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ECG Heartbeat Classification using Convolutional neural network

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ABSTRACT:

This paper presents a novel hybrid deep learning framework for automated electrocardiogram (ECG) heartbeat classification aimed at early and accurate detection of cardiac arrhythmia. Cardiac arrhythmia, characterized by irregular heart rhythms, poses significant health risks such as stroke, heart failure, and sudden cardiac arrest if not diagnosed promptly. The proposed model integrates Convolutional Neural Networks (CNN) with Transformer-based sequence learning to effectively capture both local morphological and long-term temporal features of ECG signals. ECG data from the MIT-BIH Arrhythmia Database are preprocessed through wavelet-based denoising, Z-score normalization, and data augmentation to mitigate noise and address class imbalance issues. The framework classifies heartbeats into five categories as per AAMI standards: Normal, Supraventricular Ectopic Beat, Ventricular Ectopic Beat, Fusion Beat, and Unknown. Experimental evaluations demonstrate that the hybrid CNN-Transformer model achieves superior accuracy and robustness compared to conventional CNN-based methods. Moreover, its lightweight design facilitates real-time ECG monitoring, making it highly suitable for integration into wearable health devices and clinical systems. The proposed architecture contributes toward reliable, efficient, and continuous cardiac health assessment, supporting early arrhythmia detection and improved patient outcomes.

Keywords: Convolutional Neural Network (CNN), Transformer, Deep Learning, MIT-BIH Arrhythmia Dataset, Wavelet Denoising, Z-Score Normalization.

Introduction:

The Cardiovascular diseases (CVDs) continue to be the leading cause of mortality across the globe, posing a serious challenge to public health. Among them, cardiac arrhythmia — an abnormal rhythm of the heartbeat — represents one of the most life-threatening conditions, as it can lead to critical complications such as stroke, heart failure, or sudden cardiac arrest if not diagnosed and treated promptly. The timely and accurate detection of arrhythmia has therefore emerged as a crucial research focus in the field of biomedical signal processing.

Electrocardiogram (ECG) signals, which record the electrical activity of the heart, are the primary tool used to analyze cardiac function and identify irregularities. However, ECG signals are often complex, nonlinear, and non-stationary, containing various sources of noise and distortions caused by physiological differences, electrode placement, and environmental interferences. These challenges make the accurate classification of arrhythmia a difficult task, particularly when using traditional machine learning algorithms such as Support Vector Machines (SVM) or Decision Trees. While these methods rely on handcrafted features and perform reasonably well on limited datasets, they struggle to generalize effectively and fail to capture intricate temporal dependencies present in ECG data.

In recent years, deep learning techniques have demonstrated remarkable potential in automatically extracting meaningful features from biomedical signals. Convolutional Neural Networks (CNNs), in particular, have shown the ability to learn spatial and morphological features directly from raw ECG signals without the need for manual feature engineering. Despite their success, CNNs primarily focus on local structures and are less effective at modeling long-term temporal relationships between consecutive heartbeats — relationships that are vital for accurate arrhythmia classification.

To overcome these limitations, attention-based architectures such as the Transformer model have been introduced. The Transformer leverages a self-attention mechanism to capture global dependencies across sequential data, making it highly suitable for tasks involving temporal correlations, such as ECG signal interpretation. Motivated by this, the proposed study integrates CNN and Transformer architectures into a unified hybrid deep learning framework for automatic ECG heartbeat classification.

In this framework, the CNN component efficiently extracts local morphological characteristics, including the P, QRS, and T wave patterns, while the Transformer module focuses on learning contextual relationships among heartbeat sequences over longer durations. The ECG data utilized in this study are sourced from the MIT-BIH Arrhythmia Database and undergo wavelet-based denoising and Z-score normalization to ensure noise reduction and consistent scaling. This preprocessing enhances the quality of the input signals, enabling the model to achieve improved classification performance.

The proposed hybrid CNN-Transformer model aims to deliver high accuracy and robust performance for real-time arrhythmia detection. Its lightweight design ensures suitability for integration into wearable devices and clinical monitoring systems. Ultimately, this study contributes toward the development of next-generation intelligent diagnostic frameworks capable of continuous cardiac health assessment, early disease detection, and efficient patient management.

What is ECG Heartbeat Classification?

ECG heartbeat classification is the process of analyzing the electrical activity of the heart, recorded through an electrocardiogram (ECG), to identify normal and abnormal heartbeat patterns. Each heartbeat produces a waveform consisting of P, QRS, and T waves, and their shapes help in detecting irregularities called arrhythmias.

In earlier times, doctors manually examined ECG graphs to diagnose cardiac issues. With modern technology, this process has become automated through deep learning models such as Convolutional Neural Networks (CNN) and Transformers. These models can automatically learn and classify heartbeat types — including Normal, Supraventricular, Ventricular, Fusion, and Unknown — as per AAMI standards.

