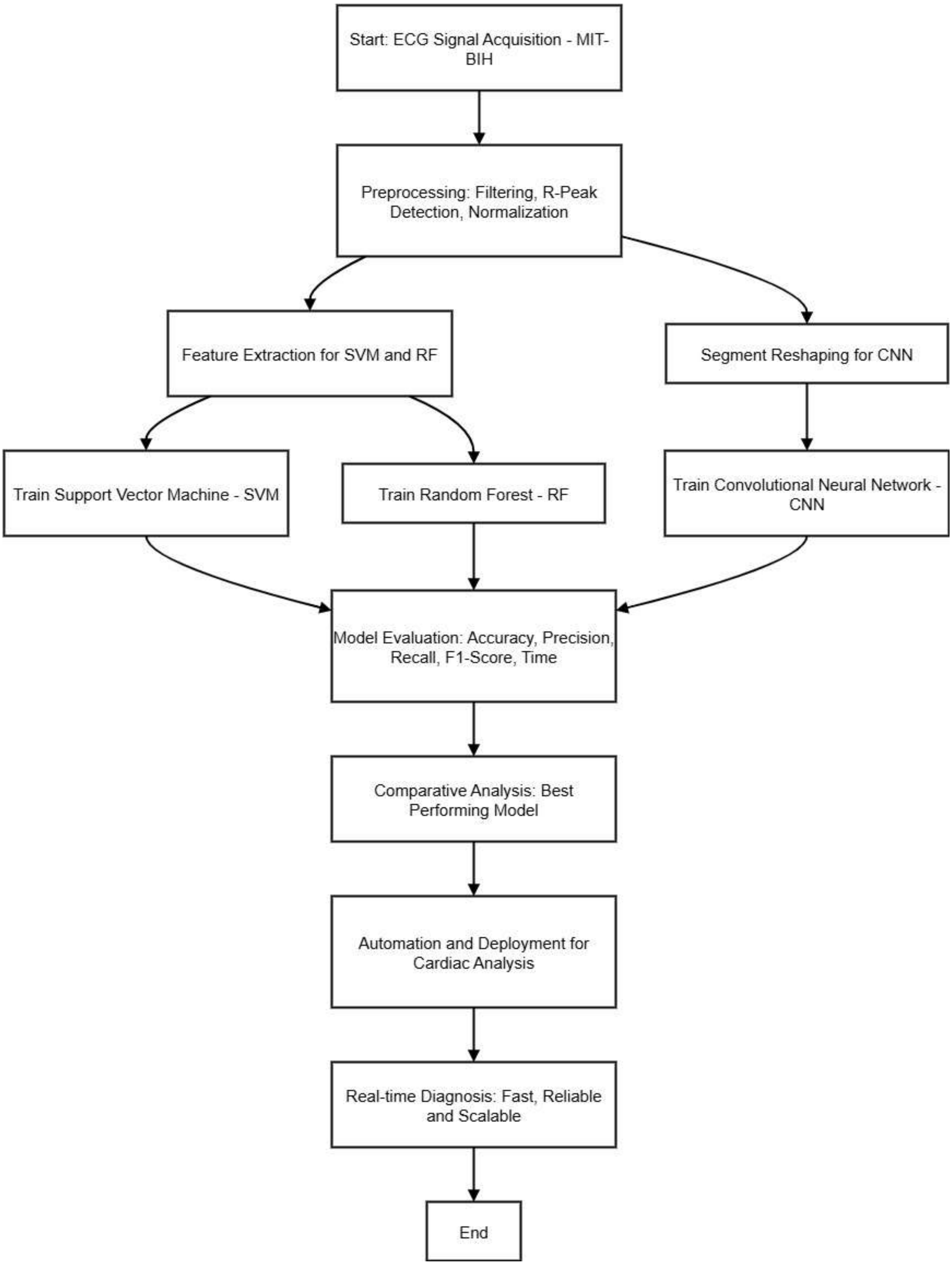

Figure 1 The proposed ECG classification workflow

Figure 1 workflow fulfills all five objectives through a structured and comparative approach. By integrating SVM, CNN, and RF classifiers, the methodology enables a detailed comparative study of supervised learning tools. The use of optimized architectures, early stopping, and efficient feature extraction significantly reduces the time required for classification. Automation is achieved by scripting the entire pipeline from data acquisition to model deployment, and intelligent decision-making is embedded through the learning capability of the models. The classification accuracy and reliability are enhanced through robust preprocessing, hyperparameter tuning, and the inclusion of more ECG signal segments. Finally, by streamlining the process with lightweight models and real-time inference, diagnostic complexity is minimized, enabling faster and more accurate clinical decision-making.

