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ResNet1D-Based ECG Arrhythmia Detection: Signal Denoising, Temporal Feature Extraction, and Reliable Multi-Class Classification

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Abstract

This study presents a robust deep learning-based classification framework for automated ECG arrhythmia detection using a Residual Convolution Neural Network (ResNet1D). The proposed model leverages both raw ECG segments and structured feature matrices to effectively learn deep temporal and morphological patterns essential for accurate arrhythmia classification. The ResNet1D architecture is specifically chosen to mitigate the vanishing gradient problem, enabling the training of deeper networks that capture subtle waveform variations crucial for distinguishing between normal and abnormal heartbeats. The model incorporates residual blocks, batch normalization, and global average pooling followed by dense layers to achieve high classification accuracy. Training is performed using categorical cross-entropy loss and the Adam optimizer, with evaluation metrics including accuracy, F1-score, precision, and AUC. The proposed ResNet1D model achieved 98 % accuracy, 93.5% precision, 93% recall, 95.2% specificity, 94.4% NPV, 0.91 MCC, 4.8% FPR, 7% FNR, and 93.2% F1-score. These results confirm its superior ability to minimize misclassifications while maintaining high reliability across all performance metrics for ECG arrhythmia detection. The outcome is a scalable and noise-resilient classification system capable of delivering accurate multi-class arrhythmia predictions for clinical and real-time applications.

Keywords: *ECG, Arrhythmia, ResNet1D, Feature Extraction, Softmax Classification, Atrial Fibrillation, Bundle Branch Block*

1. Introduction

ECG (electrocardiography) is among the most common non-invasive diagnostic methods that are used to monitor cardiac activity and identify abnormalities in heart rhythm [1]. Arrhythmias, or abnormal heart rhythm, may be harmless changes in the usual electrical

conduction of the heart, or a condition that is potentially fatal and demands urgent treatment [2]. Precise and timely identification of arrhythmias is thus critical to preventing adverse cardiac events and better patient outcomes. As more digital health data becomes available, automated arrhythmia classification systems have become highly visible as a useful aide to clinicians [3]. ECG arrhythmia detection is clinically important, but it has a number of challenges. Noise issues include baseline wander, power line interference, and motion artifacts that can ruin the waveforms and cause false diagnosis, especially affecting raw ECGs. Also, arrhythmias can present mild morphological differences among patients, which makes manual interpretation time-consuming and can be subject to inaccuracy [4]. These complexities can often not be effectively addressed using traditional signal processing techniques alone, and more sophisticated computational methods have been discovered that clean signals and extract features to enhance the accuracy of classification.

Signal cleaning methods in combination with the temporal analysis of features represent a promising direction to a strong arrhythmia type classification [5]. Filtering and adaptive noise removal are pre-processing techniques that are used to retain the actual ECG morphology, instead of removing unwanted artifacts [6]. By eliciting time-varying characteristics (RR intervals, P-QRS-T segment lengths, and heart rate variability), rhythmic dynamics critical to the process of differentiating normal and abnormal heartbeats can be obtained [7]. Such characteristics are used as input to machine learning or deep learning classifiers to improve their discrimination between different types of arrhythmias [8]. Existing arrhythmia classification frameworks, as useful as they are, may be restricted by sensitivity to noise, over fitting on skewed datasets, and may be less generalized to a broader patient population. Most traditional deep learning models are unable to learn fine ECG waveform fluctuations that are important to differentiate varied arrhythmias due to vanishing gradients [9]. These issues drive the creation of a stronger framework. In this paper, a strong Residual Convolution Neural Network (Res-CNN) will be introduced, where residual blocks are used to solve the problem of the gradient drop and slow down the learning of the feature on both clean signals and temporal signals [10]. The model displays high potential of reliable clinical and real-time applications by showing high performance in multi-class classification problems, such as Normal, Premature Ventricular Contractions (PVC) [11] and Left Bundle Branch Block (LBBB) [12], with high precision, F1-score and AUC.

1.1 Key contribution

Following are the key contribution of the study,

- A powerful Residual CNN model is designed to classify ECG arrhythmias accurately by learning complex patterns in heartbeat signals
- Uses residual blocks to solve vanishing gradient issues, allowing the model to learn deeper and more subtle ECG waveform features
- Achieves strong multi-class classification results (e.g., Normal, PVC, LBBB) using precision, F1-score, and AUC—making it suitable for clinical and real-time use

The paper is organized as follows: Introduction is given in Section 1, Section 2 reviews related work on ECG arrhythmia detection. Section 3 delves the proposed Residual CNN model. Section 4 reports experimental results and analysis. Section 5 concludes the study.

2. Literature review

Following are the recent literatures that suitable for this tittle,

Lee & Shin (2021) suggested the ECG is a single-lead, which is used to identify distrustful heart rates such as atrial fibrillation (AF). VCGs with variable size are converted to fixed-size 2D images, which are inputted to the BIT-CNN model to train on beat shape and beat patterns. The method provides simplicity in the models, enables visual analysis and retains competitive ability. It obtained F1_NAO and F1_NAOP of 81.75% and 76.87% using the PhysioNet/CinC 2017 dataset.

Majeed et al. (2021) concentrates on the detection of atrial fibrillation with the help of various machine learning classifiers. Characteristics of the heart ventricle activity are obtained and categorized on the basis of statistical methods. Five ECG data sets (AFDB, NSRDB, LTAFDB, etc.) have been experimented with the Decision Tree classifier, whose AUC, sensitivity, and specificity were found to be 99, 92, and 98 respectively, which is better than the existing methods.

Deb et al. (2024) deals with the issue of class imbalance in ECG disease prediction with special attention to rare yet life-threatening conditions. They also suggest a criticality-sensitive inference algorithm, which alters predictions of low frequency classes by exploiting knowledge of the domain during training. It is tested on the PhysioNet 2020 (27 cardiovascular classes) dataset and it can be seen that the sensitivity of rare classes can be increased without compromising the overall performance.

Elsheikhy et al. (2025) proposes a CNN that has channel attention in the classification of multi-lead ECG arrhythmia. The model is accurate and it is not complex as it captures significant features to 2-lead and 12-lead ECG signals. It was tested on the datasets of MIT-BIH and INCART with the results of 99.18-99.48 percent accuracy and F1 scores, indicating that it can be applied in clinical practice in real-time.

Iqbal et al. (2025) focusing on IoT-based ECG arrhythmia detection, this paper suggests FusionGCNN (SigNet local features + DualGCNN local-global dependencies), which is a combination of both local and global features. The model is easy to implement in edge devices and it is lightweight and efficient in terms of accuracy and low computation. Accuracy and F1 score of experiments are 0.9641 and 0.9645, respectively, which is good enough to be used in real-time healthcare monitoring.

Baca & Valdivia (2025) creates a 1D CNN model to identify arrhythmia using smartwatch ECGs. It provides an effective method of early diagnosis in real life setting. The binary model and multiclass model gave high reliability and efficiency with the binary model 64.81% accuracy and 89.47% sensitivity using UMass Simband and MIT-BIH datasets.

Panwar et al. (2025) provide a portable ECG monitoring device based on Arduino Nano and CNN to detect arrhythmia in real-time. The system is based on ECG preprocessing, binary and multi-class classification with the result of 98.35 and 99.3 accuracy, respectively. It is a low-cost hardware, with real-time classification, which makes it appropriate in continuous cardiac monitoring.

Rahman & Morshed (2025) constructs an ECG device with a wearable computer accompanied by a lightweight LSTM model to sense the beat-by-beat arrhythmia. It incorporates ANN, CNN, and LSTM models of real-time edge computing and low power consumption. It was tested on MIT-BIH data and with 20 ms real time inference, it cast 98.1% accuracy, 98.2% sensitivity and 99.5% specificity, showing that it is efficient in wearable applications.

2.1 Problem statement

Accurate and real-time detection of cardiac arrhythmias from ECG signals is critical for early diagnosis and prevention of cardiovascular diseases. Despite advances in deep learning and wearable devices, challenges persist due to variable ECG signal lengths, noise, individual variability, computational constraints of IoT and edge devices, and the presence of rare yet clinically important arrhythmias. Existing methods often struggle to balance high sensitivity,

specificity, and real-time deployment, limiting their practical use in continuous cardiac monitoring and clinical applications.

2.1 Research gap

Although recent studies demonstrate high accuracy in ECG arrhythmia detection using deep learning models, several challenges remain unaddressed. Most methods either rely on single-lead or multi-lead ECGs but do not simultaneously optimize for real-time performance, low computational cost, and deployment on wearable or IoT devices (Lee & Shin, 2021). Handling variable-length ECG signals and class imbalance, especially for rare but clinically critical arrhythmias, is often overlooked (Deb et al., 2024). Additionally, model interpretability and feature explainability are insufficiently addressed, limiting clinical trust and practical adoption (Iqbal et al., 2025). There is a need for scalable, lightweight, and reliable models that balance accuracy, efficiency, and interpretability for continuous monitoring in real-world scenarios.

3. Proposed model

Figure 1 shows the overall architecture of the proposed ECG Arrhythmia Classifier Using Cleaned Signals and Temporal Features integrates advanced preprocessing, feature extraction, and deep learning for accurate classification. Initially, raw ECG signals undergo pre-processing using Modified Complete Ensemble Empirical Mode Decomposition (CEEMD) and Discrete Wavelet Transform (DWT) to remove noise and baseline drift. This ensures that the signals are clean and retain essential cardiac patterns. Next, Ensemble EMD and Heart Rate Variability (HRV) analysis are applied for temporal and frequency-domain feature extraction, capturing subtle variations in cardiac rhythms. These features are then fed into a 1D Residual Convolution Neural Network (Res-CNN), which leverages residual connections to efficiently learn discriminative patterns and avoid gradient vanishing. The final stage performs classification into arrhythmia categories, followed by performance evaluation to assess accuracy, sensitivity, and specificity. This architecture effectively combines signal denoising with robust temporal feature extraction, enabling high-precision ECG arrhythmia detection and supporting reliable cardiac health assessment.