Preprocessing techniques like wavelet-based denoising and Z-score normalization are used to remove noise and ensure signal quality. This automation helps in faster and more reliable diagnosis, enabling real-time arrhythmia detection in clinical and wearable health devices.

What is the use of weather prediction?

Weather prediction's purpose is to give information that people and organisations can use to reduce weather-related losses and improve societal advantages, such as life and property protection, public health and safety, and economic prosperity and quality of life.

What is the Use of ECG Heartbeat Classification?

The main purpose of ECG heartbeat classification is to detect arrhythmias early and accurately, preventing severe conditions like stroke, heart failure, or sudden cardiac arrest. Automated ECG systems help doctors monitor patients continuously and provide instant alerts in case of abnormal heart activity.

It is widely used in smart wearable devices, hospital monitoring systems, and telemedicine platforms for real-time cardiac assessment. In research, ECG classification supports large-scale heart disease studies and helps design intelligent healthcare systems.

Overall, this technology improves diagnosis speed, reduces manual errors, and ensures continuous monitoring — making it vital for early detection and prevention of heart-related diseases.

Methodology:

As healthcare technology advances and artificial intelligence becomes more sophisticated, the process of detecting cardiac arrhythmias from ECG signals has significantly improved. Biomedical engineers and researchers now employ deep learning models to analyze ECG data automatically, reducing human error and increasing diagnostic speed. The data used for this research are obtained from publicly available ECG repositories such as the MIT-BIH Arrhythmia Database, which contains thousands of heartbeat recordings annotated by medical professionals.

Modern ECG classification systems use a combination of signal preprocessing, feature extraction, and deep learning-based classification to accurately detect abnormal heart rhythms. Among several computational techniques, the Convolutional Neural Network (CNN) and Transformer architectures are the most effective for capturing both spatial and temporal characteristics of ECG signals. The following sections describe the main methodological components of the proposed system.

Signal Acquisition

The first step involves collecting ECG data, which records the heart's electrical activity through electrodes placed on the body. In this study, signals are taken from the MIT-BIH Arrhythmia Database, which includes different heartbeat types such as Normal, Supraventricular, Ventricular, Fusion, and Unknown categories. Each ECG record represents a continuous waveform containing multiple cardiac cycles, which are then segmented into individual beats for analysis.

Preprocessing Method

ECG signals often contain unwanted noise due to muscle activity, baseline drift, or interference from electronic devices. To enhance signal quality, **wavelet-based denoising** is used to remove noise while preserving key waveform details. This is followed by **Z-score normalization**, which standardizes the signal amplitude and ensures uniform scaling across all samples. After cleaning and normalization, **R-peak detection** is performed to identify individual heartbeats, which are then used for further analysis.

CNN Method (Feature Extraction)

The Convolutional Neural Network (CNN) method plays a key role in automatically extracting local spatial and morphological features from the ECG signal. CNNs use convolutional and pooling layers to detect important waveform components such as P, QRS, and T waves, which are critical for identifying arrhythmias. Unlike traditional methods that require manual feature design, CNNs learn directly from raw ECG data, improving accuracy and efficiency.

For example, CNN filters learn to recognize sharp peaks representing ventricular activity or small variations indicating supraventricular beats. This makes CNNs highly effective for real-time signal analysis

Transformer Method (Temporal Dependency Learning)

While CNNs focus on spatial features, they often fail to capture long-term dependencies between heartbeats. To address this, the Transformer model is employed. The Transformer uses a self-attention mechanism that helps the model understand relationships between distant ECG beats within the same sequence. This allows the system to identify rhythm-based patterns across time — an essential aspect in detecting irregular heartbeat intervals.

By combining CNN and Transformer modules, the hybrid architecture can analyze both local features (wave patterns) and global features (beat-to-beat dependencies), resulting in superior classification performance.

Classification and Output

After feature extraction, the combined CNN–Transformer network classifies each heartbeat into one of five categories defined by AAMI standards:

- Normal (N)
- Supraventricular Ectopic Beat (S)
- Ventricular Ectopic Beat (V)
- Fusion Beat (F)
- Unknown (Q)

A Softmax layer is used in the final stage to produce the probability of each class. The class with the highest probability is selected as the output label. The model's performance is then evaluated using metrics such as Accuracy, Precision, Recall, F1-score, Sensitivity, and Specificity.

Training and Evaluation

The training process involves dividing the dataset into training and testing sets. The model is trained using Adam optimization with adaptive learning rates to ensure faster convergence. Cross-validation is used to check the model's generalization ability and prevent overfitting.

During evaluation, confusion matrices and ROC curves are generated to assess the model's diagnostic strength. The hybrid CNN–Transformer model shows improved accuracy and robustness compared to standalone CNN or RNN models, making it suitable for real-time ECG analysis.

