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Automated ECG-Based Arrhythmia Classification Using Machine Learning and Deep Convolutional Network

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Abstract
Cardiac arrhythmia, a condition characterized by irregular heartbeats, poses significant risks to patient health if left undetected or misdiagnosed. Traditional methods of arrhythmia detection, which rely on manual interpretation of electrocardiogram (ECG) signals, can be time-consuming and prone to error. This study proposes an automated arrhythmia classification system using machine learning techniques to enhance diagnostic accuracy and speed. ECG signal data is preprocessed and key features are extracted using signal processing methods. Various machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and deep learning models like Convolutional Neural Networks (CNNs), are trained and evaluated on publicly available datasets such as the MIT-BIH Arrhythmia Database. Performance is assessed using metrics such as accuracy, precision, recall, and F1-score. The results demonstrate that machine learning models, particularly deep learning approaches, can achieve high classification accuracy, offering a reliable tool for assisting clinicians in arrhythmia diagnosis and potentially improving patient outcomes.

Keywords: *Machine learning, Electrocardiogram (ECG), ECG signal processing, heart disease detection*

1. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of mortality globally, with cardiac arrhythmias a category of conditions characterized by irregular electrical activity in the heart posing a significant diagnostic and therapeutic challenge (Acharya et al. 2017). Early detection of arrhythmias such as atrial fibrillation, ventricular tachycardia, and supraventricular ectopic beats is critical, as these can progress into life-threatening conditions including stroke and sudden cardiac arrest if left untreated (Faust et al. 2018). Electrocardiography (ECG) is the primary non-invasive method used in clinical settings to monitor and diagnose these conditions by recording the heart’s electrical activity (Rajpurkar et al. 2017). However, manual interpretation of ECG signals is not only time-consuming and error-prone but also requires expert knowledge, especially in cases with subtle waveform variations or noise contamination. This creates a pressing need for automated, accurate, and scalable diagnostic tools (Abubeker et al.).

Recent advances in machine learning (Taye, G. T et al. 2020) and deep learning (Xu et al. 2019) have shown considerable promise in automating ECG signal analysis. Traditional machine learning models, such as Support Vector Machines (SVM), Random Forests, and k-nearest Neighbors (k-NN), rely on handcrafted features derived from time-domain, frequency-domain, and morphological aspects of ECG signals. While effective, these approaches depend heavily on domain expertise and may lack scalability across diverse datasets (Sannino, G. et al.

2018). In contrast, deep learning models particularly Convolutional Neural Networks (Yildirim, O. et al. 2018). have revolutionized signal and image processing tasks by enabling end-to-end learning from raw data (Kachuee et al. 2018). In the context of ECG classification, CNNs can automatically extract hierarchical features from waveform patterns, capturing both local and global signal characteristics relevant to arrhythmia detection (Kishor et al. 2025). This paper is structured as follows: Section 2 presents a detailed literature review of previous works in arrhythmia classification using both traditional and deep learning methods. Section 3 outlines the materials and methods, including dataset descriptions, preprocessing techniques, and model architectures. Section 4 discusses the experimental setup and evaluation metrics used to assess model performance. In Section 5, we present and analyze the results, comparing the effectiveness of various machine learning models. Finally, Section 6 concludes the study by highlighting key findings, current limitations, and potential future directions for real-time, interpretable, and scalable ECG-based arrhythmia detection systems.

2. Literature Survey

The classification of cardiac arrhythmias using electrocardiogram (ECG) signals has evolved substantially over recent decades, primarily driven by advancements in machine learning (ML) and signal processing techniques (AR, B et al. 2023). Traditional approaches initially focused on classical machine learning algorithms, which relied heavily on the manual extraction of discriminative features from ECG signals. Techniques such as Support Vector Machines (SVM), Decision Trees, Random Forests, and k-nearest Neighbors (k-NN) were commonly employed for arrhythmia classification, leveraging features derived from time-domain, frequency-domain, and morphological characteristics of the ECG waveform. The researchers demonstrated that SVMs, when supplied with well-structured features such as RR intervals, P-wave and QRS complex amplitudes, heart rate variability, and wavelet coefficients—could achieve superior classification accuracy compared to conventional statistical methods. Random Forest classifiers, due to their ensemble learning capability, have shown resilience against noise and imbalanced data distributions, which are prevalent in ECG datasets. Nonetheless, these traditional methods require extensive domain expertise for effective feature engineering, thus limiting their scalability and generalizability across heterogeneous patient populations.