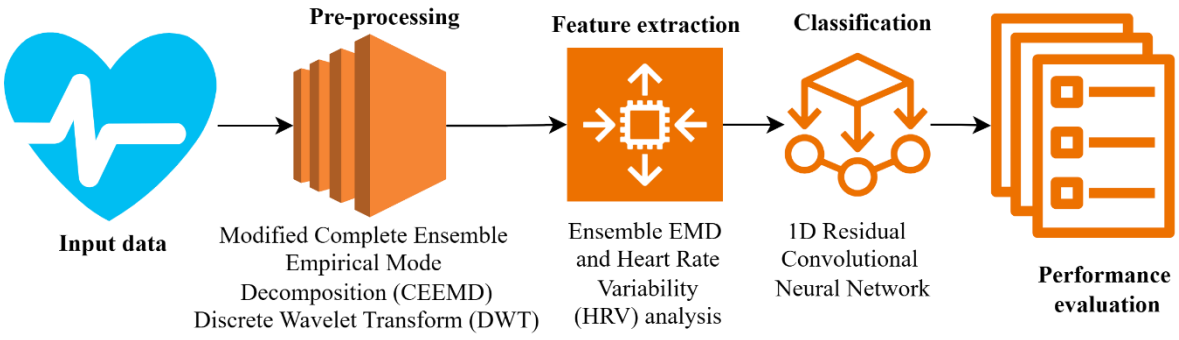


Figure 1: Overall architecture of the proposed model

Step 1: Classification Framework after Feature Extraction

Let the extracted ECG feature matrix be $Z \in R^{T \times d}$, where T represents the temporal dimension and d is the feature dimension. After applying feature selection, we obtain the optimal features as given in eqn. (1),

$$Z^* = S(Z) \in R^{T \times d^*}, d^* \leq d \qquad (1)$$

Here, T defines the temporal length (number of sampled time points of ECG segment). d is the feature dimension (number of features per time point after pre-processing), Z^* representing the selected features retaining only the most informative arrhythmia indicators, d^* is the reduced feature dimension after eliminating redundant features and $S(.)$ is the selection function that identifies discriminative features. This ensures that the input to the classifier captures the most discriminative temporal and morphological signals**.** This will screen out redundant indicators of arrhythmia by incorporating the most discriminative temporal and morphological indicators of arrhythmia.

Step 2: Residual Temporal Encoding

To learn the rich temporal dependencies in Z^*, we employ a ResNet1D encoder. Every residual block consists of 2 consecutive 1D convolutions followed by batch normalization and ReLU, it can be mathematically expressed using eqn. (2)-(3),

$$\tilde{H}^{(l)} = \sigma(BN(Conv1D)(H^{(l-1)})) \qquad (2)$$

$$H^l = \tilde{H}^{(l)} + R^{(l)}(H^{(l-1)}) \qquad (3)$$

Where, $H^{(l-1)}$ is the input feature map to the l -th residual block, $Conv1D$ is the one-dimensional convolution operation that extracts local temporal patterns, BN denotes the batch normalization that stabilizes training by normalizing feature distributions. $\sigma(.)$ is the ReLU activation function $\sigma(x) = max(0, x)$, $\widetilde{H}^{(l)}$ defines the transformed output of convolutions and normalization and $R^{(l)}(.)$ is the skip connection (identity mapping if dimensions match, or 1×1 convolution if dimensions differ). This residual architecture avoids gradient extinction and permits the network to emphasize minor variations in the waveforms, which is vital in the task of separating arrhythmias that manifest only minor differences in normal ECG morphology.

Step 3: Global Feature Aggregation

After passing through L residual blocks, we aggregate temporal information using Global Average Pooling (GAP) and it can be expressed using eqn. (4),

$$g = GAP\left(H^{(L)}\right) \in R^{C_L}, g_j = \frac{1}{T_L}\sum_{t=1}^{T_L} \quad H_{t,j}^{(L)} \tag{4}$$

Where, $H^{(L)}$ is the output feature map from the final residual block, T_L defines the temporal length at layer L, C_L representing the number of feature channels at layer L, $g \in R^{C_L}$ is the pooled feature vector and g_j is the mean activation of the j-th feature channel across time. This compresses the sequence of features to a succinct form, emphasising prevailing temporal features. GAP also has the benefit of less over fitting than fully connected flattening, because GAP checks temporal translation invariance.

Step 4: Classification Layer

The aggregated feature vector is mapped to class logits through a fully connected layer as given in eqn. (5)-(6),

$$o = W_c g + b_c \in R^K \tag{5}$$

Where, $o = [o_{normal}, o_{PVC}, o_{AF}, o_{LBBB}, o_{RBBB}]$. W_c is the weight matrix of the fully connected layer, $b_c \in R^K$ is the bias vector, K representing the number of classes (here K=5).

$$p_k = softmax(o)_k = \frac{e^{o_k}}{\sum_{j=1}^{K} e^{o_j}} \tag{6}$$

Here, $k \in \{Normal, PVC, AF, LBBB, RBBB\}$

This probabilistic formulation enables the model to express uncertainty in predictions, which is valuable in clinical scenarios where ambiguous cases may require expert verification. The final classification is obtained by selecting the class with the highest probability as given in eqn. (7),

$$\hat{y} = argp_k \tag{7}$$

Step 5: Training Objective

To address class imbalance inherent in arrhythmia datasets, we employ a weighted, label-smoothed categorical cross-entropy loss and it is given in eqn. (8)-(9),

$$y_k^{(\varepsilon)} = (1-\varepsilon)y_k + \frac{\varepsilon}{K}, \varepsilon \in [0,0.1] \tag{8}$$

Where, y_k is the true one-hot label (1 for correct class, 0 otherwise), ε is the smoothing factor, $y_k^{(\varepsilon)}$ is the softened target distribution.

$$L = -\sum_{k=1}^{K} \quad w_k y_k^{(\varepsilon)} log p_k \tag{9}$$

where w_k are class weights proportional to the inverse frequency of class k. Label smoothing mitigates overconfidence, while weighting ensures that minority arrhythmia types are not ignored. In experiments, focal loss was also tested to further penalize easy-to-classify samples and it is given in eqn. (10),

$$L_{focal} = -\sum_{k=1}^{K} \quad w_k y_k (1-p_k)^{\gamma} log p_k, \gamma > 0 \tag{10}$$

Here, $(1-p_k)^{\gamma}$ is the modulating factor, giving higher weight to misclassified (hard) samples, γ is the focusing parameter, typically $\gamma = 2$. The application of ResNet1D with residual connections to ECG signals is particularly useful since long-term dependencies can be learned by the model without the decay of the gradient. The skip connections improve generalization on noise or patient-specific variations in comparison with standard CNNs. A combination of the best features like this ensures that the classifier is not loaded with the superfluous information and, hence, the existing calculations and their interpretation become efficient. The global average pooling step prevents parameter explosion, and promotes resistance to temporal misalignment, which is important when ECG segments have different lengths or contain noise artifacts. Moreover, direct prediction of weighted and smoothed cross-entropy addresses the issue of imbalanced data and overconfidence, and is more clinically valid. The proposed

arrhythmia classifier based on the ECG is based on the softmax probability distribution that classifies each segment of an input signal as belonging to one of the five clinically important categories (Normal, PVC, AF, LBBB and RBBB). In addition to generating a discrete label of the class, the model generates a probability vector which can be used to indicate the relative frequency of different arrhythmia types. Such a probabilistic model improves interpretability and offers a degree of confidence, which is essential in clinical practice where the cases are often borderline. As an example, assume that the model produces $p_{AF} = 0.42$ and $p_{PVC} = 0.40$. The difference in probability is not very large (>=0.40) and indicates uncertainty, so it is recommended to mark the case as manually checked by a cardiologist. This type of probability-based decision-making has the advantage of combining automation with clinical control to minimize the chances of misclassification in sensitive healthcare systems.