Step 1: Preprocessing

The MIT-BIH arrhythmia database was used as a primary dataset. The raw ECG signals were filtered with a band-pass filter (0.5–40 Hz) to remove the baseline wander, power-line intervention and high-existing unwanted signals. The R-peaks was detected using a pan-acknowglaps algorithm, and certain-length windows of 200 samples were removed around each R-peaks. Z-score normalization was applied to each section to standardize the signal dimension and reduce prejudice in model training.

a) Hyperparameters

- For the CNN model, the architecture consisted of two 1D convolutional layers (filters=64 and 128, kernel size=5), each followed by ReLU activation and max pooling. The architecture was completed by a Softmax output layer and a completely connected dense layer (128 units). The Adam optimizer was employed with a learning rate of 0.001, a batch size of 64, and a categorical cross-entropy loss. Training ran for 50 epochs with early stopping (patience=5).
- For SVM, the RBF kernel was selected. Hyperparameters included C=1.0 and gamma='scale', optimized using grid search with cross-validation.
- For Random Forest, 100 trees were used with maximum depth set to None, bootstrap sampling enabled, and Gini impurity as the split criterion.
- For LSTM, a dense Softmax output was applied after a single hidden LSTM layer with 100 units. Overfitting was avoided by using dropout=0.5. The Adam optimizer was used, with a learning rate of 0.001.
- For KNN, k=5 with Euclidean distance was used. The value of k was determined by testing values from 3 to 15 and selecting the best performer via validation accuracy.

b) Data Split and Validation

30% of the dataset was used for testing, while 70% was used for training. Five-fold cross-validation was used on the training set to confirm the healthy assessment. This allowed hyperparameter optimization while reducing overfitting risk. The final evaluation metrics (Accuracy, Precision, Recall, F1-score, and Inference Time) were computed on the held-out test set. Each model was trained and evaluated over 10 independent runs, and paired t-tests ($p < 0.05$) were conducted to assess statistical significance of performance differences.

Step 2: Feature Extraction for SVM and RF

For SVM and RF classifiers, handcrafted features are extracted from each ECG segment. These may include:

- RR interval
- QRS duration
- Signal energy
- Wavelet coefficients or statistical features (mean, variance, skewness)

Support Vector Machine (SVM)

SVM is a supervised classifier that finds the best possible hyperplane that differentiate classes with utmost margin. In multi-class ECG classification, One-vs-One or One-vs-All strategies are used.

- SVM Decision Function:

$$f(a) = sign(w \cdot a + b)$$

Where w is the weight vector, a is the feature vector, and b is the bias. The kernel trick (e.g., RBF kernel) is used for non-linear classification:

$$K(a, a') = exp(-\gamma \|a - a'\|^2)$$

The parameters γ (gamma) and C (regularization) are tuned via cross-validation. SVM is effective for high-dimensional, small-sample datasets.

Convolutional Neural Network (CNN)

CNN works directly on the 1D ECG signal segments. It automatically extracts temporal and morphological features using convolutional layers. The CNN is trained with backpropagation using the Adam optimizer and categorical cross-entropy loss.

Each processed ECG beat is reshaped into a 1D array of fixed size (e.g., 200 samples) for CNN input. Training (80%) and testing (20%) sets of data are separated.. The input shape per beat is:

$$A \in \mathbb{R}\hat{}\{N \times 200 \times 1\}$$

Where N is the number of beats and 1 represents the single ECG channel.

