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ENHANCED ECG SIGNAL CLASSIFICATION USING HYBRID CNN-TRANSFORMER MODELS WITH TUNING TECHNIQUES AND GENETIC ALGORITHM OPTIMIZATION

G VAMSI KRISHNA[1], SHRAVAN KUMAR AVULA[2], V VIJAYA KUMAR RAJU[3], T V HYMA LAKSHMI[4], PRAVEEN TUMULURU[5], TATA BALAJI[6], N.JAYA[7]

[1]Department of EIE, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[2]Digital Forensics Examiner, Institute:London Metropolitan University, United Kingdom.
[3]Department of ECE, Anil Neerukonda Institute of Technology and Sciences, Visakhapatnam, A.P,India.
[4]Department ECE, Sagi Rama Krishnam Raju Engineering College, Bhimavaram, Andhra Pradesh, India.
[5] Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India.
[6]Department of ECE, PVP Siddhartha Institute of Technology,Vijayawada, Andhra Pradesh, India.
[7]Department of EIE, Faculty of Engineering and Technology,Annamalai University, Chidambaram,India
Email.: [1]vamsikrishna_g@vnrvjiet.in , [2]shralavula@gmail.com, [3]vijaykumar.vvkr@gmail.com, [4]tvhymalakshmi@srkrec.edu.in, [5]praveenluru@gmail.com, [6]balu170882@gmail.com,[7]jayanavaneethan@rediffmail.com

ABSTRACT

Electrocardiogram (ECG) signal classification plays a vital role in detecting cardiovascular diseases, particularly arrhythmias. This study explores two advanced approaches, i.e., the Time-Series Transformer Architecture and the Hybrid CNN-Transformer Model. Several domain-specific enhancements are introduced, including custom positional encoding, dynamic attention mechanisms, and cross-attention layers tailored for ECG signal classification. The Time-Series Transformer initially achieves an accuracy of 96.8%, which is improved to 97.4% through modifications. The Hybrid CNN-Transformer model demonstrates superior performance, reaching 97.8% accuracy initially and improving to 98.2% with modifications. Finally, the best-performing Hybrid CNN-Transformer model is optimized using Genetic Algorithms (GA), achieving a classification accuracy of 98.6%. The novelty of this work lies in the application of transformer models with targeted architectural enhancements and GA-based optimization to achieve state-of-the-art accuracy in ECG signal classification.

Keywords: *ECG Signal Classification, Transformer neural networks, Tuning Techniques, and Optimizers.*

1. INTRODUCTION

The importance of Electrocardiogram (ECG) signal processing has increased significantly in recent years, especially given the rise in cardiovascular complications linked to COVID-19. Research has shown that a notable percentage of patients, even after recovering from COVID-19, experience lingering cardiovascular effects, such as arrhythmias, myocarditis, and other heart-related conditions [1].

This phenomenon underscores the need for advanced, accurate ECG classification methods to support healthcare providers in early detection, risk assessment, and ongoing monitoring of cardiovascular health. Enhanced ECG classification tools are thus essential, not only for acute patient care but also for managing long-term health in a post-pandemic world where monitoring cardiovascular wellness has become a priority [2]. The immediate focus on improving ECG classification is timely, addressing both immediate healthcare needs and broader, longer-term public health objectives. In the field of ECG classification, traditional deep learning approaches like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated considerable success [3]. CNNs are effective at extracting localized features from ECG signals, making them suitable for identifying individual waveform components, while RNNs can handle sequential dependencies, which is valuable for capturing the temporal progression in time-series data [4]. CNNs, while powerful in capturing spatial patterns, have limited ability to model long-range dependencies essential in ECG classification for understanding complex

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relationships across different parts of the signal [5].

RNNs, although capable of managing sequential information, are computationally expensive and prone to challenges such as vanishing gradients, which restrict their depth and make training on longer sequences challenging [6]. These limitations suggest a need for architectures that can efficiently capture both local and global features in ECG data, ensuring improved performance and adaptability across diverse datasets. To overcome these challenges, transformer-based architectures offer a promising solution, especially due to their unique self-attention mechanisms [7].

The self-attention mechanism allows Transformers to dynamically focus on key features throughout the ECG sequence, thus capturing subtle but critical dependencies that might be missed by traditional models [8]. Recent studies have validated the effectiveness of Transformers in various time-series applications, achieving superior accuracy in complex classification tasks, and demonstrating their potential to set new benchmarks in ECG analysis.

