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Enhancing ECG Classification Using GAN-Augmented DCT Features and Attention Mechanisms

Vharshni K.[1], Angelin Gladston[2]

Department of Computer Science and Engineering, College of Engineering, Guindy, Anna University, Chennai, India.

E-mail: [1]vharshnikalyan@gmail.com, [2]angelingladston@gmail.com

Abstract

Electrocardiogram (ECG) classification plays a major role in the early detection and diagnosis of heart disorders. The present ECG signals are noisy, temporally complex and also inter-class similar in characteristics, this makes the classification very complex. In this research, a deep learning approach is proposed for ECG classification with the integration of an attention-enhanced convolutional neural network model and a DCT-based feature extractor. Firstly, ECG5000 dataset is pre-processed through Z-score normalization, after which the dataset is converted to the DCT space in order to obtain a compact spectral feature and at the same time reduce noise while preserving discriminative spectral feature components. Next, the obtained features are normalized using spectral normalization and inputted into the proposed deep learning approach for classification. Th proposed model employs a patch-based self-attention mechanism focusing on specific spectral regions for diagnosis followed by convolutional feature extraction and global average pooling. The accuracy, precision, recall, F1-score, AUROC and AUPRC metrics are used to evaluate the proposed model on ECG5000 dataset. The experimental results show a classification accuracy of 95.6%, demonstrating that DCT-based spectral features and attention-guided deep learning collectively provide powerful, fast, and reliable tools for ECG automatic classification and cardiac abnormality detection.

Keywords: Electrocardiogram (ECG), Generative Adversarial Network (GAN), Discrete Cosine Transform (DCT), Self-Attention Mechanism, Deep Learning, ECG Classification.

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1. Introduction

Cardiovascular diseases (CVDs) ranks as one of the most common causes of mortality around the world and thus an early and accurate diagnosis is essential for reducing the risk of life-threatening cardiac events and achieving patient benefit. Of all the diagnostic methods available, one of the most commonly used is electrocardiogram (ECG) as it is a non-invasive, low-cost and reliable evaluation of heart electricity status. ECG recordings capture relevant information related to variable cardiac rhythm, conduction abnormality, and structural disorders, which facilitates the recognition of diverse arrhythmias. Nevertheless, clinical expertise is heavily relied on for the manual interpretation of ECG signals, which is largely influenced by inter-observer variability thereby increasing workload in healthcare environments with a large database of patients. In addition, the increasing popularity of wearable sensors and continuous cardiac monitoring systems has further increased the uncertainty of ECG data that requires immediate attention. These challenges increase the requirements for intelligence and automated ECG classification frameworks to accurately, reliably yet efficiently diagnose cardiac status with lesser reliance on human interpretation.

Machine learning and deep learning methods have enabled automated ECG analysis to achieve unprecedented performance in recent years. The classical approaches for automated ECG analysis include feature extraction along with statistical classification algorithms, while recent advances include CNN, RNN, deep learning architecture, frequency domain signal processing, and attention mechanisms to learn discriminative feature representation from ECG signals. Although significant achievements in terms of classification performance and robustness have been demonstrated, many issues and challenges still need to be addressed. Feature extraction from ECG signals is a challenging problem owing to vulnerability of signals of such type to noise, waveform variation and complex temporal properties. In addition, all the existing approaches rely on time-domain properties and are inefficient in exploiting discriminatory properties of the path based on attractive spectral properties. In addition, if the discriminative feature representation is not learned properly and attention mechanisms are not used in frequency-domain ECG signal processing, deep learning algorithms may lack generalization ability when applied to unknown data. All the discussed limitations motivate the development of a more efficient approach for ECG analysis that learns informative spectral features and contextual semantics in order to classify heartbeat signals according to the diagnostic categories.

An integrated hybrid deep learning architecture is proposed to address these issues by adopting DCT based feature extraction along with GANs for learning the representation of features followed by spectral normalization and an attention-oriented CNN for automatic classification of ECG. In the proposed approach, the ECG signals are transformed to frequency domain representations, where the features are improved in terms of representation for training the model and self-attention method is applied to focus on the significant spectral bands before classification. The main contribution of this work is to summarize frequency-domain analysis, feature representation enhancement, spectral normalization and attention-based deep learning together in an end-to-end framework to establish an automated heartbeat classification. Experimental results validate the proposed framework as both efficient and accurate solution for performing intelligent ECG analysis, suitable for its application in Computer-Aided Diagnosis (CAD) as well as novel health monitoring systems.