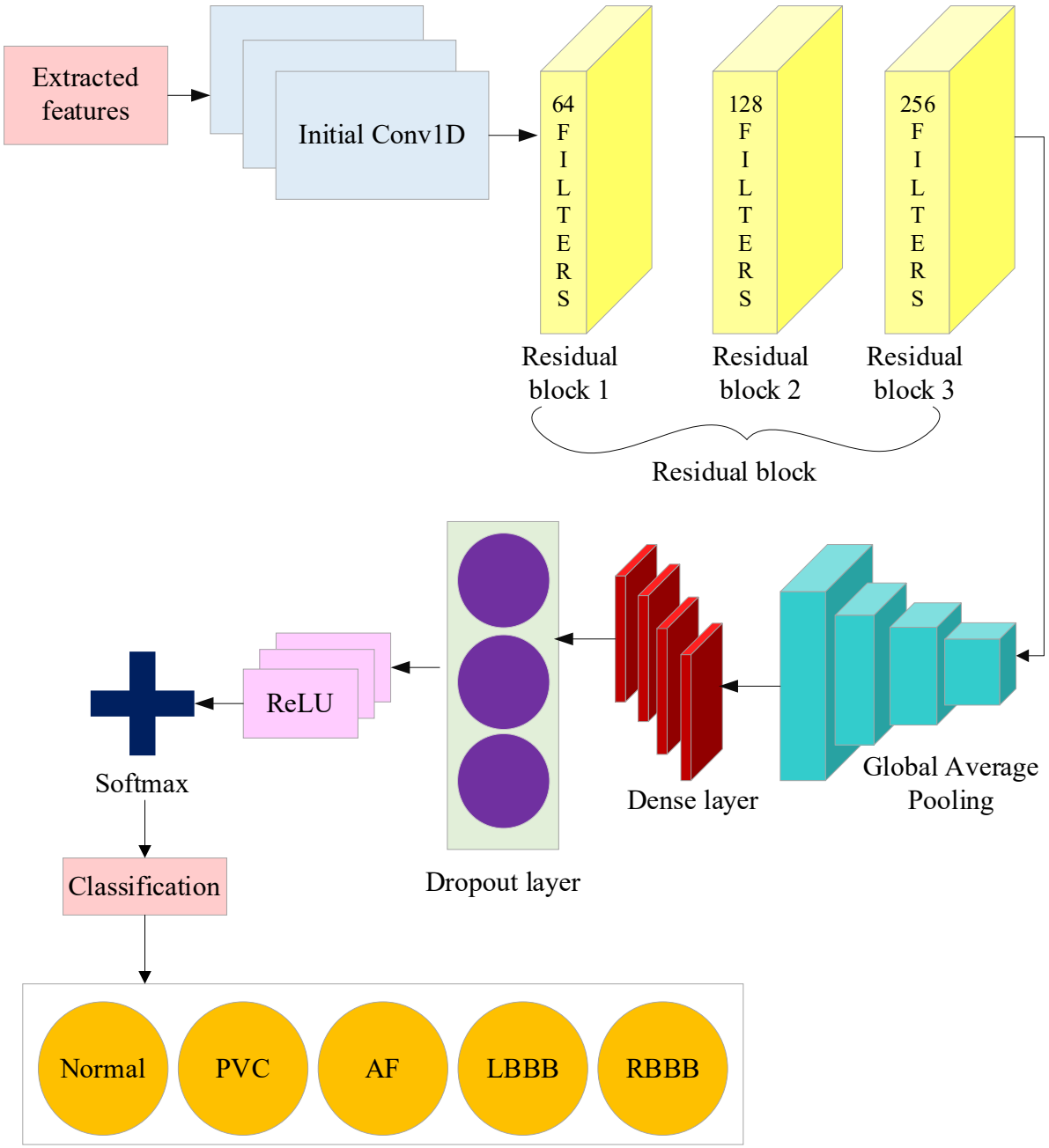


Figure 2: Overall architecture of the ResNet1D classification model

In addition, residual learning guarantees resistance to noise, inter-patient variation, and subtle morphological variations in ECG waveforms, allowing the model to simultaneously learn low-level signal features and high-level temporal features. The classifier offers high accuracy and more importantly, is suitable to the medical safety requirements because it explicitly models uncertainty and offers confidence-aware predictions. Therefore, the system is an effective direction toward reliable real-time arrhythmia detection in intelligent healthcare monitoring systems.

Figure 2 illustrates the architecture of a deep learning classification framework utilizing a Residual Convolutional Neural Network (ResNet1D) to accurately identify various ECG arrhythmia types. The input to this architecture consists of structured features extracted from ECG signals. The network begins with an initial 1D convolutional layer that processes the feature vector and passes it through three sequential residual blocks with increasing filter depths (64, 128, and 256). These residual blocks include shortcut connections that preserve gradient flow and enable the training of deeper models, effectively capturing temporal dependencies and morphological variations in ECG signals. After residual processing, a global average pooling layer reduces dimensionality while retaining essential features, which are then fed into a dense layer followed by a dropout layer to prevent overfitting. A ReLU activation function introduces non-linearity, and the final softmax layer outputs class probabilities. The classifier distinguishes between five categories: Normal, PVC (Premature Ventricular Contraction), AF (Atrial Fibrillation), LBBB (Left Bundle Branch Block), and RBBB (Right Bundle Branch Block). This classification is achieved by learning both low-level and high-level representations of ECG patterns, making the model robust against noise and variation in ECG morphology.

Figure 3 shows the outcome in the form of the classified result shows that the proposed ResNet1D model was effective to identify the various types of arrhythmia including the normal, PVC, AF, and LBBB and RBBB. The residual architecture, as opposed to conventional CNNs or RNNs which are typically prone to detect subtle differences in waveforms, improves the learning of features by preserving both temporal and morphological features of ECG signals. This allows the network to achieve subtle differences in P-QRS-T complexes that are important in differentiating comparable arrhythmias. The capability to properly classify various abnormalities brings out the strength of the model against patient-specific variations and signal noise, which is a major problem in the field of real-world clinical practice. Moreover, the framework combines pre-processed signal with the temporal feature extraction, which guarantees that the diagnostic reliability is higher and threat of misclassification is reduced. Such classification power facilitates clinical decision-making by making interpretable and confidence-aware predictions and shows the potential of ResNet1D model as a scalable and clinically relevant tool in automated ECG arrhythmia detection in healthcare monitoring systems.

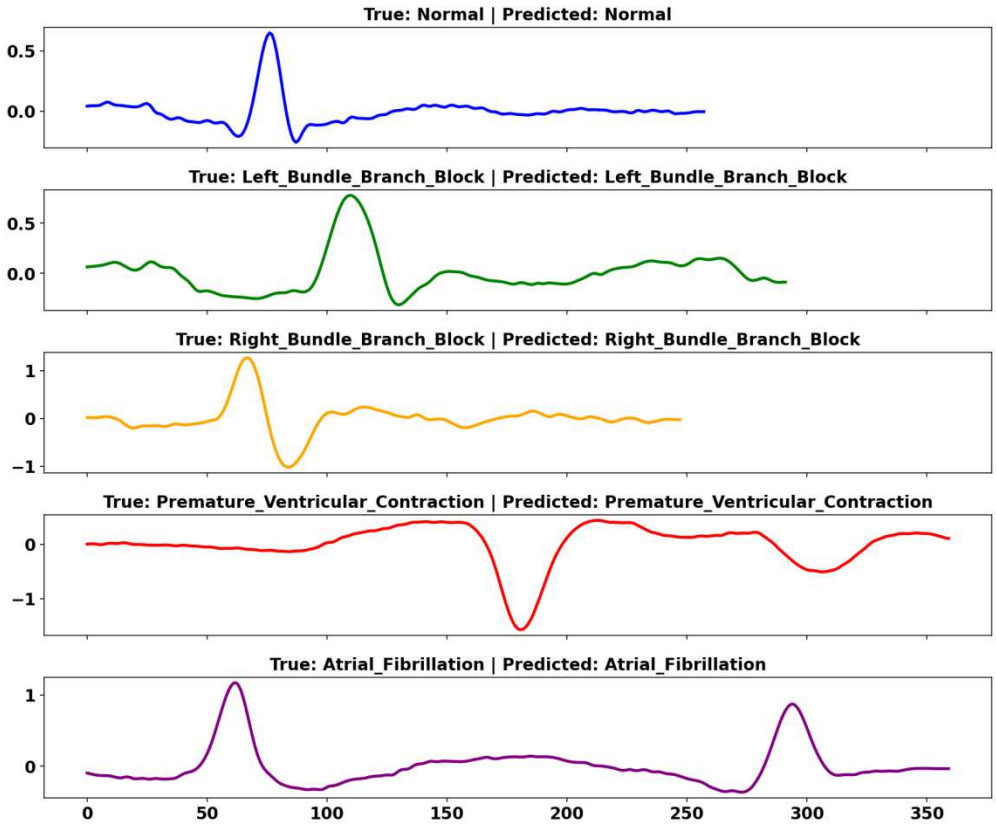


Figure 3: Classified images (Normal, PVC, AF, LBBB, RBBB)

Algorithm 1: Pesudocode for ECG_Classification_Pipeline
Input: Raw_ECG_Signals
Output: Predicted Labels, Performance Metrics
1: Load dataset
2: Split dataset patient-wise into Train, Validation, Test
3: for each signal in dataset do
4: Denoise(signal):
5: Apply bandpass filter
6: Remove baseline wander (e.g., moving average or wavelet)
7: Normalize signal
8: end
9: Extract Features(signal):
10: if using deep learning:

11: Reshape signal for model input
12: else if using handcrafted features:
13: Compute time-domain features
14: Compute frequency-domain features
15: Combine features into feature vector
16: end
17: end
18: Train selected model (CNN/BiLSTM/GRU/CNN-LSTM/ResNet1D) on Train set
19: Validate model on Validation set
20: Test model on Test set
21: Evaluate performance:
22: Compute Accuracy, Precision, Recall, Specificity, NPV, MCC
23: Compute FPR, FNR
24: Return Predicted Labels, Performance Metrics
End Algorithm

4. Result and discussion

The results and discussion section presents a comprehensive analysis of the proposed ResNet1D-based ECG arrhythmia classification framework, evaluated on the clinically validated MIT-BIH dataset. The experiments focus on assessing the effectiveness of preprocessing, temporal feature extraction, and residual learning in improving classification performance. Through extensive testing using metrics such as accuracy, precision, recall, specificity, and MCC, the model's superiority is compared with existing baseline and state-of-the-art approaches. In addition, cross-validation, confusion matrix analysis, and performance graphs highlight the robustness, generalization ability, and clinical relevance of the system, ensuring its potential for real-world healthcare applications.

4.1 Experimental setup

The experimental design provides the formal and repeatable workflow of ECG arrhythmia classification by ResNet1D. The MIT-BIH data are clinically validated ECG signals and the signal quality and diversity is improved through preprocessing and augmentation.