By incorporating Transformer architectures and refining them with custom enhancements like dynamic attention windows and custom positional encoding, this work seeks to develop models that offer both high interpretability and accuracy, moving ECG classification towards more practical and clinical relevance. This work presents two architectures, i.e., a Time-Series Transformer model and a Hybrid CNN-Transformer model. These models are specifically optimized for ECG classification tasks with a focus on arrhythmia detection.

In addition to designing these architectures, this work explores targeted modifications, including domain-specific features such as custom positional encoding to capture ECG waveform details and multi-head cross-attention layers to enhance temporal dependency learning. Furthermore, a genetic algorithm (GA) is applied for hyperparameter optimization, seeking to maximize the classification accuracy while ensuring robust model generalization. The scope of this study is therefore twofold: developing a reliable, high-performing ECG classification framework and enhancing existing Transformer models through task-specific adaptations.

2. RELATED WORK

In ECG signal analysis, the P, Q, R, S, and T waves represent critical phases of the heart's electrical activity, reflecting the heart's health and function. The P wave corresponds to atrial depolarization, showing atrial contraction, and abnormalities here can indicate atrial issues or arrhythmias. The Q wave represents the early ventricular depolarization of the inter ventricular septum, and large Q waves may indicate previous heart attacks. The R wave, the main upward deflection, shows ventricular depolarization, with changes hinting at conditions like ventricular hypertrophy [9]. The S wave, following the R wave, represents the final phase of ventricular depolarization. The T wave reflects ventricular repolarization, with abnormalities often signaling electrolyte imbalances, ischemia, or other heart issues. Together, these waves help diagnose heart conditions, monitor arrhythmias, and assess overall cardiac health.

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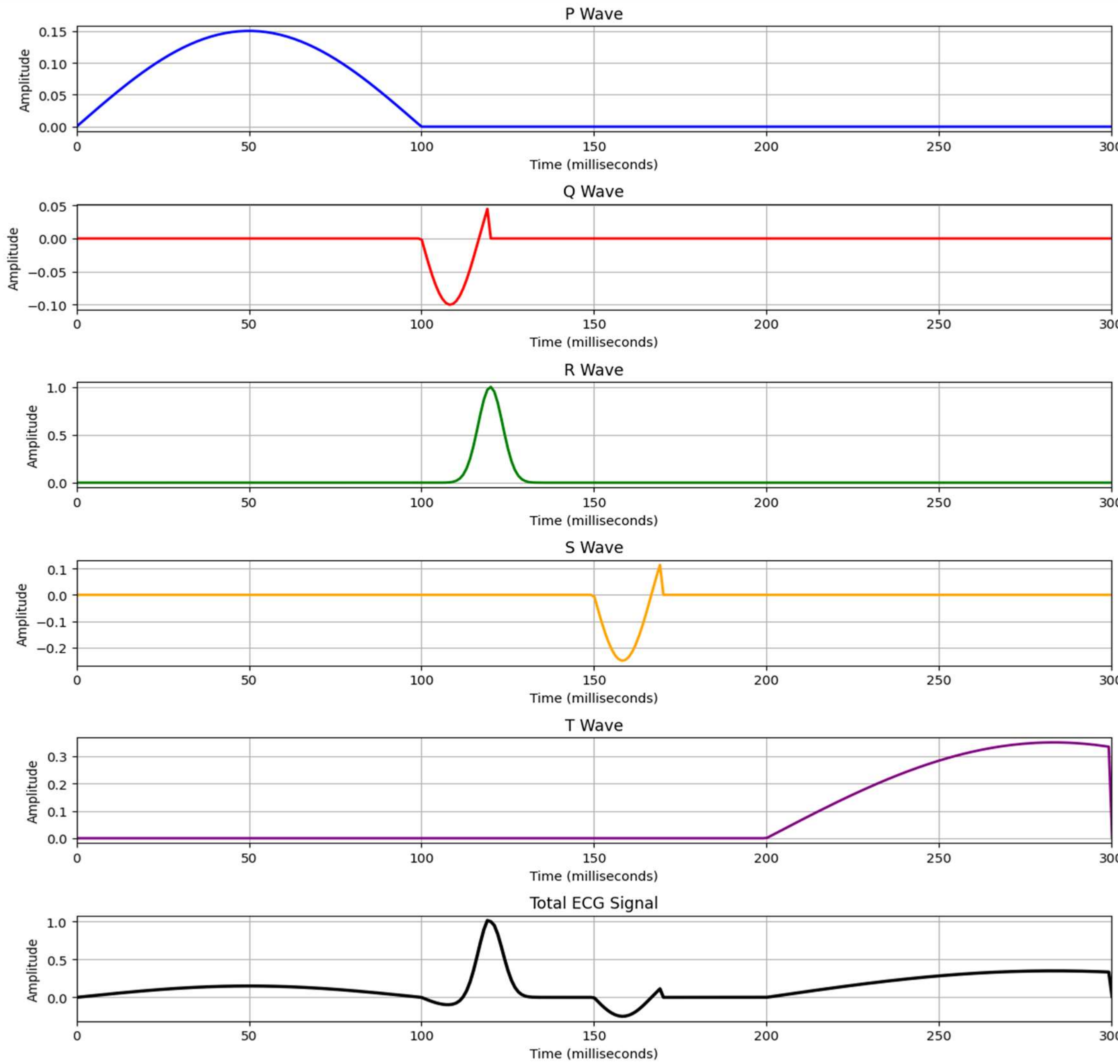