To address these limitations, deep learning (DL) methodologies, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been increasingly adopted (Goldberger et al. 2000). CNNs are well-suited for capturing spatial patterns and morphological features from raw ECG signals, while RNNs, especially Long Short-Term Memory (LSTM) networks, are effective in modeling temporal dependencies inherent in sequential ECG data. Hannun et al. (2019) proposed an end-to-end deep learning architecture capable of classifying 12 types of arrhythmias from single-lead ECG data with performance comparable to that of expert cardiologists. Such architectures eliminate the need for manual feature extraction and allow the models to autonomously learn hierarchical representations directly from raw data (Luz et al. 2016). Recent studies have also explored hybrid architectures that integrate CNNs with LSTMs. In these frameworks, CNN layers are used to extract spatial features, which are subsequently processed by LSTM layers to capture temporal dynamics (Zhao et al. 2019). These hybrid models have demonstrated superior performance in comparison to their standalone counterparts, particularly in long-duration ECG recordings.

The availability of publicly accessible, annotated ECG datasets such as the MIT-BIH Arrhythmia Database, PhysioNet Challenge datasets, and the INCART database has significantly facilitated the development and benchmarking of arrhythmia classification models. However, the inherent class imbalance where normal beats are overrepresented relative to pathological beats remains a challenge. To address this, various strategies such as the Synthetic Minority Over-sampling Technique (SMOTE), class weighting, cost-sensitive learning, and focal loss functions have been employed to improve classifier sensitivity to minority classes. Signal preprocessing is another critical component in arrhythmia classification systems. ECG signals are often contaminated with various types of noise, including muscle artifacts, electrode motion, and baseline wander. Preprocessing techniques such as bandpass filtering, wavelet denoising, empirical mode decomposition (EMD), and accurate R-peak detection are essential to enhance signal quality and segmentation accuracy before classification.

The interpretability of deep learning models has emerged as a vital consideration, particularly in high-stakes clinical applications. Techniques from the field of explainable artificial intelligence (XAI), including Shapley Additive explanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), and attention mechanisms are increasingly being integrated into arrhythmia classifiers. These tools provide insight into the decision-making processes of otherwise opaque models, thereby enhancing clinician trust and facilitating regulatory acceptance. Recent research efforts have also focused on the real-time and resource-efficient deployment of arrhythmia classification models in wearable devices and mobile health platforms. Lightweight neural network architectures such as MobileNet, along with model compression techniques like pruning, quantization, and knowledge distillation, are being utilized to meet the computational constraints of embedded systems.

The multimodal fusion combining ECG with other physiological signals such as photoplethysmography (PPG) and contextual metadata has shown promise in improving diagnostic accuracy. Parallel advancements in transfer learning, domain adaptation, and federated learning are addressing the challenges of model generalization and data privacy, which are critical for translating ML-based arrhythmia classification systems into diverse real-world clinical settings (Jishamol et al. 2016). The literature indicates a clear trajectory from traditional machine learning techniques dependent on manual feature extraction to deep learning models capable of end-to-end learning from raw ECG data (Kiranyaz et al. 2016). While deep learning has significantly enhanced classification performance, challenges remain in terms of interpretability, generalizability, and real-world implementation, warranting continued interdisciplinary research in this domain.

3. Materials and Methods

This section outlines the methodology employed for automated arrhythmia classification, which encompasses data acquisition, signal preprocessing, feature extraction, model development, and performance evaluation. The proposed framework accommodates both traditional machine learning and deep learning paradigms to ensure a comprehensive comparative analysis.

