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A Comparative Deep Learning Framework for ECG Signal Classification with Explainable AI Insights

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Abstract
Signals from electrocardiograms (ECGs) are an essential diagnostic tool for identifying cardiovascular diseases, which continue to be the leading cause of death worldwide [2], [3]. However, the development of automated analytical frameworks is required because traditional manual interpretation of ECG recordings is labour-intensive, time-consuming, and prone to human error [9]. With a focus on differentiating between normal and abnormal heartbeats, this study suggests a sophisticated and comprehensible deep learning-based methodology for the classification of ECG signals. To improve signal fidelity and reduce noise artefacts, the suggested framework uses advanced signal preprocessing methods like bandpass filtering, notch filtering, and baseline wander elimination. Stable model training is made possible by subsequent segmentation and normalization processes, which guarantee consistent data representation [14]. Several resampling techniques, including Random Oversampling, SMOTE, ADASYN, and SMOTE-Tomek, were systematically assessed to address the common problem of class imbalance; SMOTE was found to be the most effective method [35].
Furthermore, by employing deep learning architectures to extract intricate temporal and morphological features from ECG signals, the framework enhances classification robustness. Explainable AI ensures that model predictions are reliable and clinically significant while also improving interpretability.

Keywords: Arrhythmia Detection, Electrocardiogram (ECG), ANN, DNN, Deep Learning, Convolutional Neural Networks (CNN), Explainable Artificial Intelligence (XAI), Data Balancing (ROS).

1. Introduction

Since cardiovascular diseases (CVDs) are a leading cause of death globally, improving patient outcomes requires early detection. Waveform elements like the P wave, QRS complex, and T wave are used in electrocardiograms (ECGs) to track heart activity. However, manual ECG analysis is labor-intensive, time-consuming, and prone to human error—especially when dealing with large datasets.Automated ECG analysis is now possible thanks to advances in artificial intelligence, and deep learning models have a lot of promise. For the detection of arrhythmias, convolutional neural networks (CNNs), hybrid CNN-LSTM models, and transformer-based methods have been extensively employed (Kumari & Goswami, 2023; He et al., 2024; Kim et al., 2025; Tudjarski et al., 2025). Despite their high accuracy, these models often lack interpretability, functioning as “black boxes.” To address this, Explainable AI techniques such as SHAP

and LIME are used to improve transparency.Another challenge is data imbalance, where normal signals dominate abnormal ones, affecting model performance. Techniques like SMOTE help resolve this issue.

2. Related works

Recent advancements in arrhythmia detection from ECG signals, focusing on studies that have utilized the benchmark datasets relevant to our research. We categorize these works by the primary dataset employed, highlighting their methodologies, key contributions and reported performance metrics.

Srivastava et al.[18] proposed rECGnition_v1.0, a multi-modal DL approach that combined ECG morphological characteristics with patient information (age, gender, BMI) for improved arrhythmia detection. The proposed approach, which combined a CNN for ECG morphological feature extraction with a Squeeze and Excitation-based Patient characteristic Encoding Network (SEPcEnet), reported an accuracy of 98.56% on the MITDB, indicating improved performance by correlating patient information with ECG morphology.

Berrahou et al.[26] proposed a 1D CNN-based model for arrhythmia detection that combined morphological ECG features with RR interval and entropy rate descriptors. The model was tested on the MITDB and achieved an accuracy of 99.17% for intra-patient and 98.73% for inter-patient classification and 98.20% accuracy on the INCART dataset. The method showed excellent generalization capabilities and class imbalance handling performance on various ECG datasets

Di et al.[24] proposed a multimodal CNN with adaptive attention for ECG arrhythmia classification. Based on Hilbert space-filling curves and recurrence plots to transform ECG signals into images, their method obtained 98.48% accuracy and 81.91% F1 score for interpatient classification and 99.70% accuracy with 97.64% F1 score for intrapatient classification on the MITDB dataset.