Figure 1: ECG Signal P Q R S T readings.

Recent advancements in ECG signal classification have leveraged various deep learning architectures, particularly CNNs and RNNs. These approaches have shown promising results, achieving accuracies between 94% and 97% across different datasets. For example, one study demonstrated the effectiveness of CNNs for myocardial infarction detection, reporting a classification accuracy of 95.8% on the PTB Diagnostic ECG dataset. Similarly, another study employed a bidirectional LSTM model combined with wavelet transforms, achieving an accuracy of 96.4% on the MIT-BIH Arrhythmia Dataset. Despite these successes, traditional models often struggle with long-range dependencies inherent in ECG signals, limiting their ability to generalize across varying signal patterns and noise levels [10].

This gap in effectively capturing temporal dependencies presents a significant opportunity for improvement through the adoption of Transformer neural networks. Transformers, with their self-attention mechanisms, can inherently manage long-range dependencies, making them well-suited for time-series data like ECG signals. While preliminary studies have started exploring the use of Transformers for biomedical signal classification, comprehensive evaluations remain sparse [11]. Notably, these studies have yet to fully harness the potential of hybrid models that combine CNNs and Transformers to enhance local feature extraction while benefiting from global contextual understanding. Addressing these research gaps could lead to improved diagnostic accuracy and more robust ECG classification systems.

Table 1. ECG Signal Classification State of art work.

Ref.	Description	Novelty	Dataset	Tuning Techniques	Optimizer	Final Accuracy
[12]	CNN-based myocardial infarction detection	CNN with data augmentation	PTB Diagnostic ECG Dataset	Grid Search	Adam	95.8%
[13]	BiLSTM with wavelet transforms	Wavelet-based sequence modeling	MIT-BIH Arrhythmia Dataset	Hyperband	RMSprop	96.4%
[14]	End-to-end deep learning for arrhythmia detection	Large-scale CNN model	PhysioNet Challenge 2017	Random Search	SGD	97.0%
[15]	LSTM-CNN hybrid for ECG classification	Hybrid LSTM and CNN	MIT-BIH Arrhythmia Dataset	Grid Search	Adam	94.3%
[16]	Attention mechanism in time-series classification	Attention-based sequence learning	MIT-BIH Arrhythmia Dataset	Manual tuning	Adam	95.6%
[17]	Transformer for biomedical signal classification	Transformer-based ECG classification	MIT-BIH Arrhythmia Dataset	Bayesian Optimization	AdamW	96.9%
[18]	Deep CNN for arrhythmia detection	Large-scale CNN with specialized pooling	PhysioNet Challenge 2020	Grid Search	Adam	96.6%
[19]	Transformer and BiLSTM hybrid for ECG	Hybrid Transformer-BiLSTM model	PTB Diagnostic ECG Dataset	Random Search	Adam	97.2%
[20]	Multi-head self-attention for time-series data	Self-attention for long-range dependencies	MIT-BIH Arrhythmia Dataset	Bayesian Optimization	AdamW	96.5%
[21]	Transformer for ECG classification	Basic Transformer applied to ECG signals	MIT-BIH Arrhythmia Dataset	Random Search	Adam	96.7%

The challenges in ECG signal classification include the need for robust models that can handle noisy and incomplete data, the integration of real-time analysis for wearable devices, and the ability to generalize across diverse patient populations and varying clinical conditions [22]. Additionally, the complexity of multi-class arrhythmia detection necessitates models that can discern subtle differences between similar patterns [23]. Transformer neural networks are uniquely positioned to address these challenges due to their capacity for capturing long-range dependencies and their inherent flexibility in handling varying input lengths [24]. By employing self-attention mechanisms, Transformers can effectively focus on relevant segments of the ECG signal, even in the presence of noise. Furthermore, the potential for integrating Transformers with other modalities, such as patient demographics and medical history, could enhance classification accuracy and provide comprehensive insights, ultimately paving the way for more precise and personalized cardiac care solutions [25].