2. Literature Review

The electrocardiogram (ECG) plays a crucial role in the early diagnosis of heart diseases. Deep learning (DL) has facilitated major breakthroughs in automated electrocardiogram (ECG) analysis because it allows the extraction of specific features from physiological signals. Previous research works are conducted on a wide range of general topics such as frequency-domain feature extraction, generative learning, attention mechanisms and/or hybrid deep learning architectures to obtain higher classification accuracy (i.e., robustness) or less interpretability.

2.1 DCT-Based ECG Feature Extraction

The Discrete Cosine Transform (DCT) method has found extensive application in generating sparse frequency domain representation by eliminating redundancy and noise. In [3], Aydogdu and Ekinci have proposed an approach using DCT along with Particle Swarm Optimization for biomedical signal analysis in streaming scenarios and reported efficient computation. In [2], Zeng et al. have used DCT along with attention mechanism for emphasizing informative frequencies in the spectrum and pointed out the significance of frequency domain representation learning. In a similar way, Haboub et al. have proposed a DCT based channel attention approach for multivariate time series classification in [5].

2.2 GAN-Based Representation Learning

GAN-based models have been used for better feature learning and representations in deep learning. Tang et al. [4] designed an advanced TimeGAN model able to learn time dependence from the sequential data. Hossain et al. [7] developed ECG-Adv-GAN for enhancing ECG signal learning using adversarial approach, whereas Mi et al. [6] added self-attention in GAN architecture for better feature representation and stability. The recent studies of Nankani and Baruah [8], Wyawahare et al. [9], and Khade et al. [10] have demonstrated the advantages of adversarial learning along with deep neural networks.

2.3 Attention-Based ECG Classification

Attention mechanisms have been playing a vital role in extracting informative spectral-temporal features from physiological signals. Haboub et al. [5] demonstratedthat attention on channels is beneficial in distinguishing between spectral features in time-series classification. On the other hand, Feng et al. [1] proposed the Adversarial Time-Frequency Attention (ATFA) architecture that incorporates both temporal and frequency-domain attention in order to enhance feature learning in the presence of noise.

2.4 Research Gap

Although there are many developments in ECG classification, the existing approaches focused only on individual factors such as frequency domain feature extraction, adversarial learning or the use of an attention mechanism. The incorporation of Discrete Cosine Transform (DCT) for spectral analysis, generative adversarial networks for feature representation, spectral normalization, and attention mechanism guided learning in one end-to-end framework. The issue of robustness enhancement of features without losing clinically significant spectral information is also a difficult task. This research motivates the development of the proposed ECG classification framework.

3. System Design

3.1 Proposed System

The proposed system integrates deep learning model in which DCT, GAN based augmentation, SN Spectral Normalization and patch wise attention driven GAN based Attention classifier are used. In contrast to the many classical ECG classifier designs with classification pipelines that depend on raw time-domain signals, the proposed design compresses ECG data into a short frequency sequence and intelligently enhances the most discriminative spectral features. This not only improves the diagnostic performance but also serve as an important method to maintain the robustness of models in real-world clinical settings, with all three aforementioned challenges: data imbalance, noise artefacts and small variations of arrhythmia.

To maximize accuracy, class imbalance and interpretability is improved by integrating DCT features, GAN-based augmentation spectral normalization and attention-enhanced CNN classifier. The proposed system architecture is shown in Figure 1. The proposed system is a modular complete end-to-end ECG classification pipeline.