Table 1. Comparison analysis of State-of-the-Art (SOA) works with our proposed work on MITDB

Study	**Model / Approach**	**Data Balancing Technique**	**XAI / Interpretability**	**Performance**
Talukder et al. (2025) [1]	**Talukder et al. (2025) [1]**	-	SHAP-based explanation	Improved arrhythmia detection accuracy
Talukder et al. (2025) [5]	Hybrid Explainable ML Model (HXAI-ML)	-	-	High ECG disease detection accuracy
Nayyab et al. (2025) [6]	Deep Learning with P-QRS-T waveform features			High ECG disease detection accuracy
Sibomana et al. (2025) [7]	ECG Chest Patch vs Smartwatch Diagnostic System			High AF detection accuracy

Pereira et al. (2025) [9]	Intelligent ECG analysis systems review			High AF detection accuracy .
Kim et al. (2025) [19]	Local-Global Temporal Fusion Network with Attention		Attention mechanism	F1 Score: 96.45%
Tudjarski et al. (2025) [20]	Transformer-based ECG Language Model			High arrhythmia classification accuracy
Proposed Framework	ANN,DNN, CNN based ECG classification with model comparision	SMOTE (Synthetic Minority Oversampling Technique)	SHAP, LIME, Feature Importance , Grad-CAM, SHAP-based explanation	arrhythmia detection ANN:98.48%, DNN:98.71%, CNN:97.98% Accuracy .

3. METHODOLOGY :

The proposed methodology focuses on the automatic classification of electrocardiogram (ECG) signals using deep learning techniques. Cardiovascular diseases remain a major global health challenge, and early detection of abnormal cardiac rhythms is essential for effective treatment and prevention.Traditional ECG analysis methods rely heavily on manual interpretation by cardiologists, which can be time-consuming and prone to human error. Recent advances in machine learning and deep learning have enabled automated ECG signal analysis with high accuracy and efficiency (9, 17).

The proposed framework integrates multiple neural network architectures to analyze ECG signals and identify abnormal cardiac patterns. Three different models were implemented and evaluated: Artificial Neural Network (ANN), Deep Neural Network (DNN), and Convolutional Neural Network (CNN).

These models were selected because neural networks are capable of learning complex patterns from biomedical signals and have demonstrated strong performance in arrhythmia detection tasks (6, 11). The first step of the methodology involves the acquisition and preparation of ECG signal data. ECG signals contain electrical activity generated by the heart and consist of characteristic waveform components such as the P wave, QRS complex, and T wave. These waveform segments provide important information about the cardiac cycle and are widely used for detecting arrhythmias and other cardiovascular abnormalities.
The ECG signal is usually affected by noise, baseline drift, and motion artifacts, which may impair the performance of the model. Hence, preprocessing is required to improve the quality of the ECG signal. The preprocessing of the ECG signal usually includes normalization, noise removal, and segmentation.
Normalization is used to ensure that the values of ECG signals are within a fixed range of numbers. This process is useful in enhancing the stability of the neural network's training process. In addition, noise

reduction filters can be used to filter out unwanted noise resulting from external sources such as muscle movement and electrodes.

The Artificial Neural Network (ANN) model was used as a baseline for ECG classification, consisting of input, hidden, and output layers where neurons perform weighted summation followed by activation functions. The model is trained using backpropagation and gradient descent but has limited capability in capturing complex ECG patterns. To overcome this, a Deep Neural Network (DNN) with multiple hidden layers was implemented, enabling hierarchical feature extraction from ECG signals and improving classification performance.

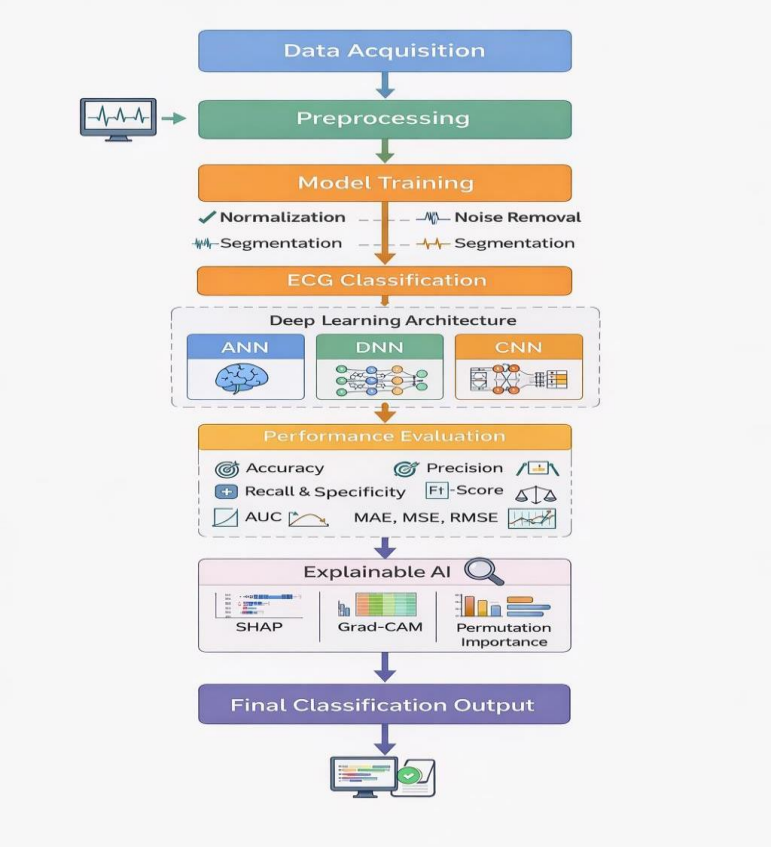
A Convolutional Neural Network (CNN) was also applied, where ECG beats were segmented using a fixed window of 360 samples around R-peaks. CNN utilizes convolutional layers, activation functions like ReLU, pooling layers, and fully connected layers to extract spatial features from signals.