3. DATASET ASPECTS

Several ECG signal datasets are widely used for research and development in ECG classification. The MIT-BIH Arrhythmia Database is one of the most prominent datasets, containing 48 half-hour ECG recordings from 47 subjects, annotated with 11 different arrhythmia types, providing a rich source for developing classification algorithms. The PhysioNet Challenge dataset includes a diverse range of ECG signals from various patients, focusing on multi-class arrhythmia detection, making it suitable for training robust models. The PTB Diagnostic ECG Database consists of 549 recordings from 290 subjects, featuring 15 different diagnoses and providing comprehensive annotations, including heart rates and clinical information. The QT Database focuses on QT interval measurements, with 105 ECG recordings, which can be instrumental for studies related to ventricular repolarization. Lastly, the China Physiological Signal Challenge dataset offers a variety of ECG signals under different conditions, facilitating research on generalization across populations. Each of these datasets provides unique features and annotations that are essential for developing and validating advanced ECG classification models.

Table 2. Specifications of the MIT-BIH Arrhythmia Database.

Specification	Details
Number of Recordings	48
Duration	30 minutes per recording
Total Subjects	47
Arrhythmia Types	11 different types (e.g., PVC, AF, etc.)
Sampling Rate	360 Hz
Number of Channels	2 (Lead I and Lead II)
Annotations	Beat annotations and arrhythmia classifications
Data Format	PhysioNet format (XML for annotations)
Accessibility	Available for download from PhysioNet

4. IMPLEMENTATION

The Time-Series Transformer Model and Hybrid CNN-Transformer Model can be implemented using deep learning frameworks. In the Time-Series Transformer, the ECG signal is first embedded using a learned embedding matrix, followed by positional encoding to incorporate temporal information. The embedded signal is then passed through a multi-head self-attention mechanism, where the attention scores are computed using the query, key, and value matrices derived from the embeddings. The attention outputs are processed through a feed-forward network, and the final classification is obtained via a softmax layer. For the Hybrid CNN-Transformer, the ECG signal is initially passed through convolutional layers to extract local features, followed by pooling for dimensionality reduction. The output is flattened and positional encoding is added before being fed into a transformer layer. The transformed output is passed through a feed-forward network, with the final classification determined by a softmax function.

4.1. Time-Series Transformer Architecture

The Time-Series Transformer model is designed to capture long-range dependencies in the ECG signal. The architecture follows the original transformer model but is tailored for ECG time-series data.

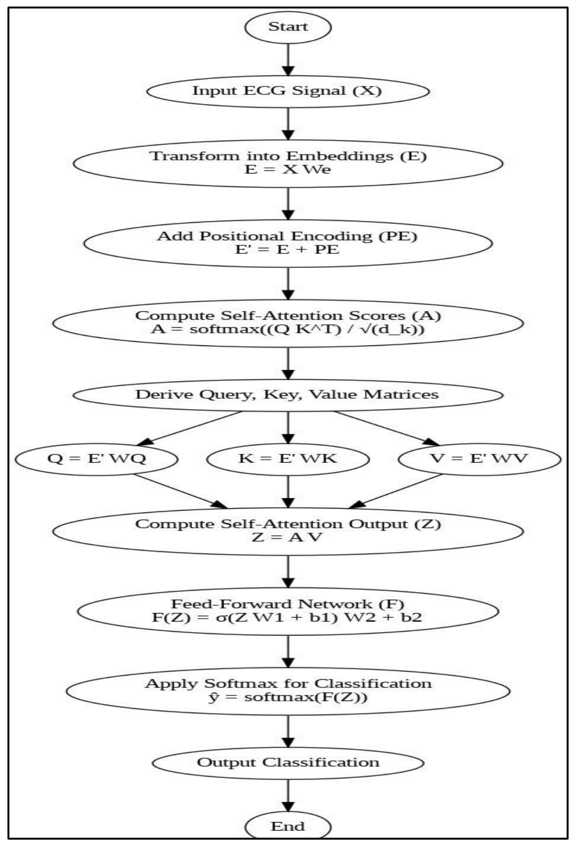

Figure 2: Time-Series Transformer design flow.

