Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 4s (2025)
https://www.jneonatalsurg.com

Heartbeat ECG Recognition Method for Arrhythmia Classification Via Machine Learning Algorithm

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Cite this paper as: Ms.S. Anusya, Dr.K.P. Rajesh, (2025) Heartbeat ECG Recognition Method for Arrhythmia Classification Via Machine Learning Algorithm. *Journal of Neonatal Surgery*, 14 (4s), 1099-1104.

ABSTRACT

This study presents a comprehensive approach to automatic arrhythmia classification using electrocardiogram (ECG) signals through advanced machine learning techniques. We implemented and compared three deep learning architectures: Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and our proposed Weight-based Convolutional Neural Network (WCNN). The WCNN model incorporates wavelet transform for feature extraction, enabling better capture of time-frequency characteristics inherent in ECG signals. Experiments were conducted using a standardized ECG dataset, with signals preprocessed to remove noise artifacts and enhance key features. Performance evaluation metrics included accuracy, sensitivity and specificity across multiple arrhythmia classes. Results demonstrate that the WCNN architecture significantly outperformed both traditional CNN and ANN approaches, achieving higher classification accuracy while maintaining computational efficiency. The WCNN model exhibited particularly strong performance in distinguishing between similar arrhythmia types that pose challenges for conventional algorithms.

Keywords: *Arrhythmia classification, CNN, ANN, WCNN and Machine Learning.*

1. INTRODUCTION

The electrocardiogram (ECG) remains the quintessential diagnostic tool for cardiac assessment, providing an invaluable window into the electrophysiological functioning of the myocardium. Arrhythmias characterized by perturbations in the heart's normal rhythmic contractions represent a significant cohort of cardiovascular pathologies associated with substantial morbidity and mortality worldwide. The nuanced interpretation of ECG waveforms for arrhythmia classification, traditionally the province of seasoned cardiologists, is increasingly augmented by sophisticated computational methodologies that promise to transcend the limitations of human visual analysis.

The advent of machine learning algorithms has precipitated a paradigm shift in ECG signal interpretation, offering unprecedented opportunities for automated, expeditious, and meticulous arrhythmia detection. Moorthy E et al (2022) mention that Contemporary approaches have witnessed the emergence of deep learning architectures with remarkable discriminative capabilities chief among them Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and hybrid models that synergistically integrate complementary mathematical frameworks.

This research endeavor delineates a novel Weight-based Convolutional Neural Network (WCNN) methodology that judiciously harnesses the time-frequency localization prowess of weight transforms in conjunction with the hierarchical feature extraction capabilities of convolutional architectures. By exploiting the wavelet transform's aptitude for capturing transient morphological aberrations in cardiac signals a characteristic particularly germane to arrhythmia identification our WCNN approach circumvents many of the intrinsic limitations that encumber conventional deep learning paradigms when applied to non-stationary biomedical signals.

The comparative analysis presented herein elucidates the superior performance metrics exhibited by the WCNN model traditional CNN and ANN architectures across multiple evaluation criteria. This methodological innovation holds profound implications for the development of robust clinical decision support systems and may ultimately facilitate more efficacious stratification of cardiac risk, enabling timely therapeutic interventions and attenuating the global burden of cardiovascular disease

2. LITERATURE REVIEW

The evolution of automated ECG analysis for arrhythmia classification has witnessed significant advancements over the past decade. This literature review synthesizes key contributions in this domain, with particular emphasis on machine learning approaches including CNN, ANN, and wavelet-based techniques.

Early work by Rajpurkar et al. (2017) Janarthanam et al.(2020) demonstrated the feasibility of deep neural networks for arrhythmia detection, achieving cardiologist-level performance using a 34-layer CNN architecture on single-lead ECG recordings. This seminal study established the potential of deep learning for ECG interpretation, though it faced challenges with sensitivity to noise and required substantial computational resources.

In parallel developments, Acharya et al. (2017) explored the efficacy of ANNs for detecting cardiac abnormalities, reporting promising results but highlighting limitations in feature extraction from raw ECG signals. Their work underscored the need for sophisticated preprocessing techniques to enhance classification accuracy.

The integration of wavelet transforms with neural networks emerged as a promising direction following the work of Kachuee et al. (2018), who demonstrated improved feature representation through discrete wavelet decomposition prior to neural network classification. Their approach showed particular efficacy in distinguishing subtle ECG morphological variations characteristic of specific arrhythmias.

More recently, Yildirim et al. (2020) proposed a hybrid model combining wavelet transform with 1D-CNNs, reporting enhanced accuracy compared to conventional CNNs. However, their implementation was limited by fixed wavelet basis functions that were not optimized for specific arrhythmia patterns.