Noise augmentation was applied to 30% of training data to improve robustness. The dataset was split into training and testing sets, followed by standardization. To handle class imbalance, techniques such as SMOTE, ADASYN, SMOTE-Tomek, and random oversampling were used, with SMOTE selected as the primary method. PCA was applied for feature visualization. Model performance was evaluated using metrics including accuracy, precision, recall, F1-score, AUC, TNR, FPR, MCC, Cohen's Kappa, MAE, MSE, and RMSE, along with confusion matrix, ROC, and precision-recall curves.

4 Data availability:

MITDB Dataset: https://www.physione t.org/content/mitdb/1.0.0/ , https://www.physionet.org/content/nstdb/1.0.0/ .

Fig. 1. Flow chart



5 Result Analysis:

Fig. 2. : CNN summary

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 360, 1)	0
conv1d (Conv1D)	(None, 360, 64)	512
batch_normalization (BatchNormalization)	(None, 360, 64)	256
max_pooling1d (MaxPooling1D)	(None, 180, 64)	0
last_conv (Conv1D)	(None, 180, 128)	41,088
batch_normalization_1 (BatchNormalization)	(None, 180, 128)	512
max_pooling1d_1 (MaxPooling1D)	(None, 90, 128)	0
global_average_pooling1d (GlobalAveragePooling1D)	(None, 128)	0
dense (Dense)	(None, 128)	16,512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 59,009 (230.50 KB)
Trainable params: 58,625 (229.00 KB)
Non-trainable params: 384 (1.50 KB)

Fig. 3. DNN summary

Model: "sequential"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 128)	46,208
dense_3 (Dense)	(None, 64)	8,256
dense_4 (Dense)	(None, 32)	2,080
dropout_1 (Dropout)	(None, 32)	0
dense_5 (Dense)	(None, 1)	33

Total params: 56,577 (221.00 KB)
Trainable params: 56,577 (221.00 KB)
Non-trainable params: 0 (0.00 B)

Fig. 4. ANN Summary

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_6 (Dense)	(None, 64)	23,104
dense_7 (Dense)	(None, 32)	2,080
dense_8 (Dense)	(None, 1)	33

Total params: 25,217 (98.50 KB)
Trainable params: 25,217 (98.50 KB)
Non-trainable params: 0 (0.00 B)

Table 2. ALL three models comparision

Metric	ANN	DNN	CNN
Accuracy	0.984851	**0.987161**	0.979786
Precision	0.950011	**0.955788**	0.935991
Recall (TPR)	0.973588	**0.979508**	0.962204
F1-Score	0.961655	**0.967503**	0.948917
AUC	0.997198	**0.997482**	0.995985
TNR (Specific-ity)	0.987581	**0.989016**	0.984048
FPR	0.012419	**0.010984**	0.015952
MCC	0.952329	**0.959616**	0.936458
Cohen's Kappa	0.952218	**0.959504**	0.936320
MAE	—	**0.012839**	0.020214
MSE	—	**0.012839**	0.020214
RMSE	—	**0.113311**	0.142176

Fig. 5. Raw ECG

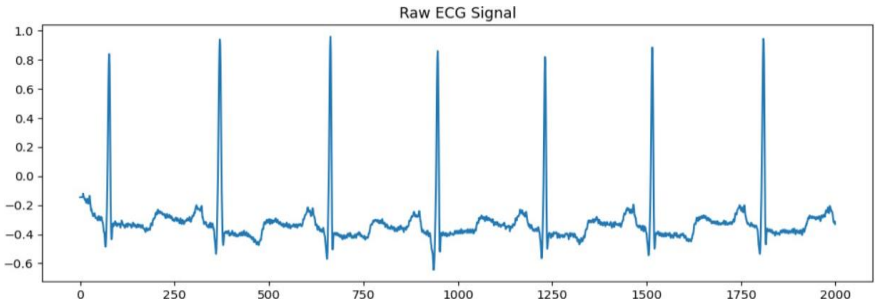


Figure 5 illustrates the raw electrocardiogram (ECG) signal obtained directly from the dataset before applying any preprocessing techniques. The waveform represents the electrical activity of the heart over time. In the signal, several repeating peaks can be observed, which correspond to the cardiac cycles, particularly the prominent R-peaks that indicate ventricular depolarization.