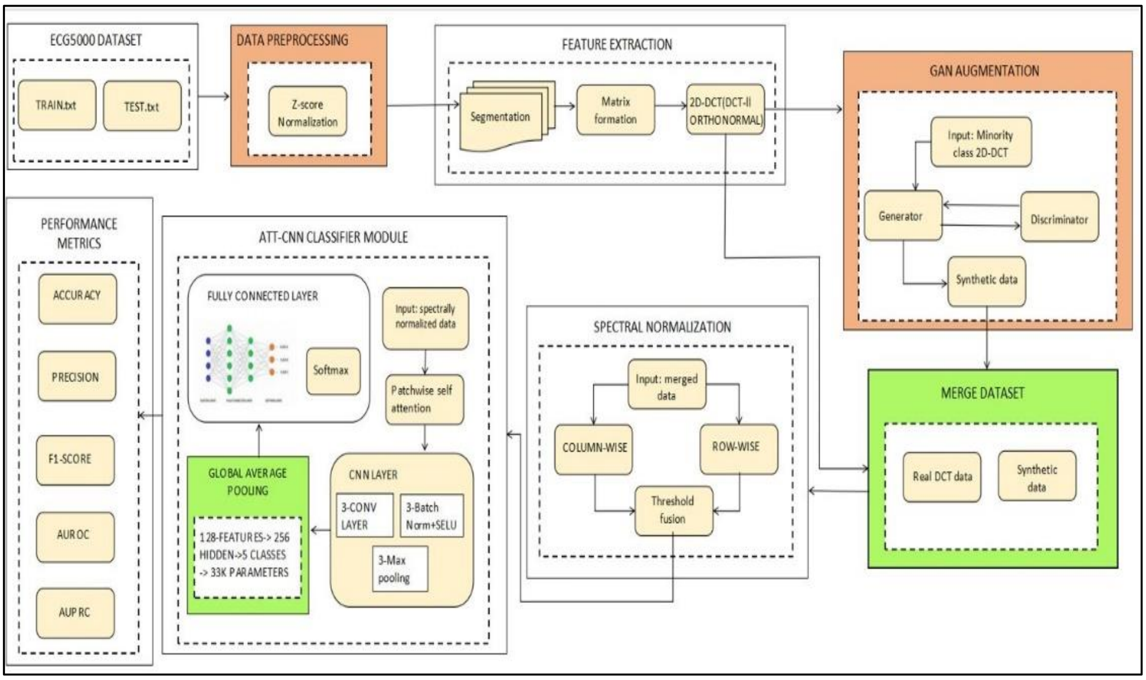

Figure 1. GAN based attention classifier architecture

The complete framework for classifying ECG signals is depicted in Figure 1. Signals in the ECG5000 are first normalized using Z-score normalization and converted into their respective frequency domains in terms of DCT. Then these features are processed in a certain way using GAN+ Spectral normalization and are then classified using the attention-based CNN.

The raw ECG time-series signals from the ECG5000 dataset are pre-processed and Z-score normalized ECG signals are generated for feature extraction. Preprocessing of the ECG5000 dataset is done using z-score normalization in order to remove the effects of amplitude differences on the data. This preprocessing is designed to improve numerical stability by reducing inconsistencies in the signals and providing normalized inputs for the extraction of subsequent DCT-based features.

The ECG classification method contains two main stages, feature representation learning and attention-based classification. The ECG5000 records will be initially processed using Z-score normalization to minimize amplitude variations. Following data normalization, the signals are split into overlapping windows to maintain local heartbeat morphology and temporal properties before being mapped to 2D-DCT representations. It produces compact frequency-domain features that retain essential discriminative spectral information while minimizing redundancy and suppressing noise using the Discrete Cosine Transform (DCT) [3-4]. These feature representations are then passed through the GAN module to enhance feature learning and are further refined by spectral normalization (SN) prior to being given as input to the attention-guided classifier.

The GAN module learns meaningful spectral characteristics during training from the ECG5000 dataset to further enhance the discriminative representation of DCT features. These enhanced feature representations are further normalized to improve consistency using row-wise and column-wise spectral normalization with threshold-based fusion to better preserve the essential frequency-domain information. Then, those normalized DCT features are processed by the proposed attention-guided convolutional neural network, which utilizes a patch-wise self-attention mechanism to select the informative spectral regions before performing hierarchical feature extraction through convolution, batch normalization, SELU activation and max-pooling operations. The final stage is global average pooling and connected for multi-class ECG classification with Softmax.