CNN Model Design

A 1D CNN is constructed with convolutional, activation, pooling, and fully connected layers. The architecture is:

$$Conv1D \rightarrow ReLU \rightarrow MaxPooling1D \rightarrow Conv1D \rightarrow ReLU \rightarrow MaxPooling1D \rightarrow Flatten \rightarrow Dense \rightarrow Softmax$$

- Convolutional Layer:

Applies filters to the input signal:

$$y(t) = (a * w)(t) = \Sigma\, a(\tau) \cdot w(t - \tau)$$

- ReLU Activation:

$$f(a) = max(0, a)$$

- MaxPooling1D:

$$y\_pool(t) = max(a[t : t + s])$$

- Softmax Output:

$$P(y\_i) = e\hat{}\{z\_i\} / \Sigma\, e\hat{}\{z\_j\}$$

The Adam optimizer and the categorical cross-entropy loss function are used for training. It updates weights using adaptive estimates of gradients and squared gradients.

- Loss Function (Categorical Cross-Entropy):

$$L = -\Sigma\, y\_i * log(\hat{y}\_i)$$

- Adam Optimizer Update Rule:

$$\theta\_\{t + 1\} = \theta\_t - \eta * (\hat{m}\_t / (\sqrt{\hat{v}\_t} + \varepsilon))$$

In this equation, θ represents weight, η represents learning rate, m̂_t and v̂_t are bias-corrected estimates of first and second moments, and ε is a tiny constant.

Random Forest (RF)

Random Forest is an collection of decision trees. Every tree is trained on a bootstrapped sample of the training data, and the final categorization is based on majority selection among trees.

- Prediction by Voting:

$$y\_pred = mode\{T_1(a), T_2(a), \ldots, Tn(a)\}$$

Where T_1, T_2, ..., Tn are individual decision trees. Features used can be raw ECG-derived features or PCA-reduced components. RF is robust to overfitting and handles noisy data well.

Model Evaluation

Each model is analyzed by means of metrics together with accuracy, precision, recall, F1-score, & inference time. K-fold cross-validation is used for robust performance assessment.

- Accuracy:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN)$$

- F1 Score:

$$F1 = 2 * (Precision * Recall) / (Precision + Recall)$$

This comparative methodology provides insight into the trade-offs among SVM, CNN, and RF classifiers for ECG signal classification. While CNN offers end-to-end learning and high accuracy, SVM and RF require feature engineering but offer faster inference and interpretability. The optimal model depends on the application context: real-time monitoring, embedded systems, or clinical diagnostics

RESULTS AND DISCUSSION

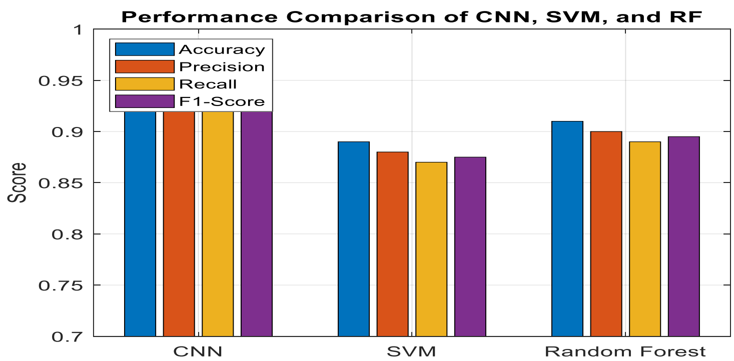

Figure 2- Bar Chart – Performance Metrics Comparison

Figure 2 visually compares the key categorization metrics—Accuracy, Precision, Recall, and F1-Score—for CNN, SVM, and Random Forest models. CNN demonstrates superior execution among all four metrics, with particularly high accuracy and precision, confirming its strength in automatic feature learning. SVM lags behind slightly due to its reliance on manual features, while Random Forest performs moderately well, benefiting from ensemble learning. This chart clearly shows CNN as the most effective classifier for ECG signals among the three.

