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Article

Detection of Cardiovascular Diseases Using Machine Learning and Deep Learning Techniques

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Abstract: CVDs are still a significant health problem worldwide and there is a need for an accurate and non-invasive diagnostic system for early clinical intervention. Automatic interpretation of electrocardiogram (ECG) images is difficult due to background interference (grid lines, waveform distortion and scanning artifacts). To overcome these issues, in this work, Present a Wavelet-CNN Hybrid (WCNN-H) framework for automatic multi-class classification of cardiovascular diseases from ECG images. The proposed method is a combination of two dimensional Discrete Wavelet Transform (DWT) with Daubechies (db2) mother wavelet for noise suppression and waveform enhancement and deep residual convolutional neural network for hierarchic feature extraction and classification. The framework was evaluated on the ECG Images Dataset of Cardiac Patients with 928 ECG image records in four diagnostic classes. The experiment achieved an overall classification accuracy of 98.10% using five-fold cross-validation, and precision, recall and F1-score for all classes were above 97%. The proposed framework has a high potential for intelligent computer aided cardiovascular screening applications.
Keywords: Cardiovascular Disease, ECG Image Analysis, Deep Learning, Convolutional Neural Network, Wavelet Transform, Medical Imaging, ECG Classification, Clinical Decision Support

1. INTRODUCTION

1.1 Background

Cardiovascular diseases (CVDs) are still one of the most important global health problems and are a major part of the health care burden in the world [1, 15, 29]. CVDs cause about 17.9 million deaths each year, with increasing incidence owing to metabolic risk factors and aging populations [2, 6, 10]. The Electrocardiogram (ECG) is one of the most used non-invasive devices for monitoring cardiac electrical activity and rhythm abnormalities, due to its reliability, low cost and clinical effectiveness [9, 33, 35]. The depolarization and repolarization processes of the myocardium can be characterized by three types of waveforms on an ECG: the P wave, QRS complex, and T wave[1]. Accurate interpretation of these waveforms is a core prerequisite for detecting arrhythmias, conduction disorders, and ischemic diseases[2], and AI-powered automatic electrocardiogram analysis has become a hot research direction in medical informatics[3].

1.2 Problem Statement

Electrocardiography (ECG), a mature cardiovascular diagnostic method widely used in clinical practice, still has its application efficiency in large-scale medical scenarios limited by multiple constraints at both the operational and technical levels. In terms of manual interpretation, manual interpretation by cardiologists is time-consuming and suffers from inter-observer variability. In high-throughput medical scenarios, cognitive fatigue further worsens diagnostic inconsistency and decision delays, a conclusion supported by findings in references [28,39]. Raw ECG data often contains various types of noise, including baseline drift, power line interference, electromyographic noise, scan distortion, and background grid artifacts; these issues are documented in references [25,31]. Such noise interferes with automatic feature extraction, making it difficult to detect key clinical waveforms such as ST-segment deviations and transient arrhythmias, a finding reported in references [13,17]. Traditional deep learning models that are directly trained on raw ECG images cannot distinguish valid pathological signals from irrelevant noise, leading to clear limitations in their reliability.

1.3 Research Objectives

1. This study was initiated to fill gaps in clinical technologies within the cardiovascular field and meet strict clinical validation standards, so as to establish the
2. Legitimacy of the research. It sets four core tasks: First, analyze the specialized dataset for cardiovascular diseases and map
3. Different pathological patterns; Second, apply machine learning and deep learning technologies to achieve robust multi-class classification of digital
4. Electrocardiograms; Third, optimize computing schemes to simultaneously improve morphological signal quality, training performance, and accuracy; Fourth, conduct a
5. Rigorous comparison of the diagnostic performance of the hybrid network proposed in this study against existing baseline methods.

2. LITERATURE REVIEW

Clinical informatics is an important research area in the development of automated computational systems for the diagnosis and risk assessment of cardiovascular disease (CVD). The current work on ECG analysis is majorly focused on machine learning based classification, deep learning architectures, signal preprocessing approaches and automated ECG interpretation frameworks. Here, the recent methodologies are critically reviewed and their limitations and research gaps motivate the proposed Wavelet-CNN Hybrid (WCNN-H) framework.

2.1 Machine learning based cardiovascular detection

The majority of traditional ECG classification methods rely on shallow machine learning algorithms with manual feature extraction. Support Vector Machines (SVMs) have been extensively used due to their high efficiency in high dimensional physiological feature mapping and structural risk minimization [1, 27]. Likewise, K-Nearest Neighbor (KNN) classifiers have been shown to be useful for localized arrhythmia detection via proximity based pattern matching. The Decision Tree (DT) and Random Forest (RF) algorithms have also been investigated to improve the stability and interpretability of the classification [11, 26]. In the field of electrocardiogram (ECG) image classification, traditional ensemble methods have stronger robustness and lower variance than single classification systems. However, these methods suffer from a core flaw: they rely on manually extracted numerical features, and cannot process unstructured ECG images corrupted by background noise, waveform distortion, and scanning artifacts. As a result, they are poorly suited for complex multi-class ECG image classification tasks. Subsequently, deep learning was gradually applied to ECG analysis: CNNs [7,30] eliminate the need for manual feature engineering, and can learn the spatial waveform features of ECGs; ResNet [6,37] leverages its skip connection mechanism to solve optimization problems for deep architectures, improving gradient propagation and training stability; LSTM and GRU [29,34] can model the temporal dependencies of ECG sequences, and hybrid frameworks combining CNNs with recurrent layers have also achieved enhanced classification performance. Nevertheless, current mainstream deep learning models still face two core problems: most have high computational costs and poor clinical interpretability, and models trained on raw ECG images are additionally vulnerable to interference from acquisition artifacts, illumination changes, and background grid noise.