The DCT feature representations extracted are processed with spectral normalization by utilizing row-wise and column-wise normalization combined with a threshold for fusion to improve discriminative frequency-domain information while maintaining consistent features. Then, both the normalized feature matrices are used as input to a GAN-based attention classifier. The spectral attention mechanism works in two stages: first, it localizes the most informative spectral bands and assigns high-level attention weights to enrich feature representation. Subsequently, each component of the attention-enhanced features passed through successive blocks of convolutional layers with batch normalization and SELU, activation layer and max-pooling operations to learn hierarchical feature representations.

Lastly, Global Average Pooling creates concise feature vectors and these are forwarded to a fully connected Softmax layer for multi-class ECG classification. The network parameters are optimized with an Adam optimizer using categorical cross-entropy loss that results in robust and stable convergence for the model.

The GAN augmentation is contributed by generation of realistic DCT matrix of the classes found in such a greater number than others of ECG5000 dataset. For example, minority arrhythmias generally have few training instances and lead some classifiers to make prejudiced predictions or miss rare yet clinically relevant patterns. To address this issue, a Generative Adversarial Network (GAN) is trained on minority-class DCT representations. The generator, trained on real spectral patterns, outputs synthetic examples follow the distribution of that data. The Discriminator determine which ones are real and which ones made by a generator. The networks are trained simultaneously using adversarial training until the Generator generates meaningful and diverse samples. This set of synthetic DCT matrices is again augmented with real data to form a supervised dataset, improving the generalization and performance of models, and reducing overfitting. GAN is used to characterize the sensitivity and induce detection performance for fair, reliable and accurate classification on minority classes against majority.

The spectral normalization ensures that real and GAN-generated DCT matrices exhibit stable, consistent energy distributions before traversing to the classifier. Due to physiological differences in ECG signals, intensity differences often occur. Differences or synthetic generation artefacts. Without normalization, the energy can mislead the classifier if there are inconsistencies. For this purpose, each DCT matrix is partitioned into several column blocks, and a dual-stage normalization both row-wise and column-wise min–max normalization is applied. These values are compared with a threshold-based fusion strategy that selects or averages elements depending on their difference. This process preserves informative spectral patterns while regularizing unstable or noisy coefficients. Spectrally normalized matrices from these outputs are smoother, energy-balanced, and more consistent in the data than before. This step enhances the reliability of the GAN based attention model, ensuring that learning is driven by meaningful spectral variations, not intensity changes.

The spectral normalization guarantees that the real and GAN-generated DCT matrices have stable energy distributions before passing through the classifier. Intensity difference is always shown because of the physiological variations in ECG signals. Differences or synthetic generation artifacts. When there are inconsistencies in the energy, it can mislead the classifier without normalization. To this end, each DCT matrix is divided into a number of column blocks, and voxel-wise min–max normalization. This method is compared to a threshold-based fusion strategy that either picks or averages each element based on the difference in magnitude of the values. It retains informative spectral patterns whilst stabilizing and penalizing unreliable coefficients. The outputs from the Autoencoders are smoother, energy-matched and consistent data versions of spectrally normalized matrices. This step increases the stability of the GAN based Attention model so that learning is caused by meaningful changes in spectral spectrum, not intensity.

3.2 GAN based Attention Classifier

Input: Spectrally normalized DCT matrices.

Output: Predicted ECG class probabilities (5-class softmax output).