Fig. 6. Filtered ECG Signal

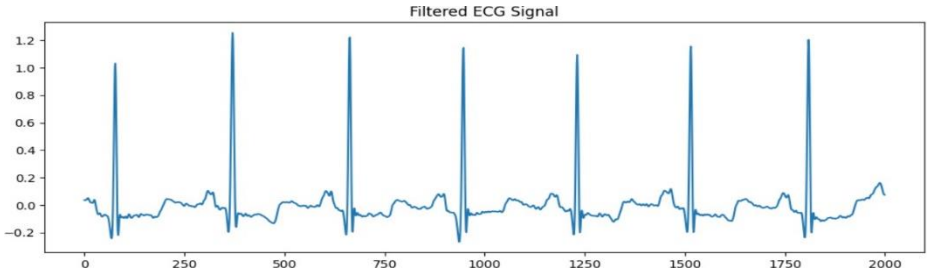


Figure 6 presents the filtered ECG signal after applying signal preprocessing techniques to remove unwanted noise and artifacts. Filtering helps eliminate disturbances such as baseline wander, high-frequency noise, and electrical interference that may be present in the raw ECG data.

Fig. 7. Z-score normalized ECG signal

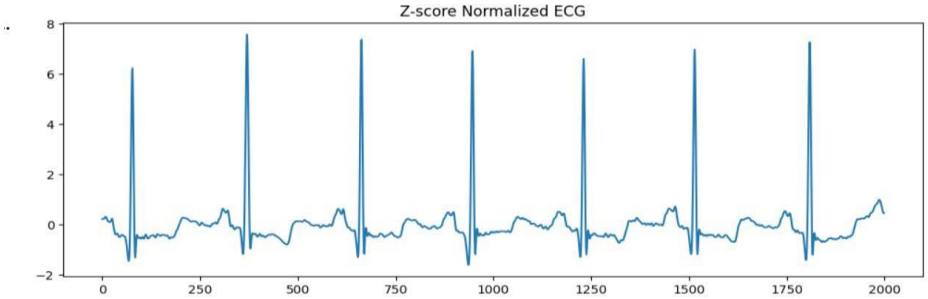


Figure 7 shows the Z-score normalized ECG signal, which is obtained after applying statistical normalization to the filtered signal. Z-score normalization transforms the data so that it has a mean of zero and a standard deviation of one.

Fig. 8. Segmented ECG

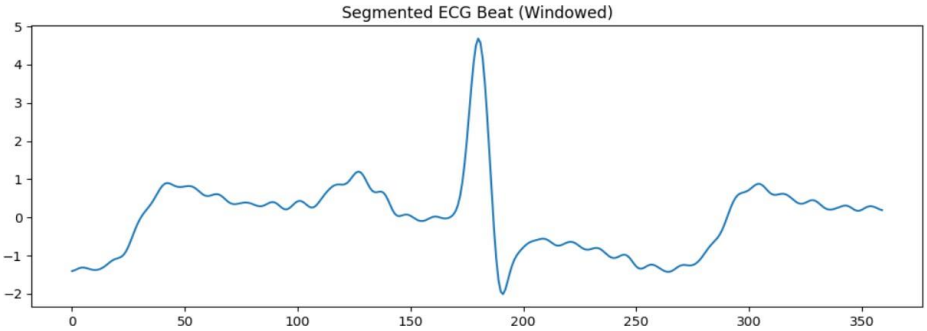


Figure 8 illustrates the segmented ECG beat obtained using a windowing technique. Instead of analyzing the entire ECG signal at once, the signal is divided into smaller segments centered around the R-peak, which represents a single heartbeat cycle.Each segment captures the important components of the ECG waveform, including the P wave, QRS complex, and T wave.