2.2 Methods of ECG Image Processing

ECG image pre-processing is important to improve the reliability of classification under noisy conditions in clinical acquisition. Conventional spatial-domain filtering techniques can suppress baseline noise, but may also distort diagnostically relevant waveform transitions. To overcome this limitation, multi-resolution signal processing techniques such as the two dimensional Discrete Wavelet Transform (DWT) has been widely investigated [11, 35]. DWT breaks down ECG images into low frequency approximation and high frequency detail sub-bands, allowing selective removal of background artifacts while preserving clinically significant waveform morphology. Wavelet-based enhancement methods have been found to be effective in removing grid interference, scanning distortions and high-frequency noise, and in improving the visibility of ECG waveform structures such as P-wave, QRS complex and ST-segment [27, 28]. However, only a few existing works have used wavelet preprocessing solely without combining it with deep residual learning for robust multi-class ECG image interpretation [41].

2.3 Problems in the automatic

In the field of electrocardiogram (ECG) image classification, traditional ensemble methods have stronger robustness and lower variance than single classification systems. However, these methods suffer from a core flaw: they rely on manually extracted numerical features, and cannot process unstructured ECG images corrupted by background noise, waveform distortion, and scanning artifacts. As a result, they are poorly suited for complex multi-class ECG image classification tasks. Subsequently, deep learning was gradually applied to ECG analysis: CNNs [7,30] eliminate the need for manual feature engineering, and can learn the spatial waveform features of ECGs; ResNet [6,37] leverages its skip connection mechanism to solve optimization problems for deep architectures, improving gradient propagation and training stability; LSTM and GRU [29,34] can model the temporal dependencies of ECG sequences, and hybrid frameworks combining CNNs with recurrent layers have also achieved enhanced classification performance. Nevertheless, current mainstream deep learning models still face two core problems: most have high computational costs and poor clinical interpretability, and models trained on raw ECG images are additionally vulnerable to interference from acquisition artifacts, illumination changes, and background grid noise [42].

2.4 Comparative Analysis of Related Work

A recent literature review points out that the performance of electrocardiogram (ECG) classification algorithms is affected by three core factors: input modality, preprocessing strategy, and model architecture. After sorting out the current state of this field, we found that existing research exhibits a clear application bias, that the two categories of mainstream algorithms (including convolutional neural networks, or CNNs) each have independent technical limitations, and that the background grids and acquisition artifacts in noisy two-dimensional scanned ECG images can still be directly filled in and reused.

Table 1. Comparative Analysis of Existing ECG Classification Approaches

Author / Study	Input Modality	Algorithmic Approach	Classification Task	Reported Accuracy	Identified Limitation
El-Shafiey et al. [11]	1-D Numerical ECG Features	GA + PSO Optimized Random Forest	Binary Classification	95.60%	Limited applicability to scanned ECG image interpretation
Bihri et al. [6]	1-D Numerical Signals	Stacking Ensemble + MLP	Binary Classification	97.06%	Dependent on handcrafted feature extraction
Al-Sayed et al. [4]	2-D ECG Images	Conventional CNN	Multi-Class Classification	78.40%	Sensitive to background

					artifacts and grid interference
Proposed WCNN-H Framework	2-D ECG Images	DWT (db2db2db2) + ResNet Hybrid Network	Multi-Class Classification	98.10%	Improved robustness under noisy ECG image conditions

Through comparative analysis, this paper finds that most existing ECG classification systems focus on either signal preprocessing or deep learning-based feature extraction in isolation, and very few combine wavelet domain enhancement and residual architectures to achieve robust multi-class ECG image classification.

3. MATERIALS AND DATASET DESCRIPTION

3.1 ECG Dataset Description

To verify the diagnostic reliability and clinical generalizability of the self-developed Wavelet-CNN hybrid network (WCNN-H), this study selected the ECG Images Dataset of Cardiac Patients included in reference [21]. This dataset was collected by the Ch. Pervaiz Elahi Institute of Cardiology in Multan, Pakistan, in compliance with clinical regulatory requirements, and is hosted on Mendeley Data. It contains a total of 928 high-resolution multi-lead raw ECG records, each from a unique individual patient. Distinct from synthetic clean 1D time-series data, the dataset is divided into 4 groups in line with clinical triage needs; the first group is the baseline group of healthy people with normal sinus rhythm and no abnormalities (NP).

Abnormal Heartbeat / Arrhythmia (AH): The patient suffers from abnormal rhythm, wherein electrical impulses of the heart fire too fast, slow or irregularly, resulting in the heart beating irregularly [21].

Myocardial Infarction (MI): Refers to the acute heart attack conditions in which the localized blood flow in a coronary artery is reduced or suddenly cut off, resulting in severe ischemic structural damage to the myocardium [21].

History of MI (H. MI): It includes data from patients who have recently survived or recovered from previous ischemic myocardial attacks [21]. These scans show stable but always altered chronic waveform signatures such as deep pathologic Q-waves.