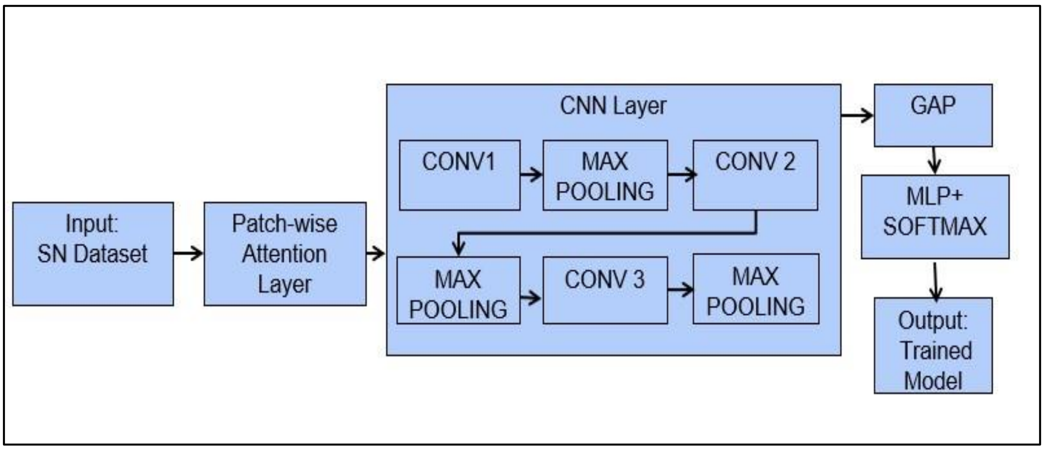

Figure 2. Architecture of the proposed GAN-assisted attention-based ECG classifier

The GAN module expands the feature learning ability of our proposed framework through refining ECG spectral features during training. Those ongoing representations help the classifier spot small heartbeat differences easier and therefore boost robustness, and thus classification.

The model training and validation process was performed to ensure that the proposed ECG classification system is sufficiently accurate and robust for all five arrhythmias. This includes GAN-augmented training, DCT spectral features along with GAN-based attention.

3.2.1 Model Training

The GAN-based attention classifier was optimized using the ECG5000 dataset with Adam optimizer and optimized at an initial learning rate of 0.001 for stable optimization during learning. A batch size of 32 was used to compromise between computational performance and convergence stability, while categorical cross-entropy was selected as the objective function for multi-class ECG classification. The conv1×1 layer all used SELU activation to enable quick feature learning, while a Softmax was applied on the output layer to estimate class probabilities. Spectral Normalization provided additional feature consistency improvement and a dropout rate of 0.5 was utilized to mitigate overfitting in the proposed model whilst sharing these parameters across each respective output layer as well, effectively lowering the effect that certain features would have on other given outputs enhancing generalizability overall.

3.2.2 Validation Techniques

- **Cross-Validation:** Conformity between different types of 5-fold and 10-fold cross-validation was monitored across various dataset partitions.
- **Overfitting-Diagnostics:** Training loss and validation accuracy were monitored to evaluate the generalization capability of the proposed model.

3.2.3 Model-Comparison

All classifiers, comprising the base CNN model, the basic DCT-CNN model, GAN trained models, and the attention model based on the GAN, have been tested under the same conditions of experiment in order to provide fair comparison. The assessment has also been done using confidence measures and confusion matrices.

4. Results and Discussion

The performance of the proposed model was tested on the ECG5000 benchmark dataset, a database for ECG classification research that includes single lead electrocardiograms labeled with five heartbeat classes [11]. The database is composed of 5,000 electrocardiograms in total, out of which 500 constitute the training set, while 4,500 are considered testing data samples, with each ECG signal having 140 time points. One of the features of the dataset under consideration is the existence of class imbalance, in particular, Classes 3, 4, and 5 have significantly fewer samples than other classes. Moreover, the electrocardiograms are subject to certain difficulties in the form of noise presence, changes in waveforms, as well as morphological patterns overlap between heartbeats.

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1.0000000e+00	1.0242946e+00	-5.9031419e-01	-1.9169491e+00	-2.8069890e+00	-3.5279051e+00	-3.6386750e+00	-2.7797674e+00
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1.0000000e+00	-8.2091791e-01	-3.1617614e+00	-4.3297681e+00	-4.6932184e+00	-4.4721152e+00	-3.2279708e+00	-1.7625326e+00

Figure 3. Representative ECG5000 signal data used for model training

ECG5000 is an extensively used benchmark dataset for automated ECG classification with a total of 5,000 single-lead ECG signals, which are sampled for a total of 140 time points. The ECG5000 dataset includes five types of heartbeat categories: one main normal category along with four other minor categories of arrhythmias. As a result of this, there is a severe imbalance in the class distribution. Moreover, the temporal alignment of all the ECG recordings makes them easy for analyzing with regard to their respective heartbeat categories. In addition to this, there is a variability in waveform and noise in the dataset. Due to these features, ECG5000 becomes a good benchmark for assessing the automated ECG classifiers.