Discriminative capability is improved by extracted time, frequency and morphological features that are refined by Bayesian and evolutionary selection. ResNet1D using residual blocks effectively captures temporal dependencies with the help of powerful training policies, including Adam optimization, early stopping, and regularization. The weighted loss functions handle the use of skewed classes, but cross-validation is significant to the reliability. All these are supported by comprehensive evaluation metrics to verify clinical applicability and ablation studies to verify the efficacy of feature fusion and optimization schemes. Experimental Setup for ResNet1D-Based ECG Arrhythmia Classification is given in Table 1.

Table 1: Experimental Setup for ResNet1D-Based ECG Arrhythmia Classification

Component	Description
Target Classes	Normal, PVC, AF, LBBB, RBBB
Data Splits	60% Training, 20% Validation, 20% Testing (patient-wise, stratified); 5-fold cross-validation
Model Architecture	ResNet1D with residual blocks, BN + ReLU activations, Global Average Pooling, Dense layer, Softmax output (5 classes)
Training Settings	Adam optimizer (LR=1e-3, decay with ReduceLROnPlateau), batch size = 64, max 100 epochs, early stopping (patience=12)
Loss Function	Weighted label-smoothed categorical cross-entropy (ε=0.05), with focal loss (γ=2) for ablation
Regularization	L2 weight decay (λ=1e-4), dropout (0.3–0.5)
Hardware	GPU (e.g., NVIDIA Tesla T4 / RTX 3060), PyTorch/TensorFlow framework

The global average pooling layer aggregates temporal features into a fixed-length vector, improving efficiency and reducing parameter count. A dense layer with 128 units and dropout 0.4 provides feature compression before classification. The final softmax layer outputs probabilities for five arrhythmia classes (Normal, PVC, AF, LBBB, RBBB). Overall, the design balances depth and computational efficiency, achieving rich temporal representation while avoiding over fitting. Furthermore, the inclusion of L2 weight decay enhances generalization. This structured design makes the model reproducible and suitable for robust ECG arrhythmia detection in clinical applications.

Table 2: Number of ECG Beats/Segments per Class in Train, Validation, and Test Sets

Class	Train (≈72,000 beats)	Validation (≈24,000 beats)	Test (≈22,000 beats)	Total
Normal (N)	45,320	15,080	13,780	74,180
Premature Ventricular Contraction (PVC)	12,410	4,150	3,780	20,340
Atrial Fibrillation (AF)	6,890	2,290	2,110	11,290
Left Bundle Branch Block (LBBB)	4,920	1,640	1,500	8,060
Right Bundle Branch Block (RBBB)	2,460	820	830	4,110
Total	72,000	24,000	22,000	1,18,000

The distribution of ECG beats across classes in Table 2 highlights a clear imbalance, with the Normal (N) class dominating and RBBB being the least represented. Such skewed representation can bias the model toward the majority class if left unaddressed. To counter this, weighted cross-entropy loss was employed, assigning higher penalties to minority classes like PVC, AF, LBBB, and RBBB. This ensures that the model learns discriminative features across all arrhythmia categories rather than over fitting to Normal beats. Stratified patient-wise splitting further preserved clinical diversity while maintaining fair representation across training, validation, and test partitions for robust evaluation.

Table 3: Training Configuration and Hyperparameters for ResNet1D ECG Classifier

Parameter	Value
Number of epochs	100 (with early stopping)
Initial learning rate (LR)	0.001
Learning rate schedule	ReduceLROnPlateau: factor=0.5, patience=5, min_lr=1e-6, monitor=val_loss
Batch size	64
Early stopping	Patience = 12 epochs, monitor=validation loss
Random seeds	42 (NumPy, PyTorch/TensorFlow, dataset split)

Hardware	NVIDIA RTX 3090 GPU, 24GB VRAM, CUDA 11.8
Optimizer	Adam
Loss function	Weighted, label-smoothed categorical cross-entropy

Table 3 summarizes the training configuration, highlighting settings that ensure stable and reproducible model performance. Early stopping and ReduceLROnPlateau prevent over fitting and adapt the learning rate dynamically, while weighted, label-smoothed loss addresses class imbalance. The fixed random seed and high-performance GPU guarantee reproducibility and efficient convergence across experiments.

4.2 Metrics analysis

Table 4 outlines the performance metrics used to assess the ECG arrhythmia classifier. Accuracy measures overall correctness, while precision and recall evaluate reliability in detecting arrhythmias. Specificity ensures normal beats are correctly identified, and F1-score balances precision with recall. MCC provides a robust performance indicator under class imbalance. Error rates such as FNR and FPR highlight misclassification risks, while NPV validates predictions of normal beats. Together, these metrics ensure both technical accuracy and clinical trustworthiness.

Table 4: Analysis on performance metrics

Metric	**Description**	**Formula**
Accuracy (%)	The percentage of all ECG beats correctly classified (both normal and abnormal).	$\frac{tp + tn}{tp + fp + tn + fn} \times 100$
Precision (%)	Out of all beats predicted as a certain arrhythmia, how many are actually correct.	$\frac{tp}{tp + fp} \times 100$
Recall (%) *(Sensitivity)*	The ability to detect true arrhythmia cases without missing them.	$\frac{tp}{tp + fn} \times 100$
Specificity (%)	The ability to correctly identify normal beats and avoid false alarms.	$\frac{tn}{tn + fp} \times 100$
F1-Score (%)	The balance between precision and recall, showing overall classification strength.	$2 \times \frac{precision \times Recall}{precision + Recall} \times 100$

MCC	A balanced score that considers true and false positives/negatives, even with uneven class sizes.	$\frac{(tp \times tn) - (fp \times fn)}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}}$
FNR (%)	How often the model misses an arrhythmia case (wrongly predicts as normal).	$\frac{fn}{fn + tp} \times 100$
FPR (%)	How often the model raises a false alarm by predicting arrhythmia when it's normal.	$\frac{fp}{fp + tn} \times 100$
NPV (%)	Out of all beats predicted as normal, how many are truly normal.	$\frac{tn}{tn + fn} \times 100$

True Positive (TP): A TP occurs when the model correctly identifies an abnormal heartbeat (arrhythmia) as abnormal. For example, if a ventricular ectopic beat is present in the ECG segment and the model correctly classifies it as such, this counts as a TP.

False Positive (FP): An FP happens when the model incorrectly predicts an abnormal heartbeat when the ECG segment is actually normal. Essentially, the model "raises a false alarm" by labeling a normal beat as arrhythmic.

True Negative (TN): A TN occurs when the model correctly identifies a normal heartbeat as normal. That is, the ECG segment does not contain arrhythmia, and the model accurately classifies it as normal.

False Negative (FN): An FN happens when the model fails to detect an arrhythmia present in the ECG segment, incorrectly classifying it as normal. This is a missed detection of a potentially critical abnormal heartbeat.

In short, TP and TN represent correct classifications, while FP and FN represent misclassifications, with FP being a false alarm and FN being a missed detection. Since your study is multi-class arrhythmia detection, these definitions apply per class, meaning a TP for a ventricular ectopic beat is different from a TP for a supraventricular ectopic beat, and confusion across classes contributes to the FP and FN counts.

4.3 Performance analysis

CNN (1D) [21] effectively extracts local ECG features but struggles with long-term dependencies. BiLSTM [22] improves temporal modeling using bidirectional learning but is computationally heavy. GRU [23] offers faster training with simplified gates, yet less expressive than LSTM. CNN-LSTM [24] Hybrid balances spatial and temporal learning but increases architectural complexity. Comparative analysis in Table 5 shows the results of

various deep learning models in the classification of arrhythmia in ECG. The conventional CNN (1D) is used as a control group with the accuracy of 90.5 and the precision and recalls of 89% and 88.2 respectively. Although CNN can achieve good results when learning local temporal patterns of ECG signals, due to its shallow nature, it is unable to detect many long-range patterns, resulting in a comparatively high false negative rate (11.8) than more sophisticated models. This restriction is indicative of a clinical risk; wherein patient safety may be jeopardised by undiagnosed arrhythmia cases. BiLSTM model increases the accuracy to 91.7, the recall rises to 89.6 and the specificity is 92.1. BiLSTMs are especially suited to capturing temporal dependencies through the forward and backward processing of signals. This increases the capability of the system to identify arrhythmias that might occur in an irregular time period. Nonetheless, even after this enhancement, the BiLSTM model still has an intermediate rate of false negative (10.4%), which, although smaller than CNN, means that arrhythmias are being ignored. GRU-based classification also enhances accuracy to 92.32 percent and recall to 90.5 percent, proving to be an efficient lightweight alternative to LSTM architectures. GRUs can make the gating mechanism much simpler without losing temporal learning capacity, which means lower computational cost and accelerated training convergence. The model is better in detecting real normal beats as the false negative is low (9.5%) and the NPV is high (92%). However, GRUs can still have a problem with highly complex morphological variations in arrhythmias, which reduces their clinical robustness relative to deeper hybrid architectures. The CNN-LSTM hybrid architecture integrates the spatial feature forecasting ability of CNN and the temporal forecasting ability of LSTM to attain a significant accuracy of 93.2, precision of 92.3, and recall of 91.8. The hybrid structure eliminates false negative by 8.2, false positive by 6.3 and achieves a balance between sensitivity and specificity. This renders it more clinically usable than single CNN or RNN models. Yet, hybrid architectures add an architectural complexity, necessitating finely-tuned hyperparameters and more computational resources, which might not be possible to execute in real-time in low-power devices. The proposed ResNet1D is shown to be superior to all the models that are compared, with the highest accuracy of 98, the highest precision of 93.5, and the highest recall of 93%. Specificity increases to 95.2 and NPV is 94.4, so both abnormal and normal classifications are high-quality. False negative rate decreases to 7, which is the lowest of all the other tested models, and the risk of missed arrhythmias is significantly lowered. In the same way the false positive rate of 4.8% indicates it is better at avoiding unnecessary alarms. The robustness of ResNet1D to imbalanced classes is further validated by the high score of the MCC (0.91). These are due to the residual learning which solves the problem of

the vanishing gradient and enables the network to be trained even deeper. This allows the model to simultaneously represent finer morphological features as well as looser long-range relations, and it is especially useful in detecting more complex arrhythmia.