Fig. 9. Class Distribution Before

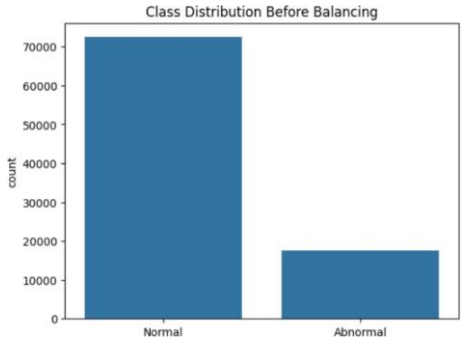


Fig. 10. Class Distribution After

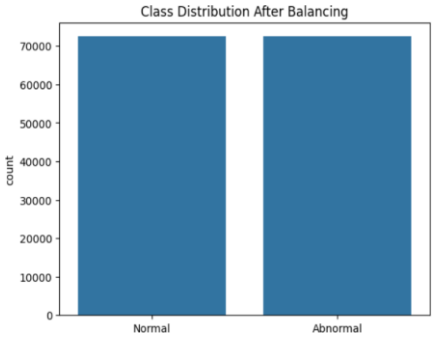
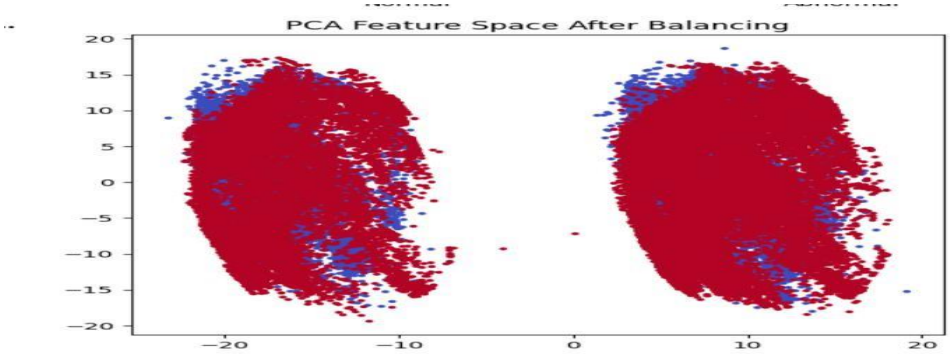


Fig. 11. PCA after balancing



The figures illustrate the dataset distribution and the impact of applying a balancing technique before training the classification models. In ECG-based medical diagnosis systems, class distribution is critical, as an imbalanced dataset can bias the model toward the majority class, reducing its ability to detect abnormal cases. Figure 9 shows the dataset before balancing, where normal ECG samples (approximately 70,000) significantly outnumber abnormal samples (around 18,000). This imbalance can lead to poor detection of abnormal heart conditions, which is a serious concern in clinical applications.

Figure 10 presents the dataset after applying the balancing technique, where both normal and abnormal classes have nearly equal representation. This ensures that the model is trained on sufficient examples from both classes, improving its ability to learn distinguishing patterns and enhancing performance, particularly in detecting abnormal signals.

Figure 11 shows the PCA visualization of the balanced dataset. By projecting high-dimensional ECG features into a two- dimensional space, PCA reveals that both classes are distributed with comparable density and form distinguishable clusters, despite slight overlap. This indicates that the extracted features are meaningful and support effective classification.

Fig. 12. ANN ROC Curve

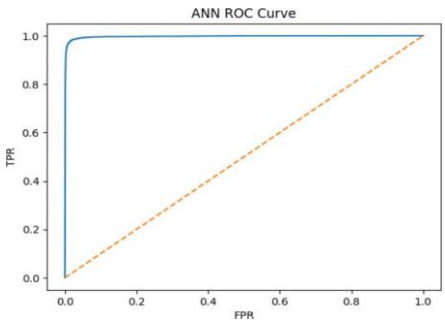
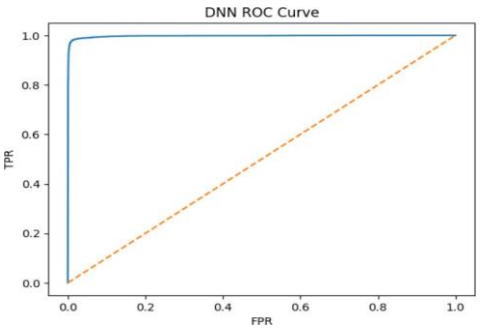