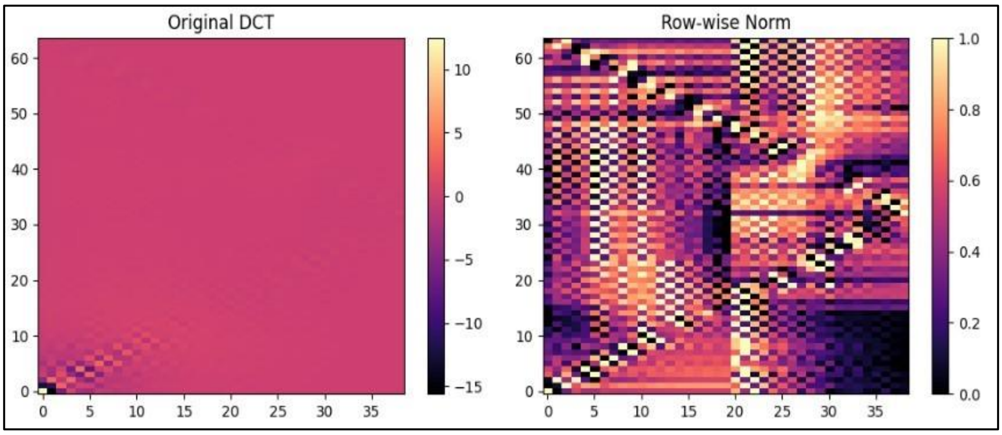

Figure 4. Original DCT and row-wise normalisation

Figure 4 shows the impact of normalization applied to the rows of the DCT feature matrix. Normalization helps to achieve more stable features by minimizing the variations in the amplitude while retaining significant spectral information for classification.

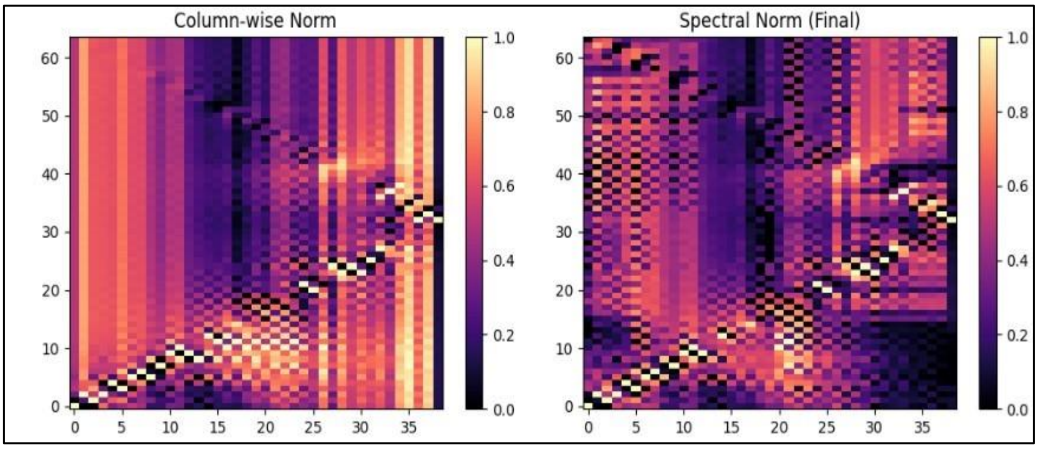

Figure 5. Column-wise and spectral normalisation

Figure 5 shows the output after applying normalization to the columns and spectrum. The combined approach of normalization produces balanced spectral representations for attention-based learning.