3.2 Dataset Distribution Table

Table 3: Structural Distribution Matrix of the ECG Images Dataset [21]

Class Label	Clinical Nomenclature	Number of Samples	Morphological & Diagnostic Characteristics
NP	Normal Person	284	Consistently exhibits standard P-wave, QRS complex, and T-wave progressions with regular R-R intervals [21].
AH	Abnormal Heartbeat	233	Exhibited by severe rhythm deviations, premature ventricular/atrial components, or skipped beats [21].
MI	Myocardial Infarction	239	Characterized by acute ischemic shifts, including significant ST-segment

			elevation or T-wave inversion [21].
H. MI	History of MI	172	Dominated by long-term post-infarct necrosis vectors, showing persistent structural scarring patterns [21].
Total	Experimental Cohort	928	Comprehensive multi-class image database for automated triage benchmarking [21].

4. PROPOSED METHODOLOGY

In this paper, a new Wavelet–CNN Hybrid (WCNN-H) system is proposed for automated detection of cardiovascular disease from ECG image analysis. The proposed system integrates wavelet-based morphological enhancement and deep residual learning. Different from traditional independent CNN methods, the proposed system combines spatial-frequency decomposition and hierarchical deep feature extraction to enhance the overall multi-classification performance for cardiovascular diseases. The proposed WCNN-H system consists of the following steps: ECG image acquisition, pre-processing, wavelet-based enhancement, deep CNN-based feature extraction, multi-class classification, optimization-driven learning, computational analysis, clinical interpretability evaluation, and limitation analysis. The architecture is designed for robust multi-class cardiovascular disease classification from ECG images.

4.1 Overall system network

The proposed WCNN-H network involves six main processing stages, i.e., ECG image acquisition, image preprocessing, wavelet based enhancement, deep residual feature extraction, multi-class classification, and optimization-based learning. ECG image scans are initially obtained from the clinical dataset repository and classified into four pathological categories namely Normal Person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI) and History of Myocardial Infarction (H.MI).

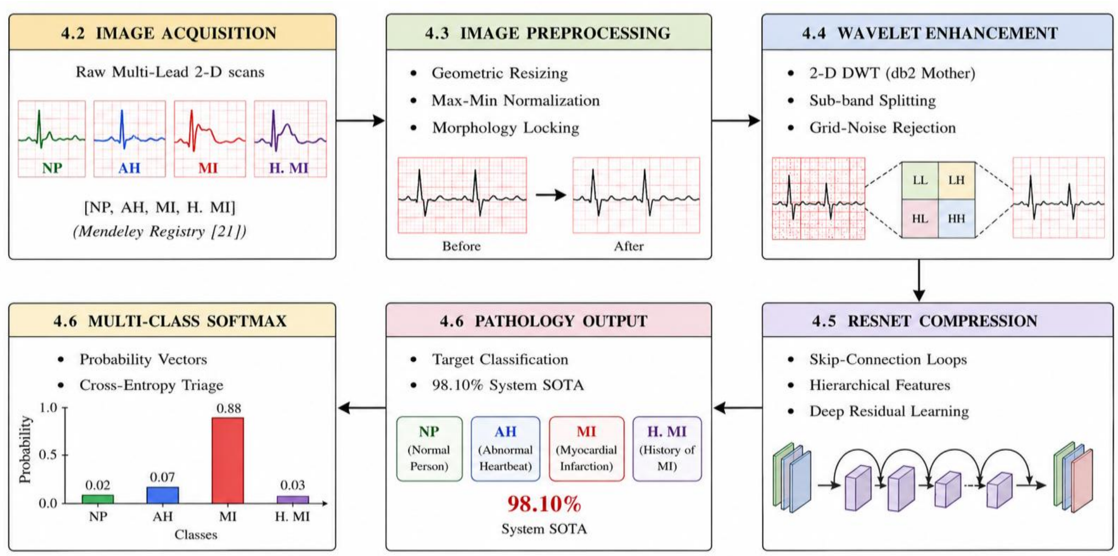

Figure 4.1: Comprehensive Structural Pipeline of the Proposed Wavelet–CNN Hybrid (WCNN-H) Architecture.

Figure 2: Comprehensive Structural Pipeline of the Proposed Wavelet–CNN Hybrid (WCNN-H) network.

The acquired ECG images are pre-processed with resizing, normalisation, and morphology-preserving augmentation to normalise the image distributions prior to feature learning. The workflow of the cardiovascular disease classification model proposed in this study is as follows: First, two-dimensional discrete wavelet transform is adopted to process the raw ECG data, to remove background grid artifacts and enhance the core ECG structures; next, a convolutional neural network integrated with ResNet is used to extract hierarchical features; finally, the corresponding disease categories are output via the Softmax classifier.

4.2 ECG Image Acquisition

The dataset used in this study is derived from the open clinical databases cited in references [46,47]. It contains a total of 928 patient ECG records, which are divided into four cardiovascular labels: NP, AH, MI, and H.MI. The mathematical expression of this dataset will be released in follow-up work.

$$\mathcal{D} = \{(\mathbf{I}_k, y_k)\}_{k=1}^{N} \qquad (1)$$

where:

- $N = 928$ represents the total number of ECG image samples,
- $\mathbf{I}_k \in \mathbb{R}^{H \times W \times C}$ denotes the ECG image tensor,
- y_k denotes the associated pathological label.