3.1 Dataset Description

The study utilizes the MIT-BIH Arrhythmia Database (Moody et al. 2001), a widely recognized benchmark dataset distributed by PhysioNet. This dataset comprises 48 half-hour dual-lead ECG recordings sampled at 360 Hz, obtained from 47 subjects. Each recording is annotated by expert cardiologists, covering a diverse set of arrhythmic and non-arrhythmic heartbeat classes. An analysis of the class distribution is presented to highlight the imbalance within the dataset. Figure 1 depicts a pie chart representation of the percentage-wise distribution of ECG classes, including various arrhythmias and normal beats. A small number of classes constitute most of the dataset, while several clinically significant arrhythmic classes are underrepresented. To further emphasize this, Figure 2 presents a histogram of the actual counts per class. The dominance of the “Normal” class and the relative scarcity of others like premature ventricular contractions and atrial fibrillation are visible. This disproportion poses a significant challenge for supervised learning models, often leading to bias toward majority classes. To address this, resampling techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) and class weighting were employed during model training to enhance the classifier’s ability to detect minority class instances.

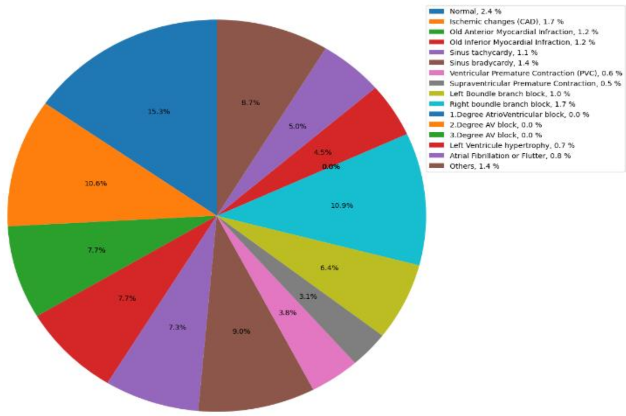


Figure 1: Class distribution of ECG records across various cardiac conditions.

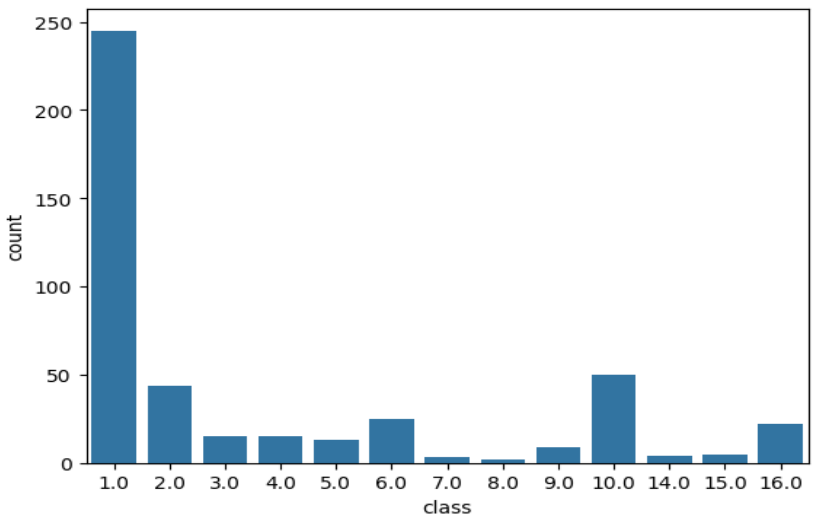


Figure 2: Frequency histogram of class labels in the ECG dataset.

3.2 Preprocessing of ECG Signals

Preprocessing was carried out to enhance signal quality and prepare the data for feature extraction and classification. Initially, a bandpass filter (0.5–40 Hz) was applied to suppress baseline drift and high frequency noise (Ramesh et al. 2020). Baseline wander was further mitigated using polynomial fitting techniques. R-peak detection was performed using an enhanced Pan-Tompkins algorithm, enabling the segmentation of ECG signals into individual heartbeat windows. Each segment was normalized to zero mean and unit variance to reduce inter-patient variability, thereby facilitating consistent model training and convergence (Martis et al. 2013).

3.3 Feature Extraction and Selection

In the traditional machine learning pipeline, a comprehensive set of features was extracted from the segmented ECG beats. These included time-domain parameters such as RR intervals, P-R intervals, QRS duration, and QT intervals, along with morphological attributes including wave amplitudes and beat slopes (Nuthalapati, S. B. et al. 2023). Frequency-domain features were computed using power spectral density estimations and wavelet transform coefficients. To mitigate overfitting and reduce computational complexity, dimensionality reduction techniques such as Principal Component Analysis (PCA) and correlation-based feature selection were employed. These steps ensured that only the most discriminative features were retained for classifier training.