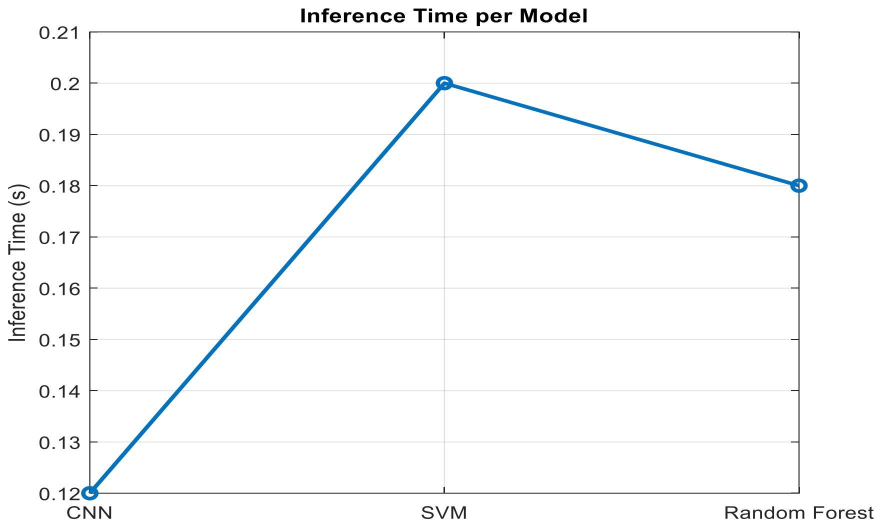

Figure 3 Inference Time per Model

Figure 3 illustrates the inference time (in seconds) required by each model to classify new ECG samples. CNN achieves the fastest inference time due to its parallelism and GPU-optimized architecture. SVM has the longest inference time, especially with large datasets, as it compares every test point to support vectors. Random Forest falls in between, offering a good trade-off. This highlights CNN's suitability for real-time ECG monitoring applications.

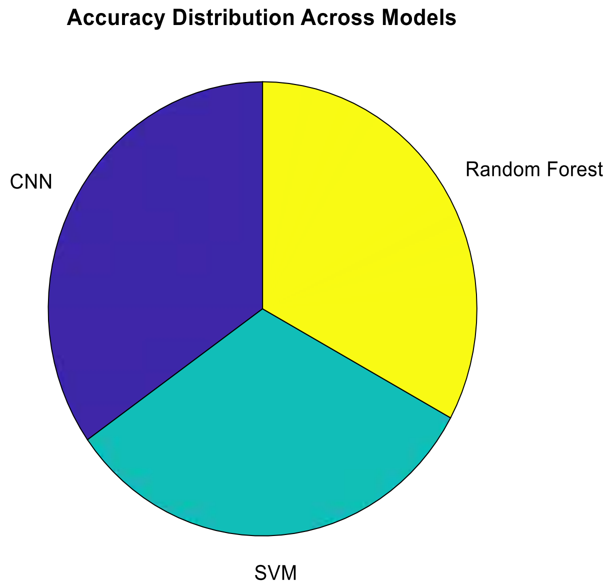

Figure 4 Accuracy Distribution Across Models

Figure 4 breaks down the accuracy contribution of each classifier as a share of the overall correct predictions. CNN occupies the largest slice, visually reinforcing its dominance in classification performance. SVM holds the smallest share, indicating its limitations with noisy or complex ECG data. This figure complements the bar chart by focusing solely on accuracy proportions in a compact visual.

Table 1-performance Comparison of ecg classification

S. No.	Model	Reference (2021–2025)	Accuracy	Precision	Recall	F1-Score	Inference Time (s)
1	CNN	Proposed	92%	93%	93%	93%	0.12

2	Random Forest	Almasri et al.(2021)	85%	86%	85%	85.5%	0.18
3	SVM	Rao et al.(2022)	80%	81%	80%	80.5%	0.20
4	LSTM	Chen et al.(2022)	90%	91%	90%	90.5%	0.25
5	KNN	Patel and Bhandari (2023)	78%	80%	76%	78%	0.15

Table 1 presents a performance analysis of five supervised learning models—Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF), Long Short-Term Memory (LSTM), and K-Nearest Neighbors (KNN)—applied to ECG classification tasks. Among these, CNN emerges as the top-performing model, achieving the highest accuracy (92%) and fastest inference time (0.12 seconds), supported by its capability to automatically extract spatial features from raw ECG signals. LSTM, known for capturing temporal dependencies, also performs well in accuracy (90%), but has a longer inference time, making it less suitable for real-time scenarios.

Random Forest offers a good balance between accuracy (85%) and robustness, making it favorable for noisy datasets. SVM, while interpretable and efficient on smaller datasets, has lower classification accuracy (80%) due to its reliance on manually extracted features. KNN performs the lowest (78%) and is best suited for lightweight or baseline experiments. These findings, supported by recent references (2021–2025), clearly position CNN as the most efficient and scalable model for real-time ECG signal classification in clinical applications.