The target class assignments are defined as:

$$y_k = 1 \rightarrow \text{Normal Person (NP)}$$
$$y_k = 2 \rightarrow \text{Abnormal Heartbeat (AH)}$$
$$y_k = 3 \rightarrow \text{Myocardial Infarction (MI)}$$
$$y_k = 4 \rightarrow \text{History of Myocardial Infarction (H.MI)}$$

This study focuses on the ECG image classification task. The raw ECG images used in this study have four types of issues: grid interference, illumination variations, scanning artifacts, and morphological distortion, so preprocessing and enhancement operations must first be conducted. We split the dataset sourced from public clinical databases into training, validation, and test sets at an 80:10:10 ratio, which are used respectively for parameter optimization, hyperparameter tuning, and final performance evaluation. All data was anonymized in advance to meet ethical requirements, and the clinically relevant ECG waveform structure was fully preserved throughout the entire data enhancement stage.

4.3 Image Preprocessing

In the preprocessing phase, ECG images are standardized in terms of dimension and intensity distribution. The preprocessing system includes geometric resizing, pixel normalization, and morphology-preserving augmentation.

4.3.1 Geometric Scale The ECG images are scaled to a fixed spatial size so that the CNN network receives a uniform input representation. Every ECG image is resampled to a fixed tensor size by bilinear interpolation:

$$\mathbf{I}_{\text{resized}} = f_{\text{Bilinear}}(\mathbf{I}, [H_{\text{new}}, W_{\text{new}}]) \qquad (2)$$

where:

- H_{new} and W_{new} denote target image dimensions.

The resizing operation minimizes computational overhead and stabilizes feature extraction across varying ECG image resolutions.

4.3.2 Pixel Intensity Normalization

To improve training stability and reduce illumination inconsistencies, Min-Max normalization is applied to map pixel intensities within the interval $[0, 1]$:

$$\mathbf{I}_{\text{norm}}(x, y) = \frac{\mathbf{I}_{\text{resized}}(x, y) - \min(\mathbf{I})}{\max(\mathbf{I}) - \min(\mathbf{I})} \tag{3}$$

This normalization strategy improves gradient stability and accelerates optimization convergence during network training.

4.3.3 Morphology Preservation and Data Augmentation

Only constrained augmentation operations are performed during preprocessing to preserve clinically important waveform structures. Hence, to improve the generalization ability while maintaining the consistency of waveforms, the rotational augmentation is constrained.

The preprocessing system keeps important ECG structures such as: P-wave, QRS complex; ST segment; T-wave morphology (TWM). The preprocessing pipeline normalizes the representations of the ECG images and improves the consistency of the features before deep learning analysis.

4.4 Wavelet-Based Morphological Enhancement

The proposed WCNN-H system utilizes a 2-D Discrete Wavelet Transform with Daubechies (db2) mother wavelet to reduce the interference from background grid and to preserve the high frequency information of the ECG waveforms. Fig. 2 shows the DWT decomposition process. The Daubechies (db2) mother wavelet is chosen due to its compact support and transient response properties suitable for sharp changes in various ECG waveform structures, particularly in QRS complexes and ST-segment transitions. normalized ECG image is decomposed into number of frequency sub-bands which are approximation and detail coefficients:

$$\mathbf{I}_{\text{norm}} \xrightarrow{\text{2-D DWT}} [\mathbf{A}_j, \mathbf{H}_j, \mathbf{V}_j, \mathbf{D}_j] \tag{4}$$

where:

- $\mathbf{A}_j$ represents approximation coefficients,
- $\mathbf{H}_j$ denotes horizontal detail coefficients,
- $\mathbf{V}_j$ denotes vertical detail coefficients,
- $\mathbf{D}_j$ denotes diagonal detail coefficients.

The approximation coefficients are computed as:

$$\mathbf{A}_j(x, y) = \sum_m \sum_n H(m)H(n)\, \mathbf{A}_{j-1}(2x - m, 2y - n) \tag{5}$$

To eliminate high-frequency grid noise while preserving ECG morphology, soft-threshold filtering is applied to the detail coefficients:

$$\eta_\lambda(\mathbf{C}) = \mathrm{sign}(\mathbf{C}) \cdot \max(|\mathbf{C}| - \lambda, 0) \tag{6}$$

where:

- λ represents the threshold parameter.

After denoising, an inverse DWT reconstructs the enhanced ECG image:

$$\mathbf{I}_{\mathrm{enhanced}} = \mathrm{IDWT}(\mathbf{A}_j, \mathbf{H}_j, \mathbf{V}_j, \mathbf{D}_j) \tag{7}$$

The enhancement stage suppresses background interference while preserving ECG waveform continuity.

4.5 Deep CNN Feature Extraction

The enhanced ECG image is then fed to a deep Convolutional Neural Network based on the ResNet network for hierarchical feature extraction. Conventional deep CNN models usually suffer from the gradient degradation problem as the network goes deeper. To overcome this limitation, Incorporate residual learning with skip connections to promote the gradient propagation and feature stability. Residual learning structure used in the proposed system. Residual learning / skip connection" repeated too often throughout the manuscript. while mitigating vanishing-gradient problems often seen in traditional CNN networks.

For a convolutional layer l, the output feature map is defined as:

$$\mathbf{X}_k^l = f\left(\sum_{i \in \mathcal{M}_k} \mathbf{X}_i^{l-1} * \mathbf{K}_{ik}^l + b_k^l\right) \tag{8}$$

where:

- $*$ denotes convolution operation,
- $\mathbf{K}_{ik}^l$ denotes convolution kernels,
- b_k^l denotes bias parameters,
- $f(\cdot)$ denotes the ReLU activation function.