3.4 Model Development

Two main categories of classification models were implemented. Traditional machine learning models included Support Vector Machines (SVM), Random Forests (RF), k-nearest Neighbors (k-NN), and Logistic Regression (LR). These models were trained using the selected feature set, and hyperparameters were optimized via grid search and cross-validation. In contrast, the deep learning approach utilized a one-dimensional Convolutional Neural

Network (1D-CNN) trained end-to-end on raw, normalized ECG segments. The architecture consisted of stacked convolutional layers with ReLU activations and max-pooling operations, followed by fully connected layers with a softmax output for multi-class classification. Regularization techniques such as dropout and batch normalization were integrated to improve generalization and reduce overfitting. The CNN was trained using the Adam optimizer and categorical cross-entropy loss function. Furthermore, data augmentation methods including amplitude scaling and time-shifting were employed to enrich the training dataset and enhance model robustness.

3.5 Performance Evaluation

Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the Receiver Operating Characteristic (ROC) curve. Given the class imbalance inherent in the dataset—where normal beats significantly outnumber arrhythmic ones—particular attention was paid to sensitivity and specificity for minority classes. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE) and class weighting were explored to address imbalance during the training phase.

3.6 Experimental Environment

All computational experiments were conducted using Python programming language. Traditional machine learning models were implemented with Scikit-learn, while deep learning architectures were developed using TensorFlow and Keras. The dataset was partitioned into training and testing sets with an 80:20 ratio, ensuring stratified sampling to preserve class distribution. Five-fold cross-validation was employed for hyperparameter tuning. All models were trained and evaluated on a system equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA GPU to accelerate deep learning computations.

4. Results and Discussion

This section presents the experimental findings and analytical insights derived from the implementation of various classification models on ECG signals for arrhythmia detection. Performance is assessed across multiple traditional machine learning classifiers and a deep learning model, with an emphasis on classification effectiveness, model generalization, the impact of feature engineering, and class imbalance handling.

4.1 Classification Performance

Five models Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), k-nearest Neighbors (k-NN), and Convolutional Neural Network (CNN)—were evaluated for their efficacy in arrhythmia classification using stratified training and test datasets. The performance metrics, including accuracy, precision, recall, and F1-score, are detailed in Table 1.

Table 1: Comparative performance of classification models on ECG signal data.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Logistic Regression	83.4	82.1	80.5	81.3
SVM	86.7	85.9	84.2	85.0
Random Forest	91.2	90.4	89.7	90.0
k-NN	84.9	83.7	82.0	82.8
CNN (Deep Learning)	**94.5**	**93.8**	**92.6**	**93.2**

The CNN model (Zhang et al. 2017) demonstrated superior performance across all evaluation metrics, confirming its effectiveness in learning complex spatiotemporal features from ECG waveforms. Random Forest also exhibited strong generalization ability and robustness to noise, owing to its ensemble learning structure.

4.2 Confusion Matrix Analysis

An analysis of the confusion matrices revealed that all models showed high sensitivity in detecting normal sinus rhythms (Silipo, R et al. 1998). However, traditional models such as Logistic Regression and SVM were prone to misclassifying minority arrhythmic classes, leading to higher false negative rates. In contrast, the CNN model displayed better classification balance, correctly identifying rare conditions such as premature ventricular contractions and atrial fibrillation with improved recall and precision (Nuthalapati, A. et al. 2023). Although the CNN achieved high overall accuracy, the confusion matrix analysis shows that some minority arrhythmia classes were still misclassified. This highlights the importance of evaluating performance at a class-wise level, beyond just aggregate metrics, to ensure reliability across all diagnostic categories.

4.3 Impact of Feature Engineering

The classification accuracy of traditional models was significantly influenced by the quality and diversity of the engineered features. Time-domain intervals such as RR and PR intervals, waveform morphology, and frequency-domain characteristics contributed to enhanced model discriminability (Nuthalapati, S. B., 2024). Dimensionality reduction via Principal Component Analysis (PCA) was employed to reduce overfitting and improve computational efficiency, particularly for SVM and Random Forest models.