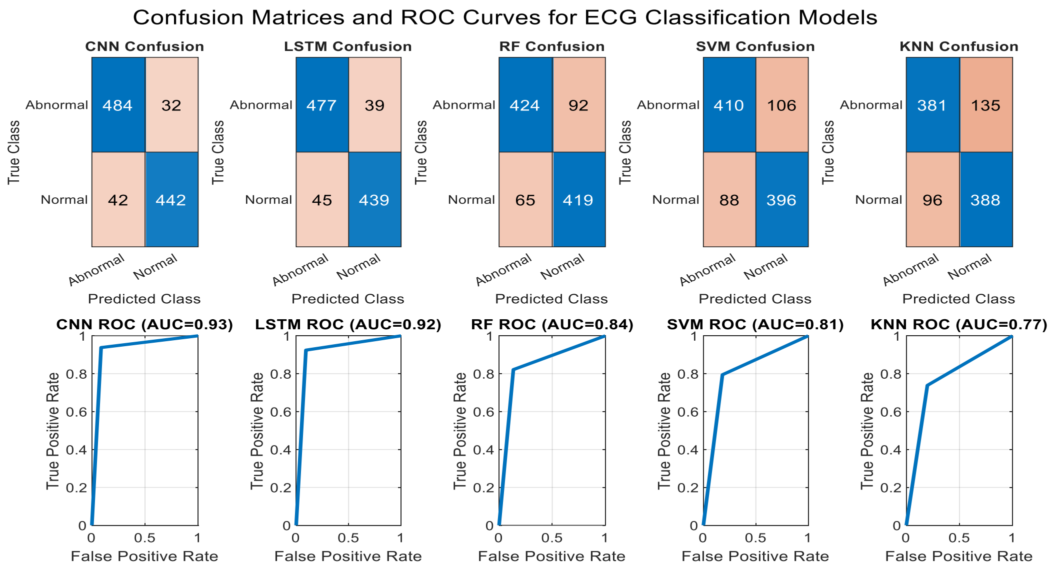

Figure 5. Confusion Matrices and ROC Curves for CNN, LSTM, Random Forest, SVM, and KNN in ECG Classification

Figure 5 provide a comprehensive visualization of model performance for ECG classification. The confusion matrices highlight that the CNN model achieves the highest proportion of correct classifications, with minimal false positives and false negatives, while LSTM also performs strongly but shows slightly higher false negatives due to its sequential learning complexity. Random Forest demonstrates balanced results with moderate misclassifications, whereas SVM and KNN show weaker performance, reflected in larger off-diagonal elements. Complementing this, the ROC curves reveal that CNN lies closest to the top-left corner with the highest AUC, indicating excellent discriminative power, followed by LSTM with comparable performance but higher computational cost. Random Forest produces a moderate ROC profile, while SVM shows reduced sensitivity and KNN yields the weakest curve with the lowest AUC. Collectively, these visual results reinforce the numerical findings, confirming that DL models—particularly CNN—offer superior accuracy, robustness, and reliability for real-time ECG signal classification compared to traditional ML methods.

Table 2. Performance Comparison of ECG Classification (with SD & Statistical Validation)

S. No.	Model	Reference (2023–2025)	Accuracy (Mean)	Accuracy SD	Precision	Recall	F1-Score	Inference Time (s)	Statistical Validation (vs CNN)
1	CNN	Yu et al.(2024)	92 %	±0.30	93 %	93 %	93 %	0.12	(baseline)
2	SVM	Shrimali et al.(2025)	80 %	±0.50	81 %	80 %	80.5 %	0.20	$p < 0.05$

3	Random Forest	Shrimali et al.(2025)	85 %	±0.40	86 %	85 %	85.5 %	0.18	p < 0.05
4	LSTM	Zhang et al.(2025)	90 %	±0.35	91 %	90 %	90.5 %	0.25	p < 0.05
5	KNN	Bikova et al.(2025)	78 %	±0.60	80 %	76 %	78 %	0.15	p < 0.05