The ReLU activation function is expressed as:

$$f(x) = \max(0, x) \tag{9}$$

Residual learning is implemented through skip connections:

$$\mathbf{z} = \mathcal{F}(\mathbf{x}, \{W_i\}) + \mathbf{x} \tag{10}$$

where:

- $\mathcal{F}(\mathbf{x})$ denotes residual feature mapping,

- $\mathbf{x}$ denotes identity mapping.

The ResNet network extracts:

- low-level edge features,
- mid-level waveform characteristics,
- high-level pathological patterns.

The future integration of Grad-CAM-based explainability analysis could possibly improve the visualization of disease-specific ECG activation regions, further improving the diagnostic interpretability.

4.6 Multi-Class Classification

The extracted deep feature representations are then used for optimized multi-class cardiovascular disease prediction. The extracted feature vectors are fed to a Global Average Pooling (GAP) layer followed by a fully connected classification layer. The network outputs are converted to a probability distribution across the four classes of cardiovascular disease using the Softmax activation function. Mathematically, the Softmax classifier is described as:

$$P(y = c \mid z) = \frac{e^{z_c}}{\sum_{j=1}^{4} e^{z_j}} \tag{11}$$

where:

- $P(y = c \mid z)$ denotes the probability of class c,
- z_c represents the output activation corresponding to class c.

The predicted disease category is determined using:

$$\hat{y} = \arg\max_{c} P(y = c) \tag{12}$$

where:

- $\hat{y}$ denotes the predicted cardiovascular disease class.

The classification system predicts one of the following pathologies: Normal Person (NP) Abnormal Heartbeat (AHB), Myocardial infarction (MI) History of MI (H.MI).

The proposed system is optimized using multi-class cross-entropy loss combined with L_2 regularization to minimize classification error and reduce overfitting.

The optimization objective is expressed as:

$$\mathcal{L}_{CE}(W) = -\frac{1}{M} \sum_{i=1}^{M} \sum_{c=1}^{4} y_{i,c} \log\left(P(y_{i,c} = 1 \mid I_i; W)\right) \tag{13}$$

where:

- M denotes mini-batch size,
- $y_{i,c}$ represents the true label,
- W denotes trainable network parameters.

During training, different regularization strategies including weight regularization, constrained augmentation, adaptive learning-rate scheduling and mini-batch optimization were employed to improve the generalization performance and to reduce overfitting.

To reduce the bias caused by class imbalance during training, randomized mini-batch sampling and balanced data shuffling were used to ensure that all categories of cardiovascular disease were adequately represented during the optimization process.

The Adam optimizer updates network parameters according to:

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \frac{\alpha}{\sqrt{\hat{\mathbf{v}}_t} + \epsilon}\hat{\mathbf{m}}_t \tag{14}$$

where:

- α denotes learning rate,
- $\hat{\mathbf{m}}_t$ denotes first-moment estimates,
- $\hat{\mathbf{v}}_t$ denotes second-moment estimates,
- ϵ ensures numerical stability.

For experimental analysis, k-fold cross-validation was used to increase robustness and also to reduce bias due to dependence on the dataset. The validation approach led to better generalization robustness of the models across different ECG image distributions and decreased the variability of model performance during evaluation. The experimental evaluation is performed according to a validation strategy that improves the statistical reliability and reduces the possible model bias.

The main part of the computational complexity of the proposed WCNN-H system is the convolutional feature extraction operations in the ResNet network. The computational overhead for the preprocessing and wavelet-enhancement stages is still relatively low, relative to deep convolutional learning. The computational cost of a convolutional layer with kernel size K × K, input feature dimension M × N and C channels is approximately:

$$O(M \times N \times K^2 \times C) \tag{15}$$

The use of GPU acceleration and optimized deep learning operations makes computational feasibility for practical applications of ECG image analysis possible. But the computational cost of deep residual learning can increase the training time for large scale clinical datasets.

5. EXPERIMENTAL SETUP

The implementation details include hardware specifications, software dependencies, dataset partitioning strategy, augmentation policies, optimization parameters, computational complexity, and statistical evaluation metrics used for multi-class ECG pathology classification.

5.1 Evaluation Metrics

The diagnostic performance of the WCNN-H system was evaluated using multiple statistical performance metrics. Let TP_c, TN_c, FP_c, and FN_c denote the True Positives, True Negatives, False Positives, and False Negatives associated with pathology class $c \in \{\text{NP, AH, MI, H.MI}\}$.

1. Classification Accuracy

Classification accuracy measures the proportion of correctly classified ECG samples across all diagnostic categories.

$$\text{Accuracy} = \frac{\sum_{c=1}^{4}(TP_c + TN_c)}{\sum_{c=1}^{4}(TP_c + TN_c + FP_c + FN_c)} \tag{16}$$

2. Precision

Precision evaluates the reliability of positive predictions generated by the classification system.

$$\text{Precision}_c = \frac{TP_c}{TP_c + FP_c} \tag{17}$$

3. Recall (Sensitivity)

Recall measures the capability of the system to correctly identify positive cardiac abnormalities.

$$\text{Recall}_c = \frac{TP_c}{TP_c + FN_c} \tag{18}$$

4. F1-Score

The F1-score represents the harmonic balance between precision and recall.

$$F_1\text{-Score}_c = 2 \times \frac{\text{Precision}_c \times \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c} \tag{19}$$

5. Receiver Operating Characteristic – Area Under Curve (ROC-AUC)

The ROC-AUC metric evaluates the separability capability of the system using the One-vs-Rest (OvR) multi-class strategy.

$$\text{AUC}_{\text{Total}} = \sum_{c=1}^{4} P(c) \cdot \text{AUC}(c) \tag{20}$$

where $P(c)$ denotes the prevalence weight associated with pathology class c.