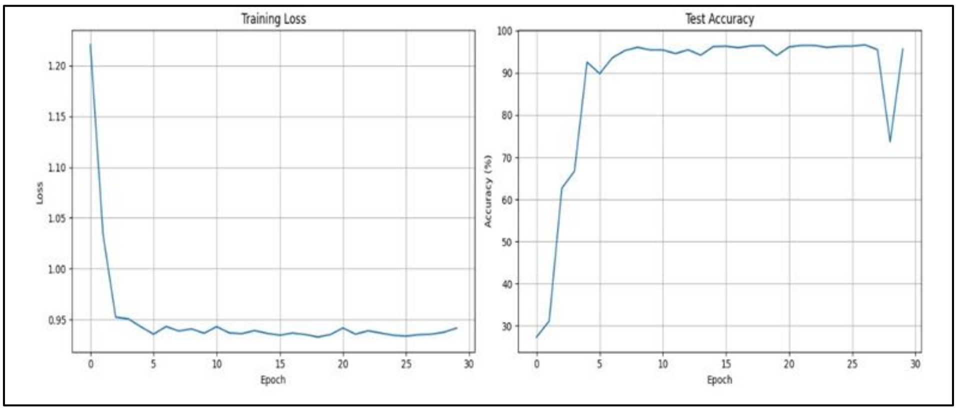

Figure 6. Convergence characteristics of GAN based attention classifier

The convergence characteristics of the proposed GAN-based Attention model are illustrated in Figure 6. It can be observed that the training loss reduces consistently whereas the test accuracy converges rapidly to about 95-96%.

Figure 7 shows the ROC and Precision-Recall curves of proposed model. The high AUROC and AUPRC scores achieved for all heartbeat classes show outstanding discriminative performance and reliable classification performance.

Five-Fold Cross Validation verifies the stability of the proposed framework. If the classifier maintains consistent accuracy for all the folds, then it reflects stable learning and good generalization capability with the new samples of ECG.

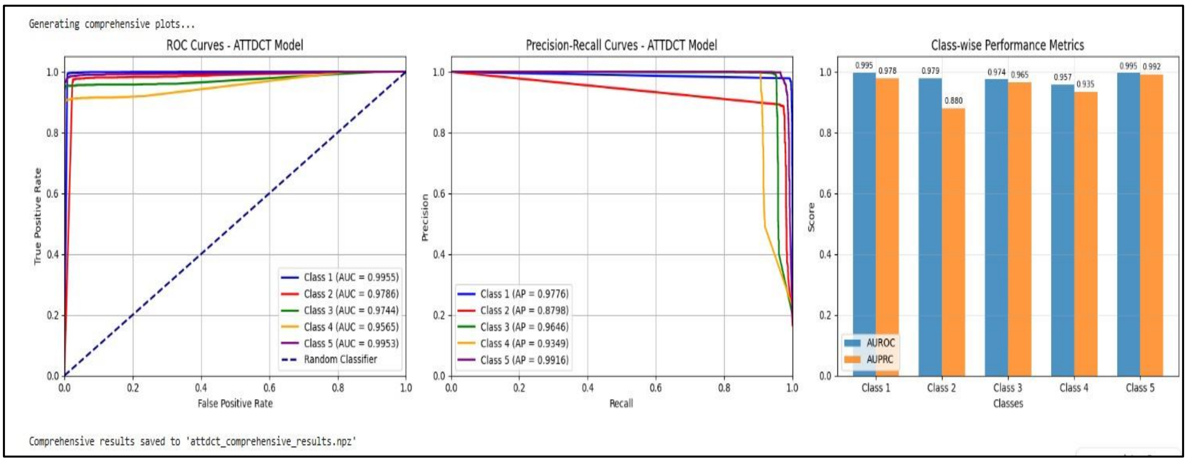

Figure 7. AUROC and AUPRC performance graph

For evaluating the performance of the ECG classifiers objective methods are adopted in this research paper. Imbalanced class problem can be observed in the ECG datasets. Threshold/ranking based methods are necessary to provide a comprehensive view of model reliability.

Table 1. Model performance comparison

Measure	Inception Time	OS-CNN	CNN-LSTM	TST	ARENAL	TDE	ATT-DCT	GAN based Attention
Acc.	0.941	0.94	0.944	0.94	0.94	0.944	0.934	0.956
Pre.	0.892	0.894	0.893	0.888	0.891	0.89	0.89	0.959
Rec.	0.912	0.91	0.911	0.905	0.913	0.908	0.911	0.953
F1	0.893	0.891	0.892	0.887	0.89	0.889	0.895	0.956
AUROC	0.965	0.963	0.964	0.96	0.966	0.962	0.966	0.98
AUPRC	0.777	0.775	0.776	0.77	0.78	0.774	0.78	0.949

The comparison between the proposed system and existing models for ECG classification is shown in Table 1. The performance of the proposed GAN based attention model results as the best among all other parameters such as accuracy, precision, recall, F1-score, AUROC, and AUPRC.