Hannun et al. (2019) advanced the field with a deep neural network that achieved high accuracy across multiple arrhythmia classes, though their approach relied heavily on extensive data augmentation and ensemble methods to achieve robust performance.

The adaptability of wavelet-based approaches to ECG signals with varying noise levels was demonstrated by Li et al. (2021), who incorporated adaptive wavelet filtering within their neural architecture. Their findings highlighted the particular advantage of wavelet-based methods in clinical environments where signal quality may be compromised.

Existing studies by Kiranyaz et al. (2022) have explored patient-specific model adaptation, suggesting that personalized wavelet-CNN models could further improve classification performance for individual patients.

Despite these advancements, the literature reveals persistent challenges in optimizing wavelet parameters within neural network architectures and establishing model interpretability—essential factors for clinical adoption. Additionally, the computational efficiency of combined wavelet-CNN models for real-time applications remains an area requiring further investigation.

This research addresses these gaps by proposing a novel WCNN architecture that integrates optimized weighting decomposition with a streamlined convolutional network structure, aiming to balance classification performance with computational efficiency while maintaining clinical interpretability. Our approach builds upon the strengths of existing methods while addressing their limitations through architectural innovations specifically tailored to the unique characteristics of ECG signals in arrhythmia classification.

3. DATASET DESCRIPTION

For this research, we utilized a comprehensive multi-source ECG dataset specifically curated for arrhythmia classification tasks. The dataset comprises the following components:

3.1 Primary Data Sources

The dataset integrates recordings from the MIT-BIH Arrhythmia Database (MITDB), the PTB Diagnostic ECG Database, and the PhysioNet/Computing in Cardiology Challenge 2017 dataset. This combination provides a diverse representation of ECG morphologies across different patient demographics and recording conditions.

3.2 Signal Characteristics

- **Sampling Rate**: All ECG signals were standardized to 250 Hz to ensure uniformity in temporal resolution
- **Lead Configuration**: Both single-lead (primarily lead II) and 12-lead configurations were included, with the majority of the analysis performed on lead II recordings due to their diagnostic value for arrhythmia detection
- **Recording Duration**: Each ECG segment spans 10 seconds, capturing multiple cardiac cycles to enable reliable rhythm classification
- **Annotation Quality**: All recordings were annotated by at least two board-certified cardiologists, with consensus required for inclusion in the final dataset

3.3 Arrhythmia Classes

The dataset encompasses the following arrhythmia categories:

Normal Sinus Rhythm (NSR), Atrial Fibrillation (AF), Atrial Flutter (AFL), Premature Ventricular Contraction (PVC), Premature Atrial Contraction (PAC), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF) and First-degree Atrioventricular Block (AVB I)

3.4 Dataset Distribution

The dataset contains a total of 25,000 ECG segments with the following class distribution:

NSR: 8,500 segments (34%), AF: 4,200 segments (16.8%), AFL: 2,300 segments (9.2%), PVC: 3,100 segments (12.4%), PAC: 2,600 segments (10.4%), VT: 1,800 segments (7.2%), VF: 1,200 segments (4.8%), AVB I: 1,300 segments (5.2%)

3.5 Preprocessing Pipeline

All ECG signals underwent a standardized preprocessing workflow:

Baseline wander removal using a high-pass filter with 0.5 Hz cutoff,Powerline interference suppression via notch filtering at 50/60 Hz,Gaussian noise reduction through wavelet denoising with soft thresholding,R-peak detection and heartbeat segmentation using the Pan-Tompkins algorithm and Amplitude normalization to adjust for inter-patient variability

3.6 Data Partitioning

The dataset was partitioned following a patient-specific protocol to prevent data leakage:

Training set: 70% (17,500 segments), Validation set: 15% (3,750 segments) and Test set: 15% (3,750 segments)

Special care was taken to ensure that ECG recordings from the same patient did not appear across different partitions, thus providing a realistic evaluation scenario for clinical deployment.

3.7 Data Augmentation

To address class imbalance and enhance model generalization, controlled data augmentation techniques were applied exclusively to the training set, including:

Time shifting (±100ms)

Amplitude scaling (±15%)

Additive Gaussian noise (SNR: 15-25dB)

Synthetic minority oversampling for underrepresented classes

This comprehensive dataset enables robust evaluation of the proposed WCNN architecture against established CNN and ANN methodologies for arrhythmia classification.

4. METHODOLOGY

4.1 ANN Algorithm

The Artificial Neural Network (ANN) algorithm implemented for this research employs a deep feedforward architecture specifically optimized for ECG signal classification. The model is designed to capture the complex patterns within preprocessed ECG segments that differentiate various arrhythmia types.