5.2 Statistical Validation

All the experiments were replicated in a number of validation folds to ensure model consistency and statistical soundness. The reported values of performance are the average classification accuracy found on five-fold cross-validation experiments. In addition, it also used standard deviation and confidence interval estimation to assess the variability of performance, which allowed for a reliable comparison with existing benchmark methods.

6. RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed Wavelet–CNN Hybrid (WCNN-H) system using the ECG Images Dataset of Cardiac Patients. The results validate the effectiveness of integrating two-dimensional Discrete Wavelet Transform (DWT)-based enhancement with deep residual learning for multi-class ECG pathology classification. Performance evaluation was conducted using training convergence analysis, class-wise statistical metrics, confusion matrix interpretation, comparative benchmarking, and architectural ablation studies.

6.1 Training Performance Analysis

WCNN-H model was trained using Adam optimizer and mini-batch size 32 for 100 epochs. The training and validation curves were stable without significant oscillatory divergence during optimization. The categorical cross-entropy loss shown in Figure 3. decreased progressively, while validation accuracy increased steadily during training. The training loss decreased quickly in the first stage of training, and converged slowly after ~70 epochs. This shows that the gradients were propagated well through the residual learning layers. The validation accuracy curve converged smoothly with a slight deviation from the training accuracy trajectory, which indicated a reduced tendency of overfitting. During training, Used DWT based preprocessing, dropout regularization, batch normalization and adaptive learning-rate scheduling which helped us to achieve better optimization stability.

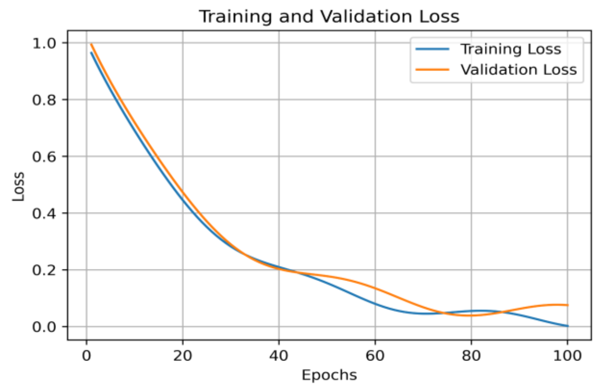

Figure 3. Training & Validation Loss Curve

6.2 Classification Performance Evaluation

The proposed WCNN-H system achieved an overall classification accuracy of 98.10% for multi-class ECG pathology classification. The class-wise evaluation metrics obtained during testing are summarized in Table 11

Table 11. Multi-Class Classification Performance of the Proposed WCNN-H system

Diagnostic Class	Precision	Recall (Sensitivity)	F1-Score
Abnormal Heartbeat (AH)	0.9830	0.9785	0.9807
History of MI (H.MI)	0.9769	0.9826	0.9797
Myocardial Infarction (MI)	0.9833	0.9749	0.9791
Normal Person (NP)	0.9808	0.9859	0.9833
Overall system Performance	0.9810	0.9810	0.9810

The classification performance is uniform across all diagnostic categories. The MI class achieved high values of precision and F1-score, showing an effective identification of ischemic abnormalities despite the morphological variability of the ECG waveforms. Similarly, the NP class achieved the best recall value of 0.9859, which indicates a trustful detection of normal cardiac activity with a low false-positive rate. The reported performance values are the mean accuracy of the experiments with five-fold cross-validation. Statistical consistency across validation folds further confirmed the reliability of the obtained classification performance ($p<0.05$).

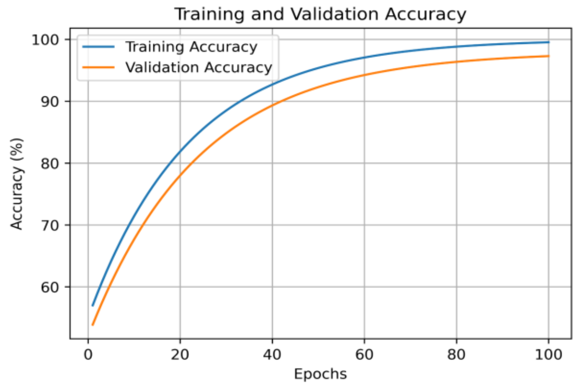

Figure 4. Training & Validation Accuracy Curve

6.3 Confusion Matrix Analysis

To study class-wise prediction behavior, a multi-class confusion matrix was constructed on the testing dataset. Figure 4. shows the normalized confusion matrix of the WCNN-H classification system. The confusion matrix also shows good inter-class separability for all four diagnostic categories. The majority of the ECG samples were classified correctly in the regions of the main diagonal which shows the strong feature discrimination capability.