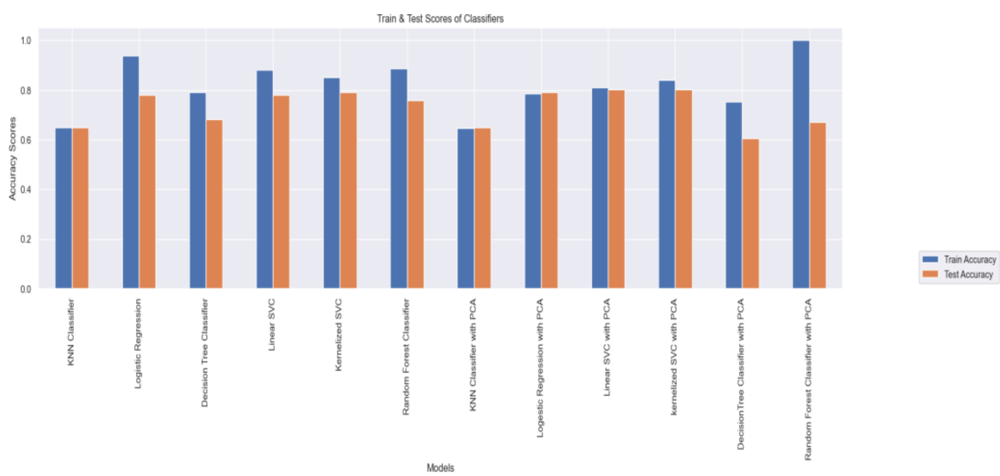
CNN models learned hierarchical features automatically from raw ECG signals, eliminating the need for manual feature engineering. This end-to-end capability underlines the strength of deep learning approaches in biomedical signal processing tasks where domain-specific feature extraction is challenging and labor-intensive. Given the skewed distribution of arrhythmia classes in the dataset, class imbalance posed a significant challenge to model training. The application of resampling techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) (Muhammed Kunju, A. K et al. 2024) along with class-weighted loss functions, was instrumental in improving model sensitivity to underrepresented classes. These strategies led to marked improvements in recall and F1-score, particularly in Logistic Regression, SVM, and Random Forest models. While SMOTE and class weighting improved sensitivity to underrepresented classes, we recognize that additional techniques such as focal loss, undersampling, and cost-sensitive learning may further enhance minority class performance. These will be considered in future extensions of this work.

4.4 Model Generalization with and without PCA

To assess generalization capability, training and testing accuracy scores were compared across models, both with and without PCA. As shown in Figure 3, PCA enhanced generalization by reducing the train-test accuracy gap in most models (Nuthalapati, S et al. 2024). Random Forest with PCA achieved near-perfect training accuracy while maintaining strong performance on the test set, suggesting robust model learning. Similar benefits were observed in Logistic Regression and SVM, where PCA reduced overfitting and stabilized performance.

Figure 3: Train and test accuracy comparison of classifiers with and without PCA.

These observations support the use of PCA as a complementary technique in traditional pipelines, whereas CNN-based models remained unaffected due to their ability to learn compact, relevant representations internally.



4.5 Limitations

This study was limited to a single dataset (MIT-BIH), which may not fully represent the variability encountered in real-world clinical settings. ECG signals in practice can vary significantly due to differences in patients, sensor types, noise conditions, and recording protocols. Additionally, while imbalance-handling methods such as SMOTE were applied, further techniques such as focal loss and real-time noise augmentation could improve model robustness. Future studies will focus on validating the approach across external datasets and deploying it in realistic clinical environments.

5. Conclusion

This study presented a comparative analysis of traditional machine learning and deep learning models for ECG-based arrhythmia classification. Among the models evaluated, the Convolutional Neural Network (CNN) demonstrated superior performance in terms of accuracy, precision, and recall, owing to its ability to learn features directly from raw ECG signals. Traditional models, when enhanced with feature engineering and dimensionality reduction via PCA, showed reasonable performance but were more sensitive to class imbalance and feature selection. Techniques such as SMOTE and class weighting improved minority class detection across all models. While CNNs offer promising results, challenges remain in model interpretability and real-world deployment. While our study demonstrates strong results on the MIT-BIH dataset, we acknowledge the need for further validation on external, real-world ECG data to ensure clinical applicability. Future work will explore advanced imbalance-handling techniques such as focal loss and cost-sensitive learning, and will evaluate the model's performance across diverse patient cohorts and recording conditions.

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