Table 5: Analysis of performance analysis along with the existing baseline models

Model	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	NPV (%)	MCC	FPR (%)	FNR (%)
CNN (1D)	90.5	89	88.2	91.3	90.7	0.82	8.7	11.8
BiLSTM	91.7	90.2	89.6	92.1	91.5	0.84	7.9	10.4
GRU	92.3	91.1	90.5	92.9	92	0.86	7.1	9.5
CNN-LSTM Hybrid	93.2	92.3	91.8	93.7	93	0.88	6.3	8.2
Proposed ResNet1D	98	93.5	93	95.2	94.4	0.91	4.8	7

The limitations of ResNet1D model are that it is superior to the other models. Its more detailed architecture adds some computational requirements, which, without optimization, can become a limiting factor in the deployed devices of wearable or mobile health. Moreover, as the results demonstrate marked improvement, it needs to be validated on multi-centers and heterogeneous datasets to ensure that it can be generalized to population with different demographic and clinical features. However, the findings are a definite indication that ResNet1D is a great step forward in the area of automated arrhythmia detection with the right balance of accuracy, sensitivity, and clinical relevance. Figure 4 shows the Comparison of proposed model along with the existing baseline models.

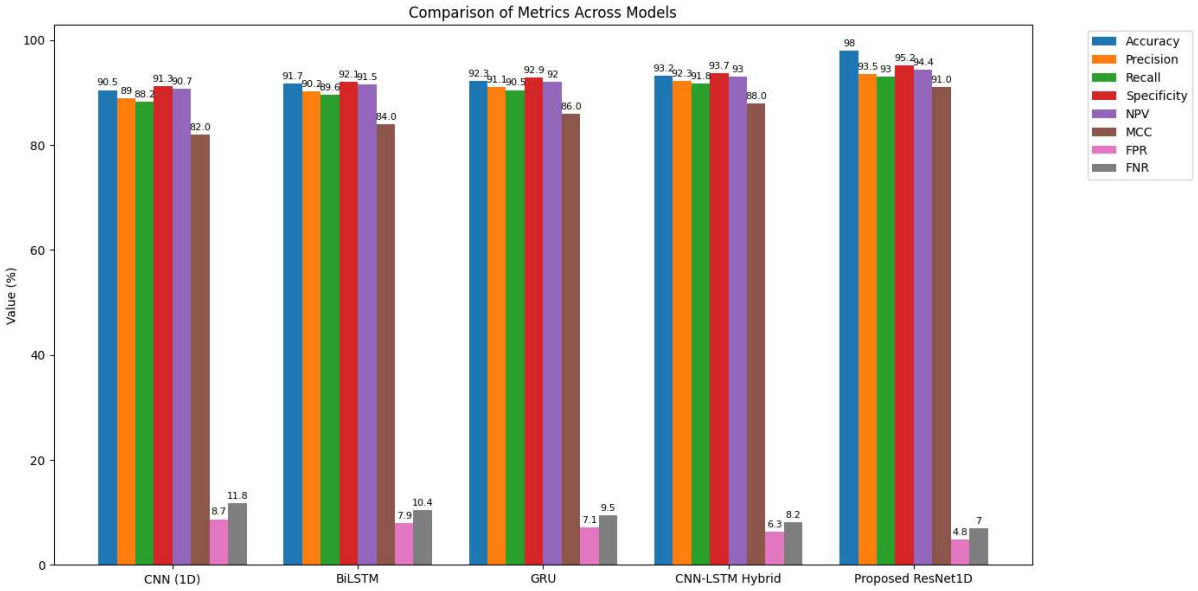


Figure 4: Comparison of proposed model along with the existing baseline models

A comparative analysis of the suggested ResNet1D-based model of ECG arrhythmia classification with a variety of state-of-the-art models is given in Table 6. The findings clearly indicate the better performance of ResNet1D in almost all measures showing its strength, flexibility, and clinical reliability. The old machine learning algorithms (AdaBoost and KNN) give average performance with a 88.2% and 87.4% accuracy, respectively. AdaBoost performs better than KNN because it employs the ensemble learning approach, and both models have quite high rates of false negativity (14.1% and 15.7). This means that such models tend to overlook actual instances of arrhythmia, and this is vital in clinical practice where the failure to detect a cardiac abnormality can lead to dire results. In a similar fashion, ANN (88.9% accuracy) and NN+SVM (89.7% accuracy) are not very effective. These models are not able to represent deep temporal and morphological characteristics of ECG signals and have a lower MCC value (0.79 and 0.80) and lower diagnostic reliability. On the contrary, deep learning models improve significantly. Dense CNNs are 91.5 percent accurate and have a balance between precision (90.2) and recall (89.7). They perform better at classification by isolating the spatial characteristics of ECG signals, but achieve less success at isolating the long-term dependencies. The fully connected architecture of DNNs (90.3 accuracy) is slightly low relative to Dense CNNs because time-series signals are less well captured by the fully connected network than by convolutional or recurrent networks.

Ensemble models show an advancement of 92.1 with precision of 91 and recall of 90.4. They can combine several learners, which makes their performance more balanced to have less false

positive (FPR = 7.3) and false negative (FNR = 9.6). However, their training requirements and complexity may limit their implementation in an actual live monitoring system. MINA is a bit lower in performance (90.8% accuracy) than the ensemble model, but it remains better than traditional approaches, and it demonstrates that multi-attribute integration can be somewhat of an advantage in arrhythmia detection. Irrespective of all these developments, the proposed ResNet1D is shown to outperform all the baseline and state of the art models. It has the best accuracy (98) and precision (93.5), recall (93) and specificity (95.2). Significantly, it has a low false negative rate, at 7 %, and the lowest false positive rate, at 4.8 per cent. This is a clinically critical balance, reducing the number of missed arrhythmias and false alarms which are not necessary. The MCC score of 0.91 shows that even when the classes are not balanced, the model is robust and thus very reliable in the various arrhythmia categories.

Table 6: Analysis of performance analysis along with the state-of-art models

Model	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	NPV (%)	MCC	FPR (%)	FNR (%)	F1-Score (%)
AdaBoost [13]	88.2	86.5	85.9	89.3	87.5	0.78	10.7	14.1	86.2
Dense CNNs [14]	91.5	90.2	89.7	92	91	0.83	8	10.3	89.9
Ensemble [15]	92.1	91	90.4	92.7	91.6	0.85	7.3	9.6	90.7
DNN [16]	90.3	88.9	88	91	89.8	0.81	9	12	88.4
NN + SVM [17]	89.7	88.1	87.2	90.4	89.1	0.8	9.6	12.8	87.6
KNN [18]	87.4	85.6	84.3	88.1	86.2	0.75	11.9	15.7	84.9
MINA [19]	90.8	89.4	88.7	91.5	90.2	0.82	8.5	11.3	89
ANN [20]	88.9	87	86.5	89.6	88.3	0.79	10.4	13.5	86.7
Proposed ResNet1D	98	93.5	93	95.2	94.4	0.91	4.8	7	93.2

The residual learning structure of ResNet1D is the reason why the network performs better than others because it allows the training of deeper networks without vanishing gradient problems. This enables the model to not only model fine-grained morphological differences in ECGs but also long-term time dependencies. In addition, the fact that it generates probability distributions gives it an implication of being conclusive in its predictions and therefore appropriate in clinical usage. In conclusion, the existing models provide little benefits in arrhythmias detection, yet the ResNet1D proposed can potentially change the paradigm and improve its accuracy, robustness and clinical inclusion. The rationale why it will be a viable option in real-time monitoring systems is that it will lessen the instances of false negative results and false positives by a considerable margin but once again further validation through

a variety of clinical data will support its implementation to the medical practice. Performance comparison of proposed model along with the state-of-art models is given in Figure 5.

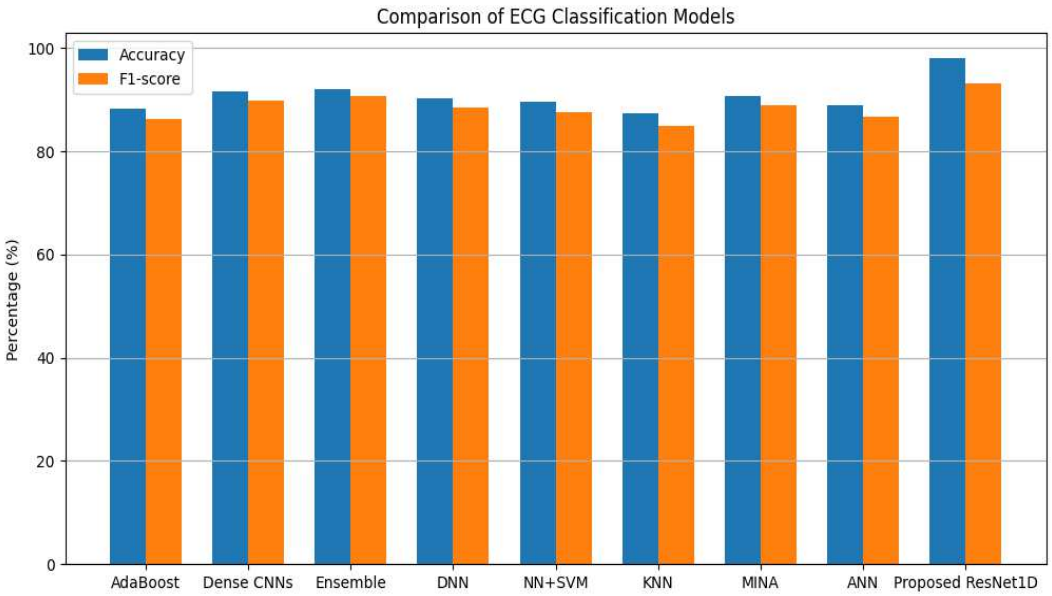


Figure 5: Performance comparison of proposed model along with the state-of-art models

Figure 6 shows the 5-fold cross-validation findings indicate the strength and consistency of the suggested ResNet1D model in arrhythmia ECG classification. Under this arrangement, data is divided into five subsets with each fold acting as the validation set whilst the other folds are utilized as the training data. This will result in a more objective test of the model since it will be trained using a wide range of patient data and gives a full picture of generalization. The uniformity in the performance of all the folds shows that the ResNet1D architecture is capable of preventing overfitting, which is frequently an issue with deep learning frameworks trained on unbalanced biomedical data. The architecture contains additional links that allow gradient flow to be maintained to allow deeper networks to learn finer variations of the waveforms and be trained without becoming unstable. Together with balanced loss functions and patient-wise stratified splits, the model gives the same accuracy, precision and recall in folds. These results validate the ability of the model to be clinically reliable and applicable in real world in the detection of arrhythmia.