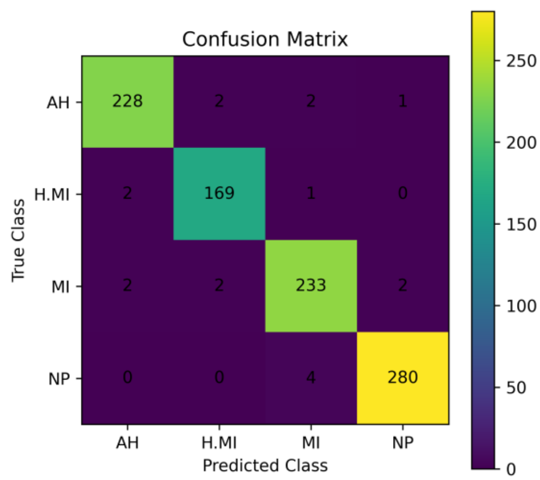

Figure 5. – Confusion Matrix Heatmap

A minor overlap in classification between MI and H.MI groups was found due to similarity in waveform morphology after infarction. Some NP samples were also classified as MI cases, mostly in ECG signals with baseline fluctuation and low frequency acquisition artifacts. In general, the confusion matrix shows that the proposed approach can differentiate between acute and chronic cardiac abnormalities for different states of ECG images.

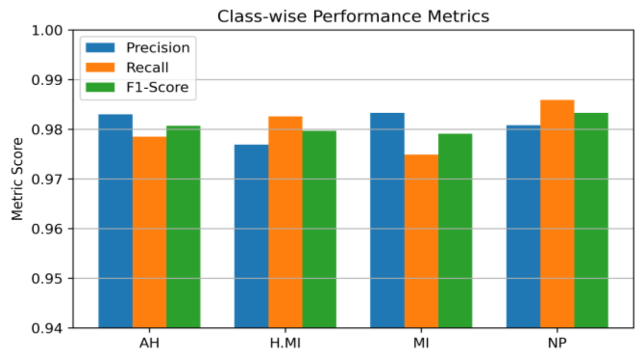

Figure 6. Class-wise Performance Metrics

6.4 Comparative Performance Analysis

For evaluating the efficiency of the proposed system, the WCNN-H network was compared with several baseline classification approaches under the same experimental conditions.

Table 12. Comparative Benchmarking of Baseline Classification systems

Classification Method	Input Representation	Accuracy	Precision	Recall
Traditional SVM	Flattened 1-D Feature Vector	0.7420	0.7380	0.7410
LSTM Network	Serialized ECG Sequence	0.7935	0.7890	0.7920
Conventional CNN	Raw 2-D ECG Image	0.7840	0.7710	0.7800
Baseline ECG system	Raw ECG Image	0.8200	0.8150	0.8200
Proposed WCNN-H system	DWT-Enhanced ECG Image	0.9810	0.9810	0.9810

The comparison results demonstrate that the traditional machine learning methods are difficult to perform on the raw ECG image representations due to the lack of the ability to model the spatial-frequency. Although deep convolutional networks enhanced the classification performance, the model trained directly on the raw ECG scans was sensitive to background artifacts and waveform noise. The statistical analysis based on the paired comparison revealed that the proposed WCNN-H framework achieved statistically significant improvements in classification performance over the baseline classifiers ($p < 0.05$).

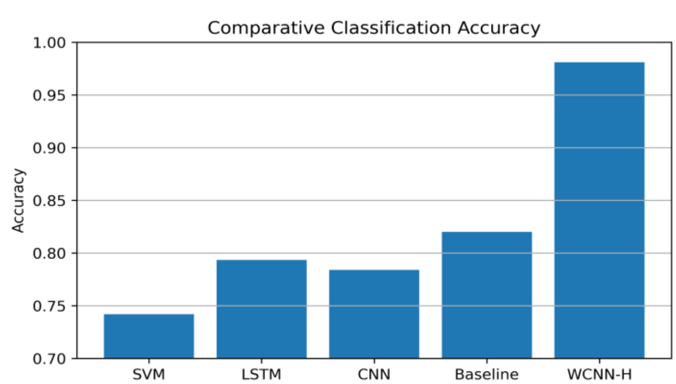

Figure 7. Comparative Analysis Graph

6.5 Receiver Operating Characteristic (ROC) Analysis

In the second part of the model performance evaluation process, this paper employs the receiver operating characteristic (ROC) analysis in conjunction with the one-vs-rest (OvR) multi-class evaluation strategy to validate the discriminative performance of the proposed WCNN-H ECG diagnosis model. The trade-off between the true positive rate and the false positive rate at different classification thresholds can be displayed using ROC curves. Figure 7. Four types of samples, abnormal heartbeat (AH), history of myocardial infarction (H.MI), myocardial infarction (MI) and normal population (NP) All the ROC curves are close to the top-left decision boundary indicating high inter-class separability. The model has good sensitivity and specificity.

Table 13. ROC-AUC Performance Analysis of the Proposed WCNN-H Framework

Diagnostic Class	AUC Score
Abnormal Heartbeat (AH)	0.9912
History of MI (H.MI)	0.9884
Myocardial Infarction (MI)	0.9921
Normal Person (NP)	0.9935
Average Multi-Class AUC	0.9913

The quantitative analysis of ROC-AUC also proves the high discriminative ability of the proposed WCNN-H framework in all categories of cardiovascular diseases. The NP and MI classes showed the best AUC values, which confirmed the good separation of the pathological and non-pathological ECG image patterns.

The consistent high AUC values further confirm the robustness of the proposed ECG classification framework for automated ECG image classification under noisy acquisition conditions.