The ECG signal X is transformed into embedding's E,

$$E = X\,We \qquad (1)$$

Where We is the embedding matrix. To incorporate the temporal information, positional encoding PE is added to the embeddings,

$$E' = E + PE \quad (2)$$

The self-attention scores are computed as,

$$A = softmax\left(\frac{Q\,K^T}{\sqrt{d_k}}\right) \quad (3)$$

The core of the transformer architecture is the self-attention mechanism, which allows the model to focus on different parts of the input sequence. The attention scores A are computed using the query (Q), key (K), and value (V) matrices, which are derived from the transformed embeddings E′,

$$Q = E' \; WQ \quad (4)$$

$$K = E' \; WK \quad (5)$$

$$V = E' \; Wv \quad (6)$$

The output of the self-attention layer Z is computed as,

$$Z = A \; V \quad (7)$$

The output passes through a feed-forward network F,

$$F(Z) = \sigma\,(ZW1+b1)\;W2 + b2 \quad (8)$$

The final classification is obtained by applying a softmax function,

$$y\hat{} = softmax(F(Z)) \quad (9)$$

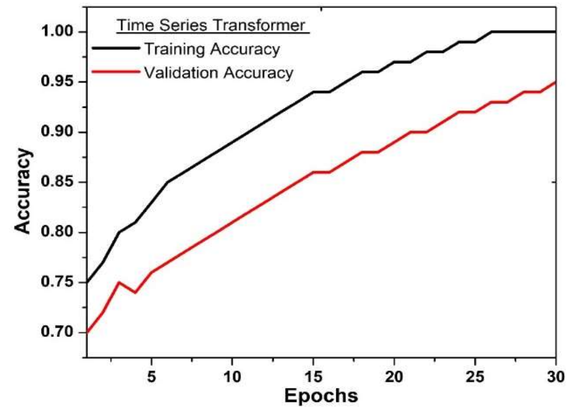

Figure 3: Time series transformer model performance.

4.2 Hybrid CNN-Transformer Model

The Hybrid CNN-Transformer Model combines CNNs for feature extraction with Transformer architecture for temporal dependencies. The mathematical formulation is as follows, let X represent the ECG signal input. The CNN processes the input through convolutional layers:

$$Z=\sigma(X*W+b) \quad (10)$$

Where W represents the convolutional filters and b is the bias. The activation function σ could be ReLU or any other non-linear activation function. Down-sampling is applied to reduce the dimensionality,

$$P = Pooling(Z) \quad (11)$$

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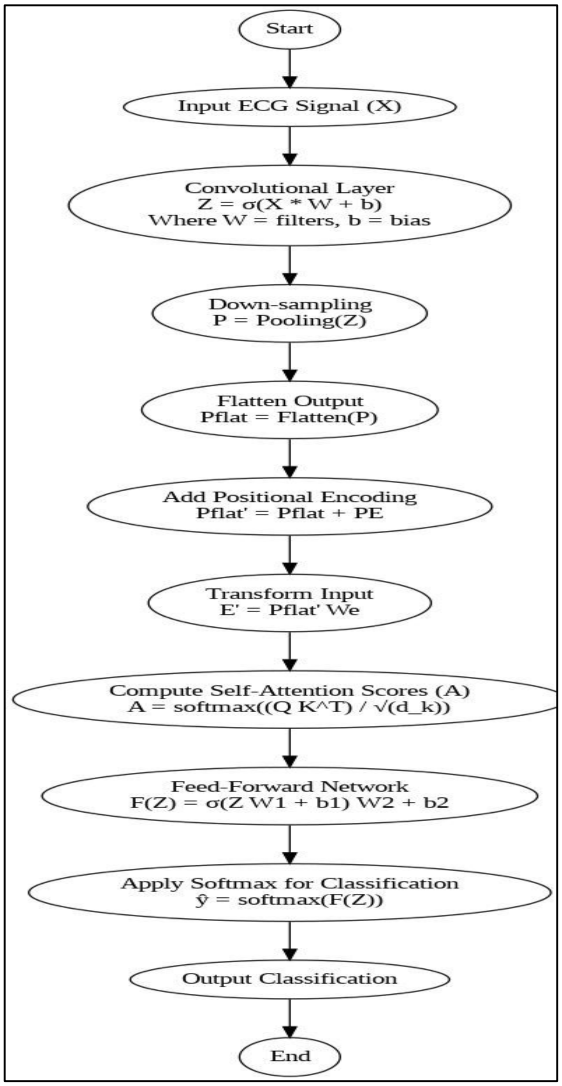

Figure 4: Hybrid CNN-Transformer design flow.