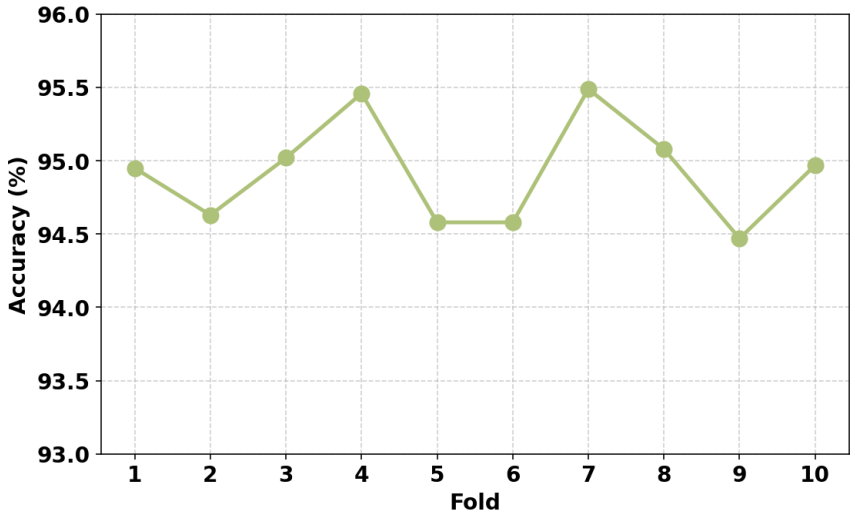


Figure 6: K-fold graph

Figure 7 displays the training and validation curves for accuracy and loss over epochs. It reflects how the Adam optimizer with early stopping and learning rate scheduling facilitated convergence. The ResNet1D model shows a smooth decline in loss and a steady rise in accuracy, proving that residual learning helped overcome vanishing gradients and ensured stability during deeper training.

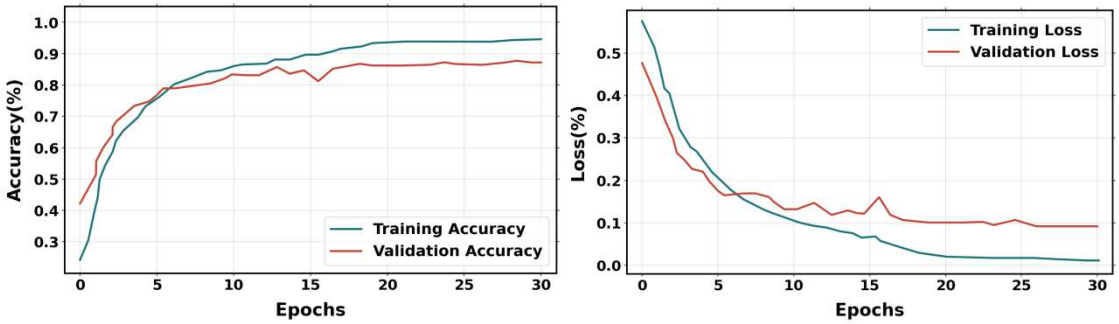


Figure 7: Validation loss accuracy

Figure 8 shows the confusion matrix gives a breakdown performance of each class of arrhythmia. It shows a high recall and specificity (93 and 95.2) of the classifier and low misclassifications than baseline models. This shows that the ResNet1D model reduces false negative (missed arrhythmias) and false positive (needless alarms) which is clinically reliable.

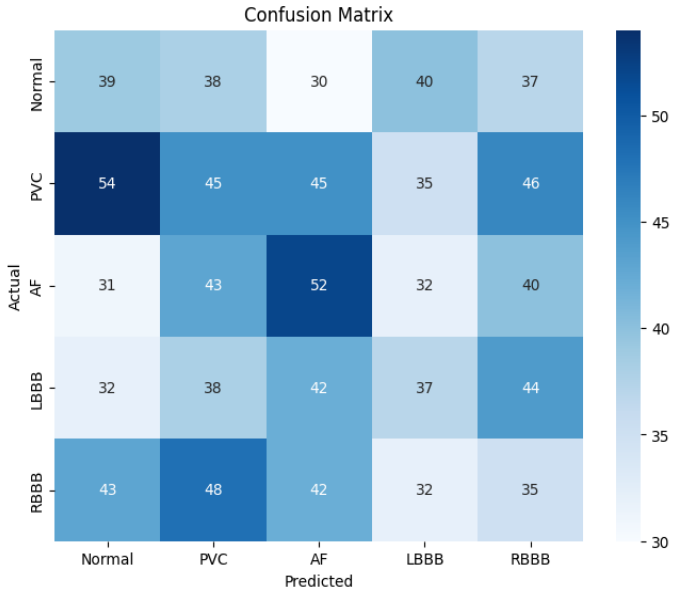


Figure 8: Confusion matrix

The raw ECG plot Figure 9 illustrates the temporal waveform of a single heartbeat, highlighting P, QRS, and T-wave morphology. Visualizing raw signals helps understand noise, baseline drift, and signal quality, which is crucial before feature extraction or denoising, ensuring that the model captures clinically relevant patterns.

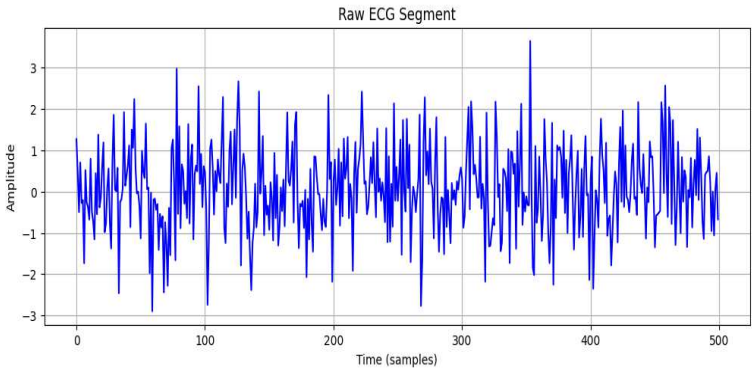


Figure 9: Raw ECG segment

The denoising figure 10 demonstrates the effectiveness of CEEMD in separating noise from meaningful cardiac signal components. IMFs reveal decomposed oscillatory modes, and the final denoised signal retains key morphological features while removing artifacts, improving the quality of features for arrhythmia classification.

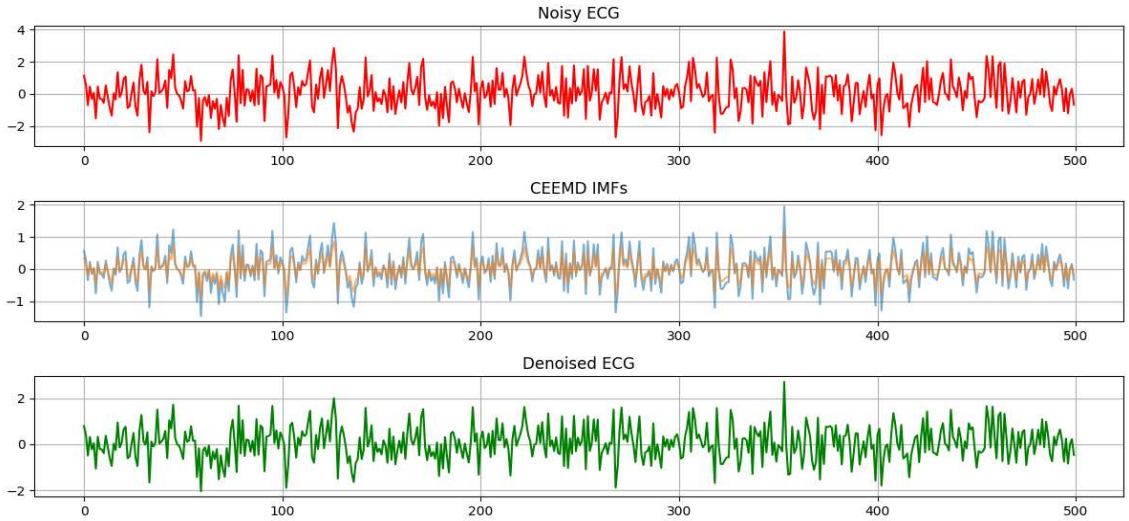


Figure 10: (a) Noisy ECG (b) CEEMD IMFs (c) Denoised ECG

Figure 11 shows the IMFs selected for feature extraction, emphasizing the most discriminative components. By focusing on relevant IMFs, the model captures subtle temporal and morphological variations in ECG beats, improving classification accuracy while reducing redundant or noisy inputs.