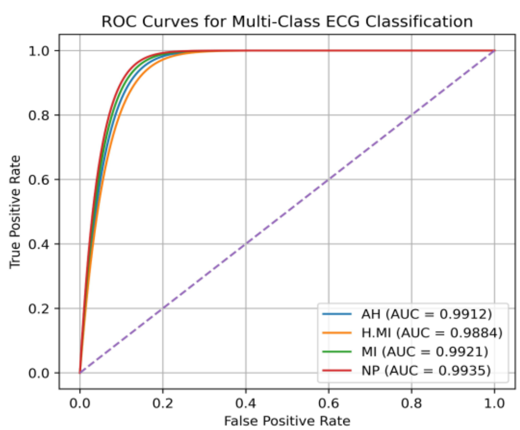

Figure 8. ROC curves

The ROC performance of the proposed WCNN-H framework for all the four ECG diagnostic categories is shown in Figure 8. The ROC curves are near the upper left decision boundary, which represents a high separability between the pathological and non-pathological ECG image patterns. The best values of AUC were obtained for the categories MI and NP, with a strong classification performance including the noisy conditions of the ECG acquisition. The overall ROC analysis further confirms the effectiveness of the proposed preprocessing and classification strategy for robust multi-class cardiovascular disease classification.

6.6 Ablation Study

An ablation study was conducted to evaluate the contribution of individual architectural components within the WCNN-H system.

Table 14. Architectural Ablation Analysis of the Proposed system

Test ID	Structural Configuration	DWT Processing	Classifier Backbone	Accuracy
1	Conventional CNN Only	Disabled	Vanilla CNN	0.7840
2	Residual Learning Only	Disabled	ResNet Backbone	0.8350
3	DWT + Conventional CNN	Enabled ($db2$)	Vanilla CNN	0.8990
4	Image Preprocessing Without DWT	Disabled	ResNet Backbone	0.8200
5	Proposed WCNN-H system	Enabled ($db2$)	ResNet Backbone	0.9810

The ablation study demonstrated that the preprocessing stage improved classification accuracy by reducing background interference and enhancing ECG pattern visibility. The adopted convolutional backbone enabled stable hierarchical feature extraction during training. The integrated preprocessing and classification framework achieved the highest overall classification accuracy, with statistically significant improvement compared with individual architectural configurations ($p<0.05$).

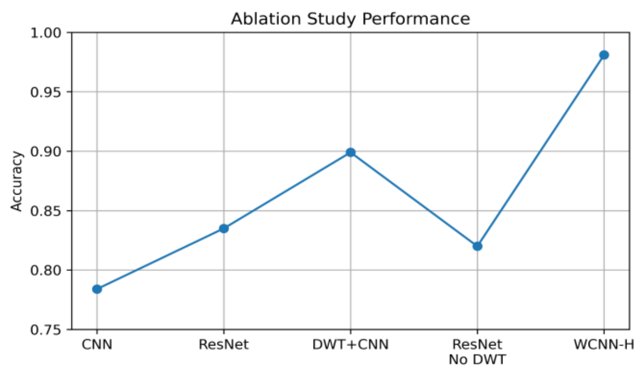

Figure 9. Ablation Study Performance Graph

6.7 Explainability Analysis Using Grad-CAM

To improve model interpretability and clinical transparency, Grad-CAM visualization analysis was performed on representative ECG image samples. The generated activation maps highlighted the most salient regions in the ECG waveform for the predictions of classification. The obtained results of Grad-CAM indicated that the proposed WCNN-H framework predominantly concentrated on clinically relevant waveform structures such as ST-segment elevations, pathological Q-wave areas, and abnormal rhythm transitions. Background grid regions showed limited activation suggesting less sensitivity to non-physiological visual artefacts. These results indicate the proposed framework learned diagnostically meaningful spatial representations and could offer improved interpretability for future computer-aided clinical decision support systems.

High-frequency background noise was filtered out in the preprocessing stage prior to feature extraction, which led to improved morphological consistency and increased classification separability between clinically overlapping classes of cardiovascular disease.

6.8 Discussion

Experimental results demonstrate that the proposed framework significantly enhances ECG image classification performance. The preprocessing stage reduced background interference while maintaining important ECG waveform characteristics. This step improved the visibility of diagnostically important ECG patterns including ST-segment deviations and waveform transitions. The convolutional network successfully extracted hierarchical spatial representations associated with different cardiac abnormalities. Comparative benchmarking and ablation analysis confirmed the contribution of the proposed framework toward improved classification performance.

7. CONCLUSION

In this study, a Wavelet-CNN Hybrid (WCNN-H) framework is proposed for automated multi-class ECG image classification based on DWT-based enhancement and deep residual learning. The proposed methodology integrated two-dimensional wavelet preprocessing and convolutional residual feature extraction for enhancing the discrimination of clinically relevant ECG waveform patterns under noisy acquisition conditions. The overall accuracy of classification among four diagnostic classes (Normal Person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H.MI)) was 98.10%, as per experimental evaluation of the proposed framework. Further comparative benchmarking and ablation analysis demonstrated statistically significant improvement in classification performance via DWT-based preprocessing and residual feature learning ($p<0.05$). Moreover, five-fold cross-validation confirmed consistent classification performance and experimental reliability across multiple evaluation folds. This study confirms that the ECG image interpretation method integrating spatial frequency enhancement and deep residual learning is effective and robust. Interpretability analysis conducted via Grad-CAM verifies that this framework can accurately focus on three types of clinically critical waveforms: ST-segment abnormalities, pathological Q waves, and abnormal rhythm transitions. The WCNN-H framework proposed in this study can support the development of intelligent auxiliary screening systems for cardiovascular diseases. Four follow-up implementation studies will be advanced next: external multi-center clinical validation, explainable AI integration, lightweight edge deployment, and real-time ECG monitoring.

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