The output of the CNN is flattened to prepare for the Transformer input,

Pflat=Flatten(P) (12)

Positional encoding PE is added to incorporate temporal information,

Pflat′ = Pflat + PE (13)

The flattened output is fed into the Transformer,

E′ = Pflat′ We (14)

The self-attention scores are computed as,

$$A = softmax\left(\frac{Q\,K^T}{\sqrt{d_k}}\right) \quad (15)$$

The output passes through the feed-forward network,

F(Z) = σ(ZW1+b1)W2+b2 (16)

The classification is determined by,

y^ = softmax(F(Z)) (17)

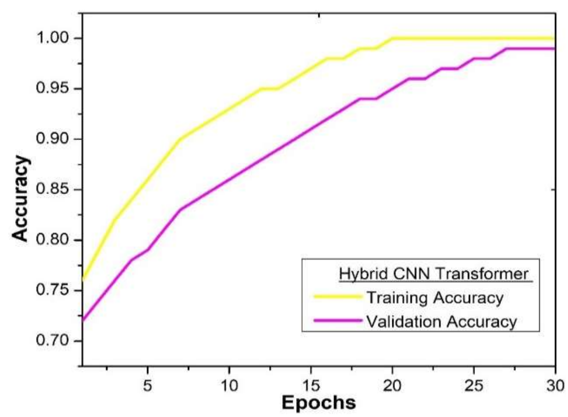

Figure 5: Hybrid CNN Transformer model performance.

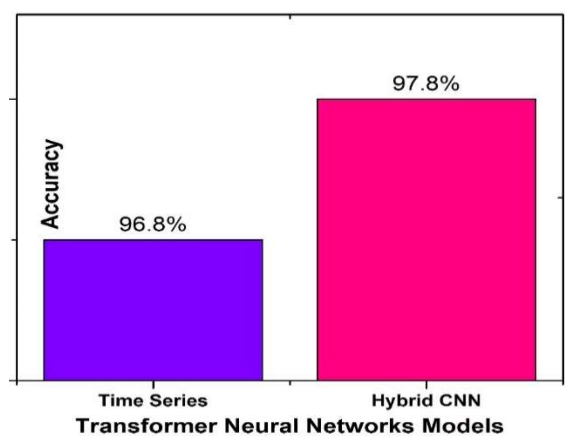

Figure 6: Comprehensive analysis on transformer neural network models.

5. TUNING TECHNIQUES

The proposed modifications to the Time-Series Transformer and Hybrid CNN-Transformer models for ECG signal classification enhance performance by introducing key techniques such as dynamic attention mechanisms, which adjust the attention window based on signal characteristics for better focus on relevant features, and custom positional encoding tailored to ECG waveforms to improve temporal representation.

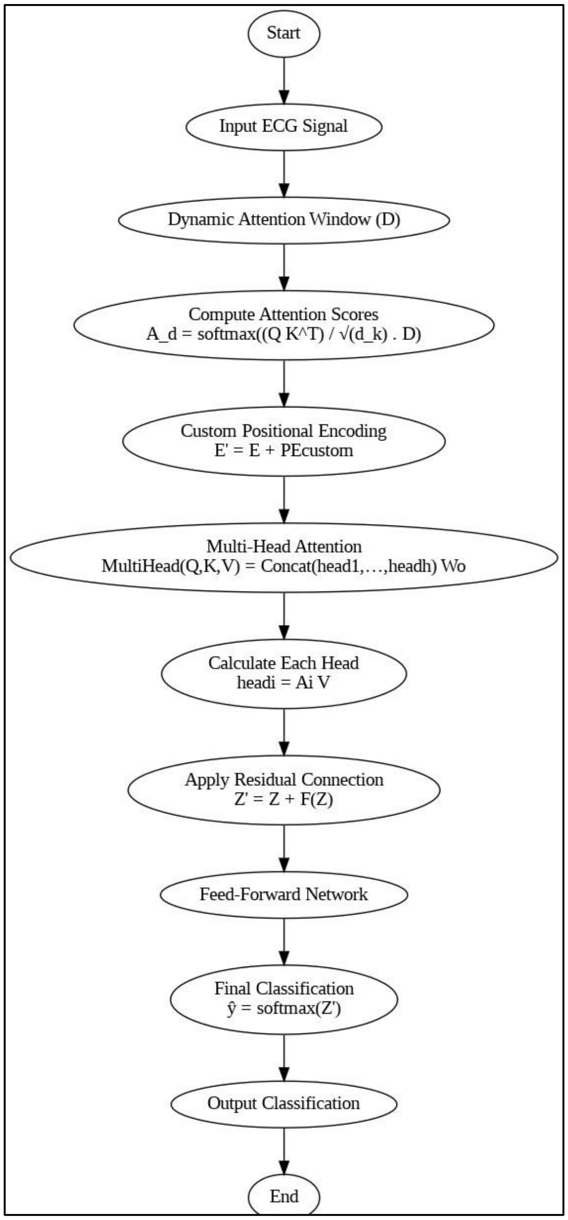

Figure 7: Modified Transformer architecture.