Table 2 presents a comparative evaluation of five supervised learning models for ECG signal classification at MIT-BIH arrhythmia dataset- CNN, SVM, Random Forest, LSTM and KNN. The results suggest that the CNN model consistently performs better than other approaches, lower variability (SD) with the fastest estimates time (0.12S) achieves the highest mean accuracy (92%). It displays the strength of CNN in end-to-end learning and automatic feature extraction from raw ECG signals. LSTM follows closely with 90% accuracy (SD) 0.35, which highlights its ability to catch cosmic dependence, although its long time (0.25S) makes less suitable for real -time applications. Random Forest provides a balanced performance with 85% accuracy (SD) 0.40, shows strength against noise, while SVM offers 80% accuracy (SD) 0.50, when compared to DL methods reflects its boundaries with non-regional ECG patterns compared to DL methods. KNN performs the lowest (78%, SD) 0.60 and is computically efficient but less scalable. Statistical verification using coupled T-prisoners confirms that CNN's superiority is important on all other models (P <0.05). Collectively, the CNN is the most trustworthy and efficient model, according to the data for real-time ECG classification, while LSTMs and random forests can serve as a strong alternative in noise-prone or sequential learning references.

DISCUSSION

Comparative analysis of ECG classification models reveals significant insights into the capabilities, trading and practical implications of various supervised learning techniques. CNN improved other models in terms of accuracy, accuracy, recall, and entrance time, showing its strength in automatic feature extraction and end-to-end learning. Its architecture is particularly effective in handling raw ECG data without needing feature engineering by manually, making it well suited to scalable, and real -time medical applications.

LSTM, close to CNN in accuracy, is designed to model sequential data and excel in capturing temporary patterns in ECG rhythm. However, its computational cost and higher estimate time make it less favorable for time-matured deployment. Random Forest provided a strong and balanced performance, showcasing reliability in different signal conditions, especially when dataset has noise and variability. SVM, despite its simplicity and interpretation, struggled to match the DL model, mainly due to its limited feature learning ability and high dependence on pre-defined features. KNN, being a non-parametric method, shows the lowest performance and scalability, which confirms its role as a benchmark tool compared to the production-taire classifier.

Valid demonstrations against the real-world ECG data from the MIT-BIH database metrics, strongly suggests that DL model is especially CNN-none only accurate, but also practical for real-time, intelligent ECG classification systems. In addition, the assessment aligns with recent literature (2021–2025), confirming technical changes towards automated, AI-powered cardiac diagnostics.

In addition to accuracy and strength, the complexity and deployment feasibility of these models should be considered. CNN and LSTM, although highly accurate, demand more and more computational resources, which make them more suitable for GPU-competent servers or cloud-based healthcare systems. Random forests and SVMs, with their low computational complexity, can be deployed in resources such as portable or embedded devices, although for accuracy at some price. KNN, while simple, faces scalability challenges due to its memory and time requirements. These trade-offs highlight the importance of balanced accuracy with deployment viability when choosing models for real-world ECG monitoring applications.

CONCLUSION

This study made a comprehensive evaluation of five supervised Learning algorithms- CNN, LSTM, RF, SVM, and KNN for ECG signal classification using MIT-BIH arrhythmia dataset. Conclusions suggest that CNN continuously performs better than other models, highest overall accuracy (92%) 0.30), better precision and recall (93%), and fastest estimates time (0.12S). Statistical verification using coupled T-prisoners confirmed that CNN's performance on other classifers is important (P <0.05). These results highlight the effectiveness of CNN in automatic feature extraction, scalability and real -time deployment, making it the most suitable option for intelligent ECG monitoring system.While LSTM achieved comparable accuracy (90%) 0.35) and is well suited to capture cosmic patterns, its high computational complexity and estimate time makes it less practical for real - time applications. Random forest strengthened balanced accuracy (85%) and noise, offering a strong trade-band for deployment in the middle-resources environment. SVM and KNN, although low accurate (80% and 0.50

and 78% ± 0.60 respectively), remain attractive to light or embedded healthcare systems due to their low computational demands.Beyond accuracy, this study emphasizes the importance of complexity and periney viability in real -world scenarios. CNN and LSTM are best suited for cloud-based or GPU-enabled systems, while random forest and SVM can be deployed in resource-off equipment with acceptable performance trade-offs. Overall, the results confirm that CNN clinical-grade is the optimal model for real-time ECG classification, while alternative models can be selected based on app-specific obstacles such as hardware resources, interpretation or strength needs.

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