Fig 13. DNN ROC Curve



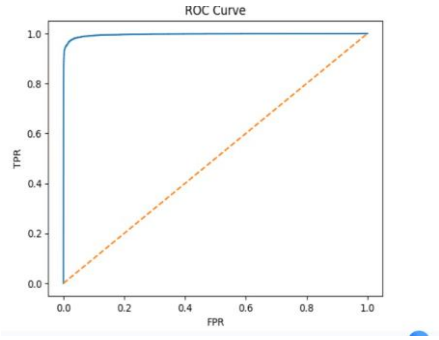


Fig. 14. CNN ROC Curve

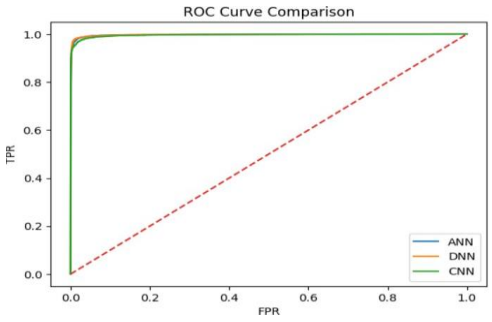


Fig. 15. ROC Curve Comparision

The ANN curve rises sharply toward the upper-left corner, showing that it achieves a high detection rate with a low false alarm rate. The CNN model also performs well, as its curve remains significantly above the diagonal line, although it appears slightly lower than the ANN and DNN in some regions, indicating minor misclassifications.The DNN model shows the best performance, with its curve closest to the upper-left corner. This indicates a very high true positive rate and minimal false positives, suggesting that the model effectively captures complex ECG patterns.In the combined ROC plot, all models perform strongly, but the DNN consistently outperforms the others, confirming its superior reliability and alignment with its higher accuracy and AUC values.

Fig. 19. Grad-CAM visualization

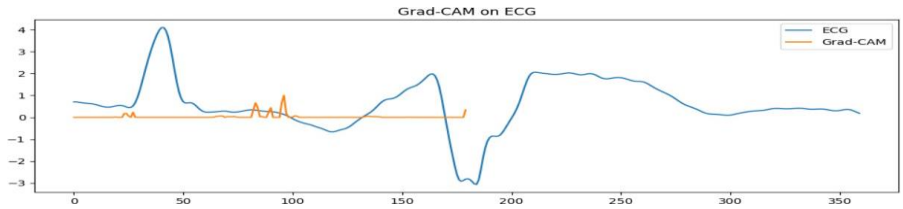


Figure 19 shows the Grad-CAM visualization applied to the ECG signal, helping interpret the model's predictions. Grad-CAM highlights important regions that contribute to classification. The blue curve represents the original ECG waveform, including key components like the P wave, QRS complex, and T wave, while the orange curve shows importance values.

The highest activations are observed near the QRS complex, indicating that the model focuses on clinically significant regions for detecting abnormalities. Other regions show low importance, suggesting minimal influence on predictions. Overall, the visualization confirms that the model relies on meaningful ECG features, improving both reliability and interpretability.

Fig.20. SHAP value with a 95% confidence interval

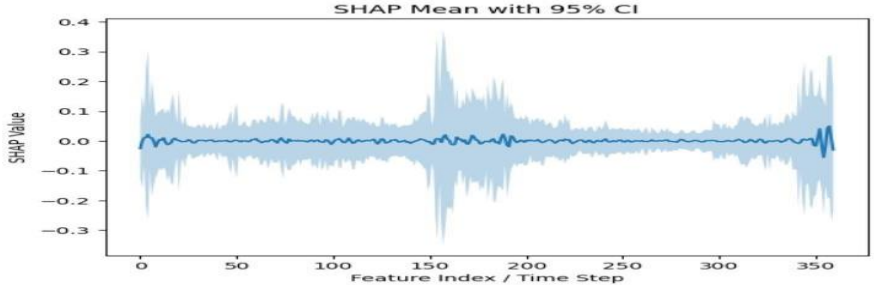


Figure 20 shows the mean SHAP values with a 95% confidence interval for ECG features, helping explain model predictions. SHAP identifies how each feature influences classification. The horizontal axis represents feature indices (time steps), while the vertical axis shows SHAP values. Positive values push predictions toward abnormal, and negative values toward normal.

The central line indicates the mean SHAP value, and the shaded region shows variability. Higher SHAP values are observed in central regions, likely corresponding to the QRS complex, indicating strong influence. Features near zero have minimal impact. Overall, the plot confirms that the model focuses on clinically important ECG patterns for accurate classification.