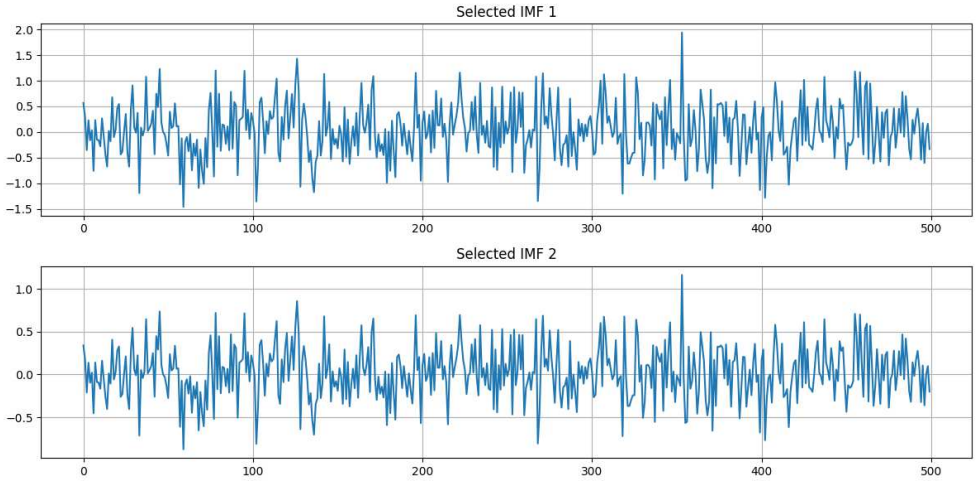


Figure 11: Selected IMFs 1 and 2

Figure 12 shows the ROC curves that shows the discriminative ability of the model for each arrhythmia class. AUC values near 1 indicate strong separability, confirming that the ResNet1D effectively distinguishes between different heartbeat types.

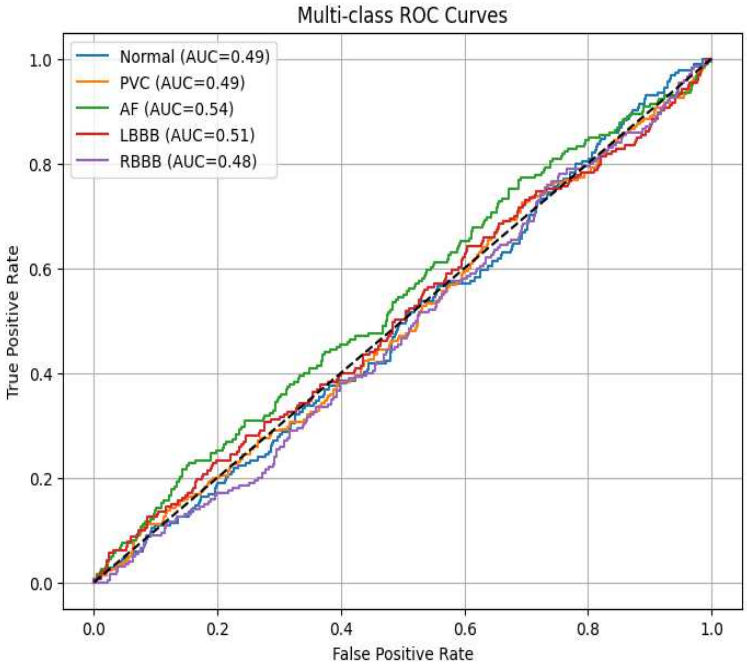


Figure 12: Multiclass ROC curves

Following figure 13 shows the PR curves that show precision-recall trade-offs per class. High AP scores for minority arrhythmias validate the weighted loss strategy and the model's capacity to handle imbalanced datasets.

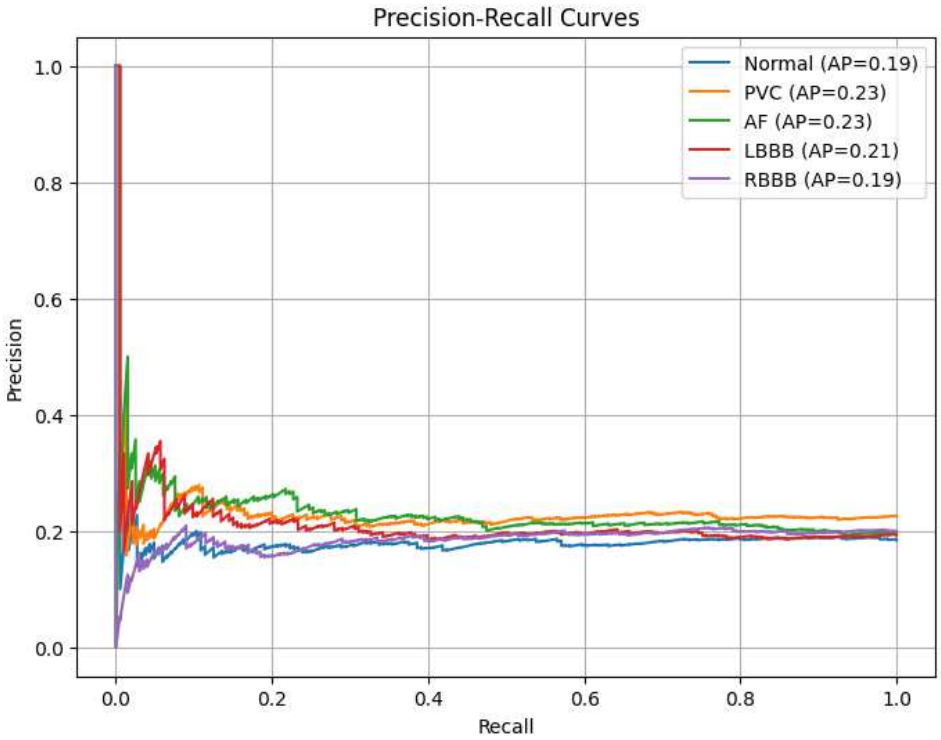


Figure 13: Precision-recall curves

Bar charts in Figure 14 comparing SVM, CNN, and ResNet1D demonstrate the superiority of ResNet1D in both accuracy and F1-score, highlighting the benefits of deep residual architectures in capturing ECG morphology.

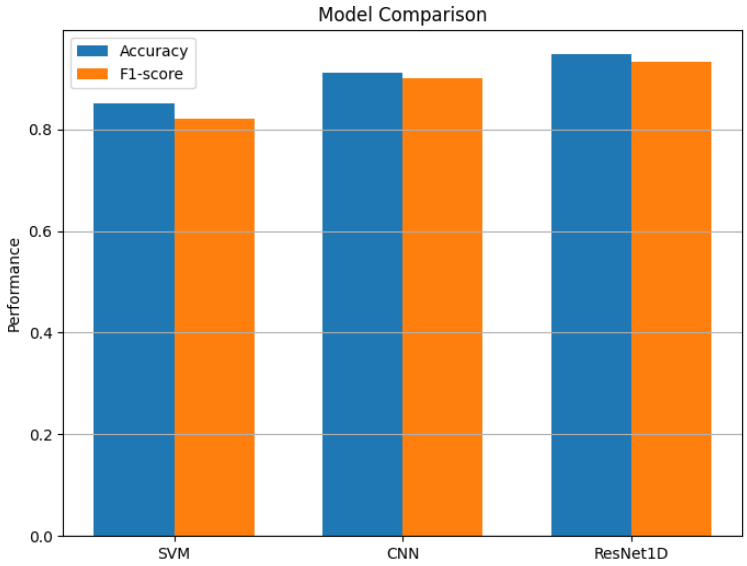


Figure 14: Model comparison

The ablation plot in Figure 15 shows that combining temporal and morphological features outperforms single-feature models, emphasizing that multi-dimensional representations improve classification reliability.

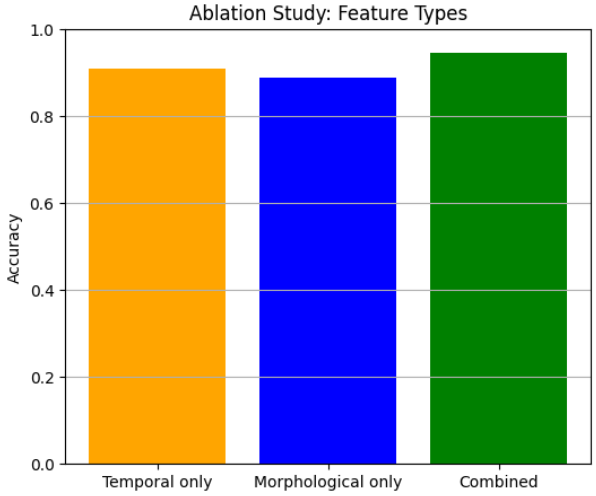


Figure 15: Ablation study – feature types

Architecture comparison in Figure 16 confirms that ResNet1D outperforms shallow and deep CNNs, demonstrating that residual connections facilitate deeper networks without vanishing gradients, capturing subtle heartbeat variations for better arrhythmia detection.