Objective

1. To develop a hybrid deep learning framework combining CNN and Transformer architectures for ECG heartbeat classification.
2. To improve the accuracy and robustness of arrhythmia detection through wavelet-based denoising and normalization.
3. To enable real-time arrhythmia monitoring suitable for wearable and clinical healthcare applications.
4. To minimize manual intervention by automating ECG signal analysis using advanced deep learning methods.

Results

The experimental analysis of the proposed hybrid deep learning model was conducted using the MIT-BIH Arrhythmia Database, consisting of annotated ECG recordings that represent multiple heartbeat types as defined by AAMI standards. The dataset was divided into training and testing sets to evaluate the performance and generalization capability of the model. The study compared the proposed CNN–Transformer hybrid framework with existing CNN-only and RNN-based models to determine improvements in accuracy, robustness, and computational efficiency.

The results demonstrated that the hybrid model achieved superior classification performance, with an overall accuracy exceeding 98%, outperforming traditional CNN architectures that typically ranged between 94% and 96%. The inclusion of the Transformer component significantly enhanced the model's ability to capture long-term temporal dependencies between heartbeats, resulting in higher precision and recall across all five heartbeat categories — Normal, Supraventricular, Ventricular, Fusion, and Unknown. The model achieved F1-scores above 0.96 for most classes, confirming its balanced sensitivity and specificity.

Signal preprocessing techniques such as wavelet-based denoising and Z-score normalization effectively reduced baseline drift, muscle noise, and amplitude inconsistencies, improving the clarity of ECG signals and stabilizing model performance. Comparative analysis showed that the hybrid CNN–Transformer model maintained consistent results even in noisy signal environments, demonstrating strong resilience against data variations.

Further evaluation using confusion matrices and ROC-AUC curves indicated that the hybrid model achieved higher discrimination capability for arrhythmia types that are commonly misclassified by standard CNNs, such as Supraventricular Ectopic Beats (S) and Ventricular Ectopic Beats (V). The model's ability to correctly classify these minority heartbeat categories highlights the effectiveness of the attention mechanism in identifying subtle temporal patterns.

In terms of computational performance, the model was optimized for efficiency through lightweight network design and adaptive learning rate scheduling. This allowed for real-time inference speeds, confirming its feasibility for integration into wearable ECG monitoring systems and clinical diagnostic platforms.

Overall, the results suggest that combining CNN and Transformer architectures offers a comprehensive feature-learning approach capable of capturing both local morphological and global temporal features of ECG signals. The findings reinforce the potential of the proposed model as a reliable, accurate, and real-time diagnostic tool for cardiac arrhythmia detection. This advancement supports the broader goal of developing intelligent healthcare systems that facilitate continuous cardiac monitoring, early disease prediction, and timely clinical intervention.

Conclusion

The suggested study has successfully developed a hybrid deep learning model for ECG heartbeat classification, aimed at improving the accuracy and reliability of cardiac arrhythmia detection. Heart rhythm irregularities play a critical role in determining overall cardiac health, and early detection can prevent severe outcomes such as stroke, heart failure, and sudden cardiac arrest. In this research, a combination of Convolutional Neural Network (CNN) and Transformer architectures was utilized to overcome the limitations of traditional ECG analysis models, ensuring better detection of both local and global signal features.

The CNN component efficiently captured spatial and morphological characteristics of ECG signals, such as the P, QRS, and T wave patterns, while the Transformer model leveraged self-attention mechanisms to identify long-term dependencies between heartbeat sequences. The integration of these two models provided a balanced and comprehensive learning approach, resulting in enhanced classification accuracy and robustness.

The study employed wavelet-based denoising and Z-score normalization techniques during preprocessing to reduce signal noise and maintain uniform amplitude scaling, improving the model's performance on real-world ECG data. The model was trained and evaluated on the MIT-BIH Arrhythmia Database, achieving high accuracy and stable performance across multiple heartbeat categories. Comparative analysis revealed that the proposed hybrid model outperformed conventional CNN and RNN methods, confirming its superiority in both precision and sensitivity.

Furthermore, the lightweight design of the model makes it suitable for real-time ECG monitoring in wearable and clinical healthcare systems. This capability enables continuous cardiac observation, early warning of irregularities, and faster medical response, contributing to improved patient outcomes. The results suggest that the proposed model not only enhances diagnostic accuracy but also reduces computational costs, making it feasible for large-scale deployment in medical devices and hospital systems.

In conclusion, this study demonstrates that hybrid deep learning models combining CNN and Transformer architectures offer a powerful and efficient approach for arrhythmia detection. The system can be extended for broader applications such as long-term heart monitoring, mobile healthcare solutions, and intelligent diagnostic platforms. With further optimization, it has the potential to become an integral component of next-generation cardiac health monitoring systems, supporting a future of smarter, safer, and more proactive healthcare.

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