Fig. 21. Permutation Feature Importance

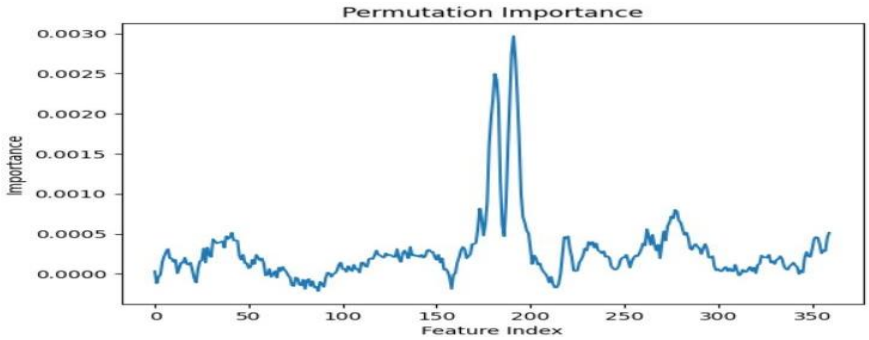


Figure 21 presents Permutation Feature Importance, which evaluates how each feature contributes to model performance. The x-axis shows feature indices (ECG time steps), and the y-axis represents importance scores. A feature is considered important if shuffling it causes a significant drop in model performance.The plot shows clear peaks around indices 170–200, indicating highly influential regions, likely corresponding to the QRS complex, which is crucial for detecting abnormalities. Many other features have near-zero importance, showing minimal impact. This uneven distribution confirms that the model focuses on specific, meaningful ECG segments, demonstrating effective learning of relevant physiological patterns and improving both accuracy and interpretability.

Fig. 22 accuracy of ANN, DNN, and CNN models

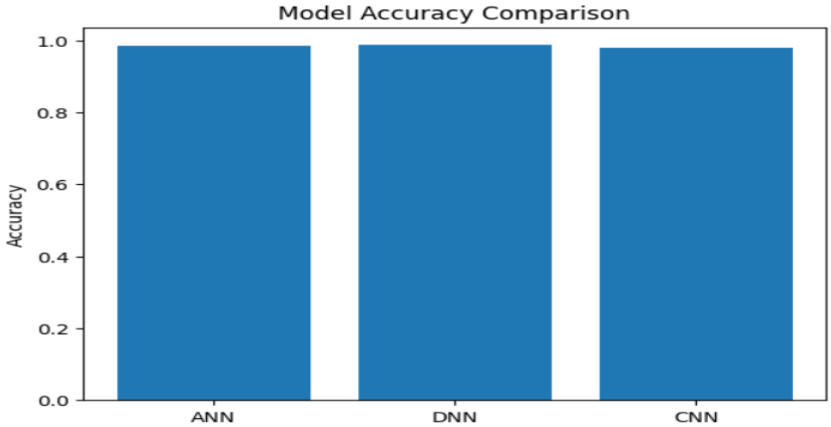
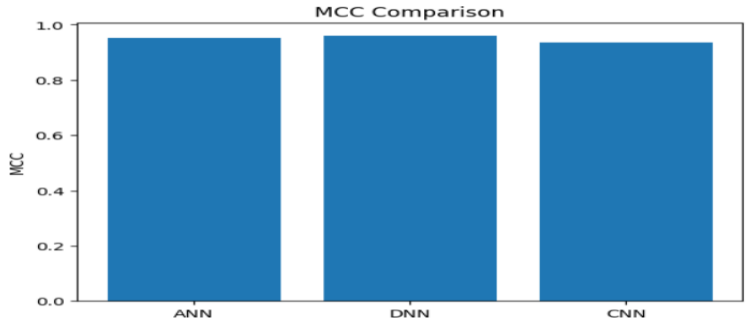


Figure 22 compares the accuracy of ANN, DNN, and CNN models for ECG classification. Accuracy measures the proportion of correctly classified samples. All three models achieve high accuracy, showing that deep learning is effective for detecting cardiac abnormalities. The ANN model achieves about 0.9848 accuracy, while the DNN model performs the best with approximately 0.9871 accuracy. The CNN model follows with around 0.9798 accuracy. The superior performance of DNN is due to its deeper architecture, which can capture complex non-linear patterns in ECG signals (6, 11).

Fig. 23. Matthews Correlation Coefficient (MCC)



The Matthews Correlation Coefficient (MCC) provides a balanced measure of model performance by considering all four outcomes of the confusion matrix (TP, TN, FP, FN). From the figure, all three models achieve very high MCC values close to 1, indicating strong overall classification quality. Among them, the DNN model shows the highest MCC, suggesting the most reliable and consistent predictions across both classes.