5. Conclusion

The hybrid deep learning framework proposed in this research work used DCT based feature extraction, spectral normalization, and attention-guided Convolutional Neural Network (CNN) to automate ECG classification. This framework reliably improved feature representation and classification performance of ECG signals by effectively capturing discriminative frequency-domain characteristics. Through the DCT based spectral analysis, attention-guided feature learning and design of a GAN module in this training framework enabled carefully categorized patterns identification from the ECG5000 dataset. The presented method showed the ability of frequency domain learning to play an important role in intelligent ECG analysis, which may serve as a vital part of clinical decision-support systems that can assist doctors or replace human interpretations during mechanical cardiac abnormality detection. Future work will focus on validation of the framework on larger multi-lead and real-world clinical ECG datasets, enhanced model interpretability using explainable artificial intelligence (XAI) techniques, as well as optimization of the proposed framework towards real-time deployment in wearable and edge-based healthcare systems for monitoring.

References

[1] Feng, Haotian, Qiang Shen, Rui Song, Lida Shi, and Hao Xu. "ATFA: Adversarial Time–Frequency Attention Network for Sensor-Based Multimodal Human Activity Recognition." Expert Systems with Applications 2024, vol 236: 121296.

[2] Ma, Xianping, Xiaokang Zhang, Man-On Pun, and Bo Huang. "A Unified Framework with Multimodal Fine-Tuning for Remote Sensing Semantic Segmentation." IEEE Transactions on Geoscience and Remote Sensing 2025: 1-15.

[3] Aydoğdu, Özge, and Murat Ekinci. "An Approach for Streaming Data Feature Extraction Based on Discrete Cosine Transform and Particle Swarm Optimization." Symmetry 2020, vol 12, no. 2: 299.

[4] Tang, Peihao, Zhen Li, Xuanlin Wang, Xueping Liu, and Peng Mou. "Time Series Data Augmentation for Energy Consumption Data Based on Improved Timegan." Sensors 2025, vol 25, no. 2: 493.

[5] Haboub, Amine, Hamza Baali, and Abdesselam Bouzerdoum. "DCT-Based Channel Attention for Multivariate Time Series Classification." IEEE Open Journal of the Computer Society 2025, vol 6: 1110-1120.

[6] Mi, Zhongjie, Xinghao Jiang, Tanfeng Sun, and Ke Xu. "GAN-Generated Image Detection with Self-Attention Mechanism Against GAN Generator Defect." IEEE Journal of Selected Topics in Signal Processing 2020, vol 14, no. 5: 969-981.

[7] Hossain, Khondker Fariha, Sharif Amit Kamran, Alireza Tavakkoli, Lei Pan, Xingjun Ma, Sutharshan Rajasegarar, and Chandan Karmaker. "ECG-Adv-GAN: Detecting ECG Adversarial Examples with Conditional Generative Adversarial Networks." In 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE, 2021: 50-56.

[8] Nankani, Deepankar, and Rashmi Dutta Baruah. "Improved Diagnostic Performance of Arrhythmia Classification Using Conditional Gan Augmented Heartbeats." In Generative Adversarial Learning: Architectures and Applications, Cham: Springer International Publishing, 2022: 275-304.

[9] Wyawahare, Medha, Milind Rane, Tushar Bhandari, Pratham Bisen, and Sandesh Bellale. "DFD-TL-GAN: Deepfake Detection Using Transfer Learning and GAN-Augmented Datasets." In 2025 2nd Asian Conference on Intelligent Technologies (ACOIT), IEEE, 2025, 1-7.

[10] Khade, Smita, Shilpa Gite, and Biswajeet Pradhan. "Robust Iris Liveness Detection Against Known and Adversarial Attacks Using GAN and Efficient Net." In Advancements in IoT Sensors and Security: Harnessing AI/ML for Secured IoT Sensor Data, Cham: Springer Nature Switzerland, 2026: 145-171.

[11] Dau, H. A., Bagnall, A., Kamgar, K., Yeh, C. C. M., Zhu, Y., Gharghabi, S., et al., "The UCR Time Series Classification Archive," October 2018. Available

[12] https://www.kaggle.com/datasets/salsabilahmid/ecg50000/data