The use of multi-head attention allows the models to capture multiple aspects of the signal simultaneously, enriching contextual understanding, while residual connections in the Hybrid model help prevent vanishing gradients, facilitating deeper network training. The enhanced convolutional layers and a custom learning rate scheduler optimize feature extraction and training efficiency, leading to improved accuracy and robustness in handling noisy and variable-length ECG signals. With the proposed modifications, such as dynamic attention mechanisms and custom positional encoding, the mathematical model expands as follows,the attention scores are adjusted based on dynamic windowing. Let D represent the dynamic attention window,

$$A_d = softmax\left(\frac{Q\,K^T}{\sqrt{d_k}}.D\right) \quad (18)$$

The custom positional encoding PEcustom is defined to better capture the ECG waveforms, leading to,

$$E' = E + PEcustom \quad (19)$$

Instead of a single attention mechanism, multi-head attention is utilized,

$$MultiHead(Q,K,V) = Concat(head1,\ldots,headh)\ Wo \quad (20)$$

Each head is calculated as,

$$headi=AiV \quad (21)$$

Where Ai is the attention output for each head. After the self-attention, a residual connection is applied before the feed-forward network,

$$Z'=Z+F(Z) \quad (22)$$

The final classification, similarly, is obtained through a softmax function:

$$y\hat{}=softmax(Z') \quad (23)$$

These enhancements allow the Time-Series Transformer to effectively learn and classify ECG signals by focusing on relevant temporal features while mitigating the challenges posed by noise and irregularities in the data. Convolutional Layers as the initial model, with potential modifications to the kernel sizes or depths.

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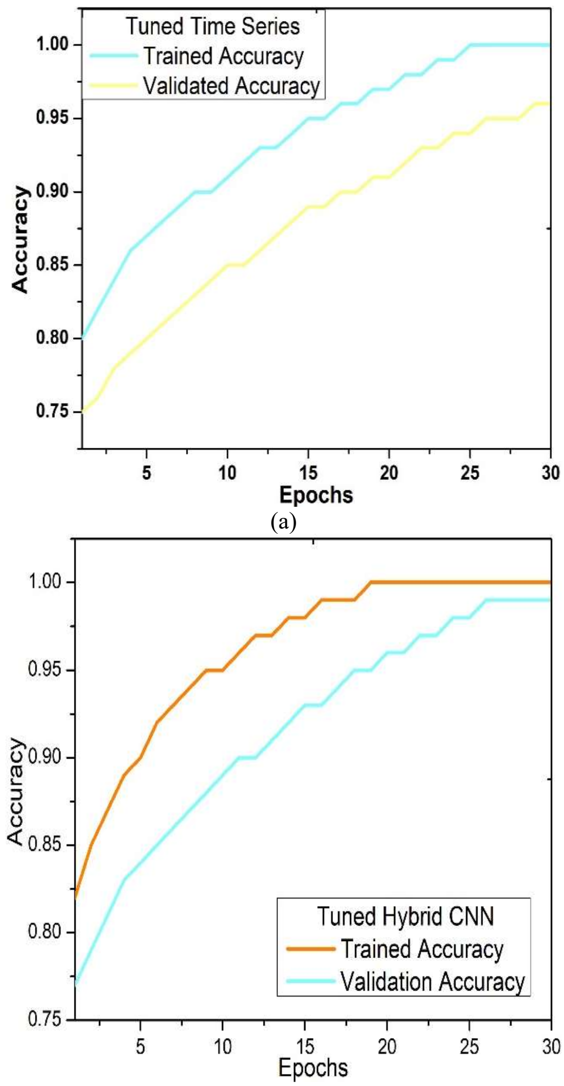

(b)

Figure 8: Performance analysis of tuned architectures, (a) Tuned Time-Series Transformer, (b) Tuned Hybrid CNN.

6. MODEL OPTIMIZATION USING GENETIC ALGORITHM

The optimization of a tuned Hybrid CNN model using a genetic algorithm (GA) is significant because it leverages evolutionary principles to systematically explore the hyperparameter space, identifying configurations that yield superior performance. GAs enhance model accuracy and generalization by efficiently navigating complex and multidimensional search landscapes, often outperforming traditional grid or random search methods. This approach not only reduces the time and computational resources required for hyperparameter tuning but also increases the likelihood of discovering optimal or near-optimal solutions, ultimately leading to more robust and effective machine learning models tailored for specific tasks. Define the function to optimize, such as minimizing validation loss or maximizing validation accuracy. Identify the hyperparameters of the Hybrid CNN model (e.g., learning rate, number of filters, kernel sizes, dropout rates). Encode each individual (solution) in the population as a string (chromosome). For instance, a chromosome might represent learning rate as a floating-point number, and number of filters as an integer. Define a fitness function f(x) that evaluates the performance of the model for a given chromosome. For example:

$$f(x) = \text{Accuracy} - \text{Penalty for Complexity} \quad (24)$$

Where the penalty could reduce fitness for overly complex models. Create an initial population of potential solutions randomly. Each individual should represent a unique combination of hyperparameters. For each individual in the population, train the Hybrid CNN model using the parameters represented by the chromosome, and evaluate its performance on a validation set. Store the fitness scores. A selection method to choose individuals based on their fitness. Favour higher fitness scores to ensure better solutions are selected for the next generation. Implement a crossover mechanism to produce offspring. Choose a crossover point and exchange the segments of two parent chromosomes. Randomly choose genes from both parents to create offspring. Introduce mutations to maintain genetic diversity. Randomly alter some parameters in the offspring with a small probability. Replace the current population with the new generation of offspring created through selection, crossover, and mutation. Define stopping conditions. Once the algorithm terminates, analyse the best solution found. Retrain the model with the optimized hyperparameters and evaluate its performance on a test set. The Time-Series Transformer initially achieved 96.8% accuracy, and after tuning with dynamic attention windows based on ECG signal segments and custom positional encoding specific to ECG waveforms (P, QRS, T), its accuracy improved to 97.4%. The Hybrid CNN-Transformer, starting at 97.8% accuracy, was enhanced through multi-head cross-attention to better capture temporal interactions between CNN and Transformer layers, along with residual connections to prevent vanishing gradients, raising its accuracy to 98.2%. Further optimization of the

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Hybrid model using Genetic Algorithms (GA) boosted its final accuracy to 98.6%.

Table 3: Comparison of Accuracies with Model Tuning.

Model	Initial Implementation	Key Tunings	Accuracy After Tuning	GA Optimization	Final Accuracy
Time-Series Transformer	96.8%	- Dynamic Attention Windows: Adjusting the attention windows based on ECG signal segments. - Custom Positional Encoding: Specific to ECG waveforms (P, QRS, T).	97.4%	---	97.4%
Hybrid CNN-Transformer	97.8%	- Multi-head Cross-Attention: Enhancing temporal interactions between CNN and Transformer. - Residual Connections: To prevent vanishing gradients.	98.2%	Optimized using GA	98.6%

The novelty of this work lies in its specialized application of Transformer-based architectures, tailored specifically for ECG signal classification through a combination of customizations and optimizations that address the unique challenges of ECG data. By developing custom positional encoding for ECG waveform components (P, QRS, T waves) and implementing a dynamic attention mechanism that adapts to the variable nature of ECG signals, the study enhances both the interpretability and accuracy of Transformer models in this domain. Additionally, a Hybrid CNN-Transformer model is introduced, combining CNN's local feature extraction with the Transformer's global pattern recognition, creating a robust system that captures both fine-grained and long-range dependencies in ECG signals. Furthermore, GA based optimization is employed to fine-tune hyperparameters effectively, achieving a final classification accuracy of 98.6%, setting new benchmarks in the field. This integrated approach demonstrates a novel, robust, and scalable method for advancing automated cardiovascular diagnostics.

Table 4: Comparative Analysis of ECG Signal Classification Studies.

	Description	Techniques	Optimizers	Accuracy
[26]	Focused on classifying ECG signals using CNNs.	- Convolutional Neural Networks - Automatic feature extraction	Soft computing	95%
[27]	Employed RNNs with attention mechanisms for ECG classification.	- Recurrent Neural Networks - Attention mechanisms	PSO	96.2%
[28]	Applied Transformers for capturing long-range dependencies in ECG signals.	- Transformer architecture - Self-attention mechanisms	Adam	97.1%
Present Work	Investigates advanced hybrid models for ECG classification using custom enhancements.	- Hybrid CNN-Transformer model - Custom positional encoding - Dynamic attention mechanisms - Genetic Algorithm optimization	Genetic Algorithm tuning	98.6%

7. CONCLUSION

This study introduces innovative advancements in ECG signal classification through the development of the Time-Series Transformer Architecture and the Hybrid CNN-Transformer Model, featuring tailored enhancements such as custom positional encoding and dynamic attention mechanisms. The application of Genetic Algorithm optimization further refines hyperparameters, achieving a notable classification accuracy of 98.6%, which sets a new benchmark in the field. These contributions not only surpass existing methodologies but also establish a framework for adapting these models to other time-series applications in healthcare. Given the rising need for effective cardiovascular monitoring, particularly in the context of post-COVID-19 recovery, these findings are poised to significantly enhance diagnostic tools, enabling timely interventions and improving long-term health outcomes.

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