Fig. 24. error metrics comparison

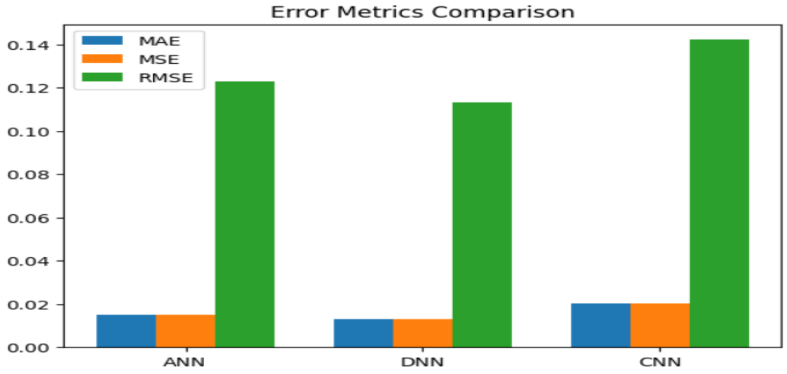


Figure 24 compares error metrics—MAE, MSE, and RMSE—for ANN, DNN, and CNN models. These metrics measure the difference between predicted and actual values, where lower values indicate better performance. The DNN model achieves the lowest errors (MAE/MSE ≈ 0.0128, RMSE ≈ 0.1133), showing the most accurate and Stable predictions. The ANN model also performs well with slightly higher errors (RMSE ≈ 0.123). The CNN model has the highest errors (RMSE ≈ 0.142), indicating minor limitations in capturing signal variations. Overall, the results confirm that DNN provides the best performance, demonstrating higher robustness and accuracy for ECG classification tasks.

Fig. 25. SHAP summary plot

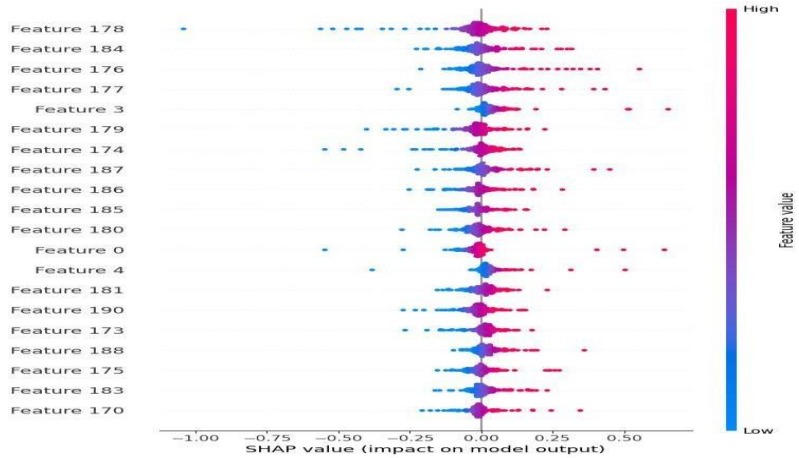


Figure 25 presents the SHAP summary plot, which explains how different features influence the predictions of the deep learning model used for ECG classification. SHAP assigns an importance value to each feature based on its contribution to the final prediction. In the plot, the horizontal axis represents SHAP values, where positive values push the prediction toward the abnormal class, while negative values indicate a contribution toward normal classification. Features are ranked on the vertical axis according to their importance.

Each point represents a sample, with color indicating feature value (red for high, blue for low). Features such as Feature 183, 184, 188, 354, and 187 appear at the top, showing the highest impact on predictions. Their wide SHAP value range suggests strong influence, particularly in detecting abnormal patterns, likely related to critical ECG components like the QRS complex.

6. Limitations:

Despite achieving high classification performance, the proposed framework exhibits certain limitations. The reliance on a specific dataset may constrain generalizabilityacross diverse clinical environments. Additionally, the models primarily perform binary classification, limiting their applicability in detecting multiple arrhythmia classes. Although explainable AI techniques are incorporated, interpretability may still require domain-specific validation. The computational complexity of deep models can also hinder real-time deployment.

7. Conclusion

The present study delineates a robust and analytically rigorous framework for automated ECG signal classification, underscoring the efficacy of deep learning paradigms in cardiovascular diagnostics. Through a comparative evaluation of ANN, CNN, and DNN architectures, the findings unequivocally demonstrate the superior representational capacity of deep neural networks in capturing intricate, non-linear electrophysiological patterns. The DNN model, in particular, exhibits heightened predictive fidelity across multiple performance indices, affirming its reliability in discerning subtle cardiac anomalies.

The present study delineates a robust and analytically rigorous framework for automated ECG signal classification, underscoring the efficacy of deep learning paradigms in cardiovascular diagnostics. Through a comparative evaluation of ANN, CNN, and DNN architectures, the findings unequivocally demonstrate the superior representational capacity of deep neural networks in capturing intricate, non-linear electrophysiological patterns. The DNN model, in particular, exhibits heightened predictive fidelity across multiple performance indices, affirming its reliability in discerning subtle cardiac anomalies.

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