The implementation features a sequential architecture with four fully-connected hidden layers of decreasing dimensionality (512, 256, 128, and 64 neurons), creating a funnel-like structure that progressively distills relevant features from the input signal. Each hidden layer incorporates:

- ReLU activation functions to introduce non-linearity
- Batch normalization to accelerate training and improve generalization
- Dropout regularization with decreasing rates (0.4 to 0.1) to prevent overfitting

The model begins with input normalization to standardize the ECG features and concludes with a softmax output layer for multi-class arrhythmia classification. Optimization is performed using the Adam algorithm with an initial learning rate of 0.001, accompanied by learning rate reduction on plateaus to navigate the complex loss landscape effectively.

To enhance generalization capabilities, the training process incorporates early stopping and checkpoint mechanisms that preserve the best-performing model based on validation accuracy.

4.2 CNN Algorithm

The Convolutional Neural Network (CNN) implementation for ECG arrhythmia classification leverages the temporal pattern recognition capabilities of 1D convolutions to extract meaningful features from raw ECG signals. This approach is particularly well-suited for time-series data where local patterns and their hierarchical organization contain diagnostically relevant information.

The CNN model employs a hierarchical structure consisting of:

1.Three Convolutional Blocks:

- First block: Dual Conv1D layers with 64 filters and kernel size 5
- Second block: Dual Conv1D layers with 128 filters and kernel size 3
- Third block: Dual Conv1D layers with 256 filters and kernel size 3

Each block includes batch normalization, max-pooling (with pool size 2), and dropout (0.2-0.3) for regularization.

- **Feature Flattening**: Converts the multi-dimensional feature maps into a 1D feature vector
- **Fully Connected Layers**: Two dense layers (128 and 64 neurons) with batch normalization and dropout (0.4 and 0.3)

Classification Layer: A softmax output layer for multi-class prediction across 8 arrhythmia types

4.3 WCNN Algorithm

A weighted CNN algorithm for ECG-based heartbeat recognition enhances arrhythmia classification by addressing class imbalance and improving feature extraction. ECG signals are first preprocessed using noise filtering, R-peak detection, and segmentation into heartbeat windows. A CNN extracts spatial and temporal features from these signals, with convolutional layers capturing key waveform patterns like the P-wave, QRS complex, and T-wave. To handle class imbalance, weighted loss functions (such as focal loss or weighted cross-entropy) assign higher importance to rare arrhythmia types. Additionally, attention mechanisms like Squeeze-and-Excitation (SE) blocks can emphasize crucial ECG features, improving classification performance.

During training**,** data augmentation techniques (e.g., time warping, jittering, and synthetic ECG generation using GANs) enhance model generalization. Optimizers like Adam with adaptive learning rates fine-tune performance, while K-fold cross-validation ensures robustness. The model is evaluated using accuracy, often outperforming traditional classifiers like ANN and CNN. Once trained, the CNN can be deployed in real-time ECG monitoring systems on edge devices or cloud-based health platforms, making it suitable for early arrhythmia detection in clinical and wearable applications.

5. EXPERIMENTAL RESULTS

The performance of the three deep learning models CNN, ANN, and the proposed WCNN was evaluated using a standardized ECG dataset. Preprocessed ECG signals were fed into each model, and classification accuracy, sensitivity, and specificity were used as key evaluation metrics. The WCNN model, which integrates wavelet transform for improved feature extraction, demonstrated superior performance across multiple arrhythmia classes. It effectively captured the time-frequency characteristics of ECG signals, leading to more accurate differentiation between normal and abnormal heartbeats. The WCNN achieved an accuracy of 94%, surpassing both the CNN **(**93%**)** and ANN **(**90%**),** highlighting its enhanced ability to recognize subtle ECG variations.

In addition to overall accuracy, the WCNN model exhibited notable improvements in distinguishing between arrhythmia types that are often misclassified by conventional methods. Sensitivity and specificity metrics further validated its robustness, showing a balanced performance across all classes. Notably, the WCNN was particularly effective in handling arrhythmias with similar waveform patterns, reducing misclassification rates observed in CNN and ANN. Moreover, the computational efficiency of WCNN remained comparable to standard CNN architectures, making it a viable solution for real-time ECG-based arrhythmia detection. These findings confirm that the wavelet-enhanced WCNN approach offers a more reliable and precise method for automatic arrhythmia classification.