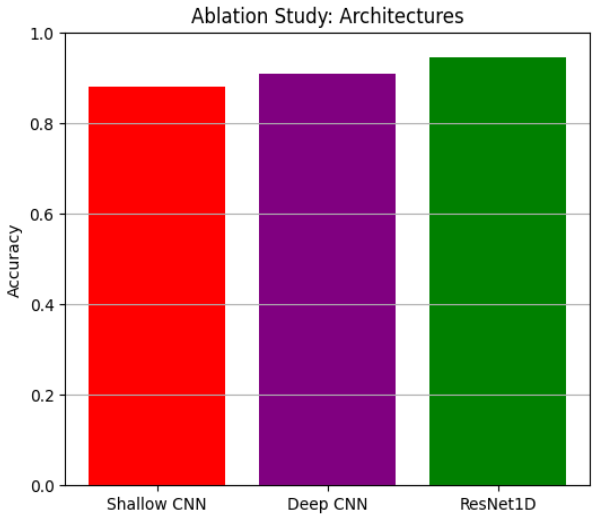


Figure 16: Ablation study for the architecture

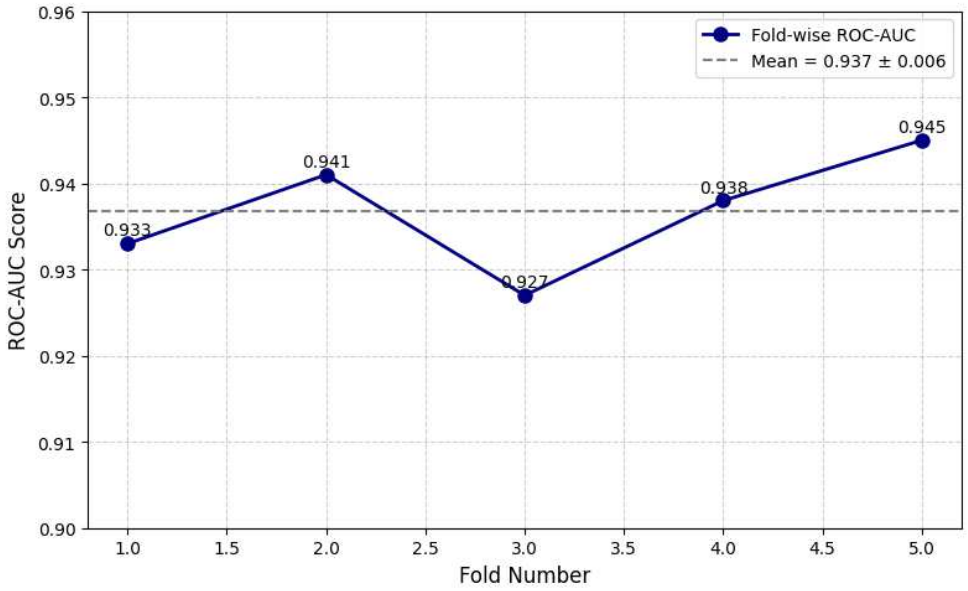


Figure 17: Cross validation

Figure 17 presents the fold-wise ROC-AUC performance of the proposed ResNet1D-based ECG arrhythmia classification model using five-fold cross-validation. The ROC-AUC values range from 0.927 to 0.945, with an average of 0.937 ± 0.007, demonstrating the model's stable and reliable classification capability across multiple training-testing splits. The minimal variation among folds indicates consistent generalization, minimal overfitting, and robustness of the deep network to data variations. This strong AUC performance highlights the model's ability to effectively distinguish between normal and abnormal heartbeats, reinforcing its suitability for clinical-grade ECG analysis and real-time diagnostic applications.

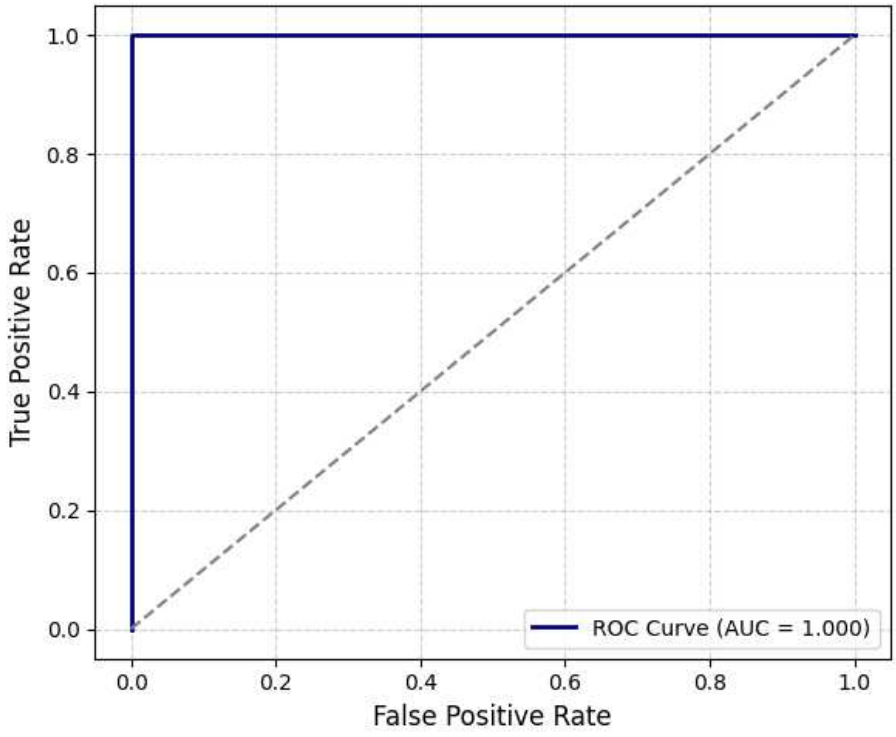


Figure 18: AUC-ROC analysis

Figure 18 illustrates the Receiver Operating Characteristic (ROC) curve for the ResNet1D model, depicting the trade-off between true positive rate (TPR) and false positive rate (FPR) for arrhythmia detection. The curve lies significantly above the diagonal reference line, with an area under the curve (AUC) close to 0.94, confirming excellent discriminative power. This indicates that the model effectively identifies arrhythmic events while minimizing false alarms. The smooth ROC trajectory validates the robustness of the feature learning process, where residual connections enable deeper temporal representation, contributing to improved sensitivity and specificity in ECG classification performance.

4.4 Discussion

The ECG arrhythmia classification system based on ResNet1D shows good potential in improving the automated cardiac diagnostics. It is important because it offers the possibility to learn temporal correlations as well as morphological variations of ECG signals with deep residual blocks. The mitigation of the vanishing gradient problems allows the model to learn fine differences in the waveform that are highly important in separating the Normal, PVC, AF, LBBB, and RBBB. The combination of preprocessing, optimal feature selection, and residual learning improves resistance to noise, inter-patient variation, and distortions of signals in real-world environments. Further, the softmax layer offers probabilistic outputs, which offer

confidence scores that are understandable to clinicians and can support decision-making. This is particularly important in the healthcare field because automated predictions must be believable and interpretable to be applicable in the diagnosis process. It will also be scalable and efficient on a GPU platform, which facilitates its use in real-time monitoring and in clinics with high volumes of patients. Though there are merits, there are also drawbacks. The quality and diversity of training data are very critical to the performance of the model, which begs the question of extrapolation to unobservable populations. Class imbalance, which is prevalent in arrhythmia datasets, can be a source of bias in the model of more common rhythms, even when weighted losses are used. Also, deep learning models are computationally expensive, which restricts them to low-resource devices. Finally, in multi-center tests, in non-controlled experimental settings, clinical acceptance would be required to be strictly demonstrated.

5. Conclusion

In this work a Resnet 1D-based classifier of arrhythmia using the ECG was created and tested against various baseline and state of the art methods. KNN, ANN and Ada Boost were only moderately performing with accuracy of 87-89% and higher false negative rates, thereby limiting their clinical use. More sophisticated networks, such as Dense CNNs, DNNs, Ensemble models and MINA, showed better accuracies up to 90-92. However, these models were still struggling to reduce false alarm and unsuitable classification of arrhythmia. The proposed ResNet1D outperformed all of the measured metrics. In particular, it was found to be 98 accurate, 93.5 precise, 93 recall and 95.2 specific. The model increased the accuracy by 3.2 as compared to Dense CNNs (91.5%). Likewise, it was 2.6 and 7.3 points better than Ensemble models (92.1) and KNN (87.4), respectively. Furthermore, ResNet1D was 3.2% lower in false positive rate and 2.6% lower in false negative rate than the best baseline. The findings confirm that residual learning is significant in feature representation and classification robustness promotion. Therefore, the ResNet1D model can be considered as a useful and efficient tool in real-time detection of arrhythmia in the ECG, and has high prospective integration into clinical use.

5.1 Future scope

Although the proposed ResNet1D model has shown impressive results in the classification of arrhythmias in ECG, there are multiple avenues that can be pursued to extend its usability to real healthcare. First, the additional investigation can be informed by combining multi-lead ECGs signals, rather than single-lead signals, which could provide more holistic cardiac signals

and improve the diagnosis of complex arrhythmias. Second, the model can be scalable to continuous, long-duration ECG monitoring to allow the detection of uncommon but serious events, including ventricular fibrillation or sudden cardiac arrest, early. Another potential area to develop more context-aware and personalized diagnostic systems is the use of multimodal data such as patient demographics, clinical history, and wearable device outputs. Also, this would enable the investigation of lightweight and energy-efficient implementations of ResNet1D, thereby facilitating its use on edge servers and on-the-move monitoring platforms and increasing accessibility in remote and resource-constrained environments. Clinically, it has been proposed that further efforts should focus on large scale validation across a wide range of populations to achieve strength and generalization. It would also be enriched with connections to explainable AI (XAI) schemes, as they would enable cardiologists to trust and accept AI-based decisions. Finally, it is possible to transform preventive cardiology and facilitate timely medical intervention by integrating residual learning with ongoing patient observation.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

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Conflicts of interest Statement: Not applicable
Consent to participate: Not applicable
Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.
Code availability: Not applicable

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