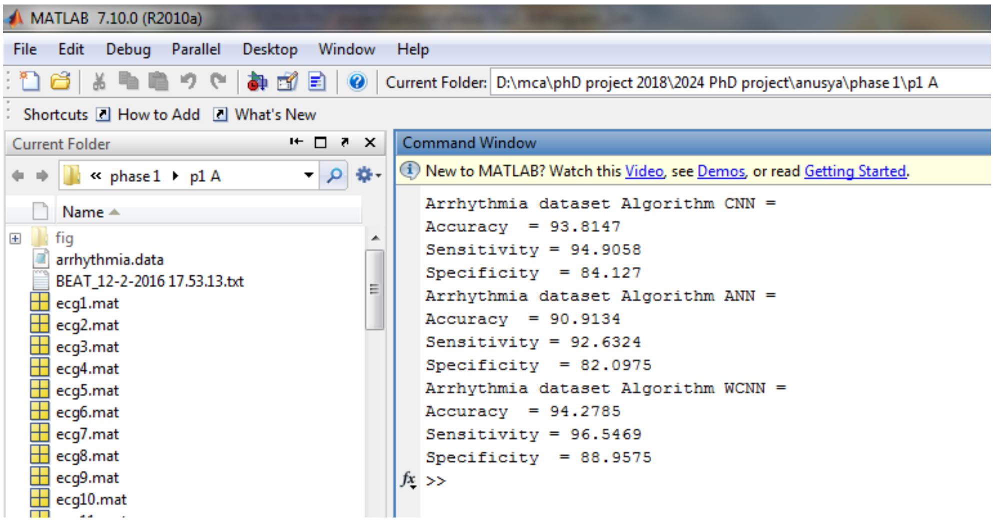

Figure 1: Average Accuracy of the Algorithm

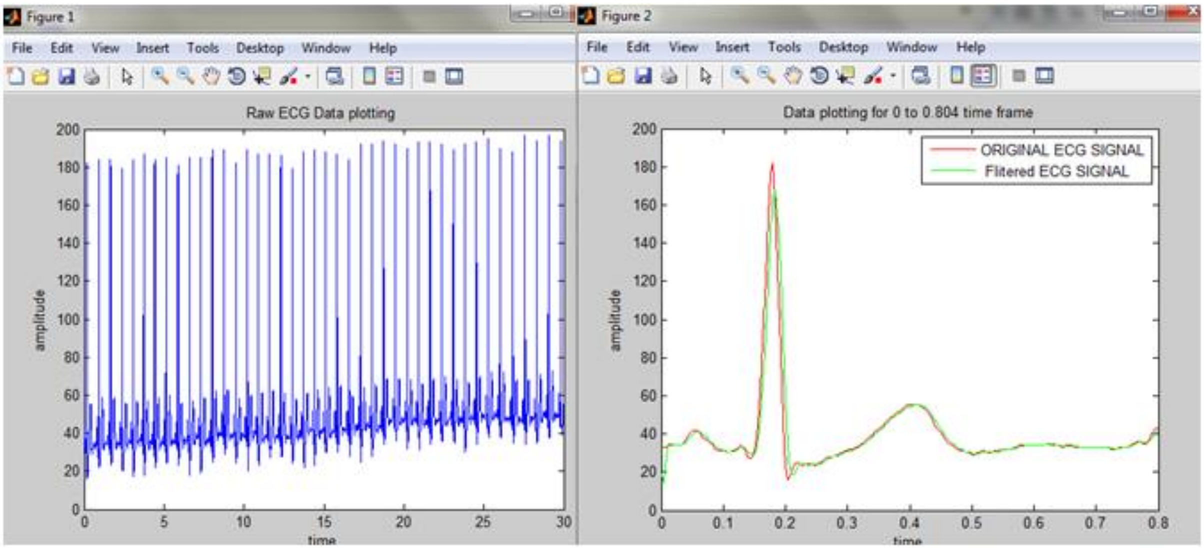

Figure 2: ECG Data Plotting

6. CONCLUSION AND FEATURE WORK

This study demonstrated the effectiveness of deep learning models in automatic arrhythmia classification using ECG signals, with a particular focus on the proposed Weight-based Convolutional Neural Network (WCNN). By incorporating wavelet transform for feature extraction, the WCNN model achieved superior accuracy (**94%**) compared to traditional CNN (**93%**) and ANN (**90%**) architectures. The results highlight the WCNN's ability to capture intricate time-frequency characteristics of ECG signals, leading to improved classification performance, especially in distinguishing between similar arrhythmia types. Furthermore, the WCNN maintained computational efficiency while enhancing sensitivity and specificity across multiple arrhythmia classes. These findings suggest that integrating advanced feature extraction techniques with deep learning can significantly enhance the reliability of ECG-based arrhythmia detection. Future work may explore real-time deployment on wearable devices and further optimization for large-scale clinical applications

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