

ECA-ECGNet: An Efficient Channel Attention-Enhanced 1D CNN for ECG Arrhythmia Detection

Maher Talal Al-Asaady¹, Mohanad Mohammed Rashid², and Mahmood Basil Mahmood³

¹ Department of Network Technologies and Intelligent Systems Engineering, Polytechnic College Mosul, Northern Technical University, Mosul, Iraq

² Department of Optometry Techniques, Mosul Medical Technical Institute, Northern Technical University, Mosul, Iraq

³ Department of Nursing Techniques, Mosul Medical Technical Institute, Northern Technical University, Mosul, Iraq

Corresponding author: Maher Talal Al-Asaady (e-mail: maher.alasaady@ntu.edu.iq), **Author(s) Email:** Mohanad Mohammed Rashid (e-mail: mohanad.rashid@ntu.edu.iq), Mahmood Basil Mahmood (e-mail: mahmood.b.mahmood@ntu.edu.iq)

Abstract Cardiovascular diseases remain a major cause of mortality worldwide, with cardiac arrhythmias representing a potentially serious condition. Although deep learning has improved automated electrocardiogram (ECG) analysis, many recent models rely on recurrent, residual, transformer-based, or multi-input architectures, thereby increasing computational complexity. Moreover, reported classification performance can vary substantially according to the adopted data-partitioning strategy. This study proposes an Efficient Channel Attention ECG Network, termed ECA-ECGNet, for automated five-class ECG beat classification using the MIT-BIH Arrhythmia Database. ECG beats were segmented, normalized, and grouped into five AAMI categories: Normal (N), Supraventricular (S), Ventricular (V), Fusion (F), and Unknown (Q). The ECA-ECGNet integrates three Conv1D-based feature-extraction blocks with lightweight ECA modules to emphasize informative channel features. To mitigate the severe class imbalance inherent in clinical ECG data, categorical focal loss was implemented during model training to dynamically scale the loss based on prediction confidence. ECA-ECGNet was assessed under complementary intra-patient and inter-patient evaluation settings. The model achieved an accuracy of 99.20%, a macro F1-score of 0.953, and a weighted F1-score of 0.992. In the inter-patient setting, complete subject groups were separated between model development and testing, resulting in an accuracy of 97.96%, a macro F1-score of 0.9165, and a weighted F1-score of 0.9798. The implementation of focal loss substantially narrowed the performance gap between majority and minority classes, demonstrating enhanced generalization for Supraventricular and Ventricular arrhythmias. Ultimately, the principal novelty of ECA-ECGNet is the synergistic application of structural channel attention and dynamic focal loss. This framework shows that diagnostic accuracy on unseen patients is achievable without high computational overhead, supporting real-time arrhythmia screening on low-resource clinical devices.

Keywords Arrhythmia detection; convolutional neural networks (CNN); efficient channel attention (ECA); ECG beat classification; MIT-BIH arrhythmia database.

1. Introduction

Cardiovascular diseases (CVDs) are among the leading causes of death worldwide, with arrhythmias representing a significant subset of these conditions [1]. According to the World Health Organization (WHO), early diagnosis and timely intervention in arrhythmia cases are critical for reducing mortality associated with CVDs [2]. Arrhythmias are abnormal heart rhythms that cause irregular, excessively fast, or abnormally slow heartbeats. This irregularity may lead to symptoms

such as chest pain, dizziness, and fainting and, in severe cases, may result in sudden cardiac death if not promptly detected and managed [3]. Therefore, continuous monitoring of cardiac activity is important for early detection and decision support [4], [5], [6]. The electrocardiogram (ECG) is a widely used non-invasive tool for detecting and monitoring arrhythmias [7], [8]. Patients with suspected arrhythmias are often advised to use Holter monitors to continuously record ECG signals over extended periods [9]. Clinicians can

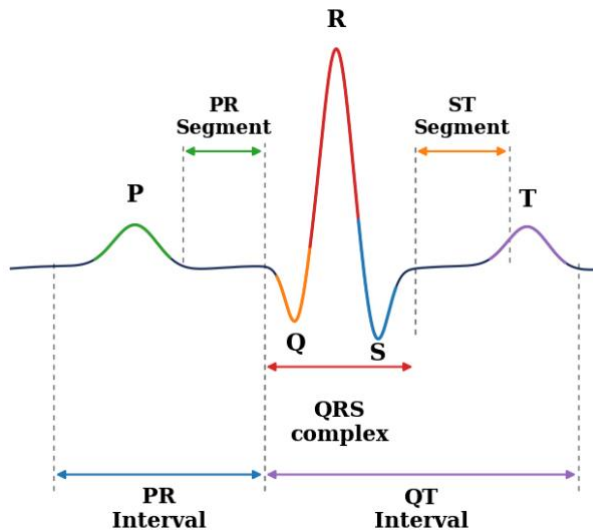


Fig. 1. Representative ECG waveform showing the P wave, QRS complex, T wave, PR segment, ST segment, PR interval, and QT interval.

identify cardiac abnormalities by analyzing the P wave, QRS, and T wave in ECG signals, as shown in Fig. 1. The P wave represents atrial contraction, the QRS complex represents ventricular contraction, and the T wave corresponds to ventricular repolarization. Variations in the amplitude, duration, or morphology of these waves may indicate abnormalities associated with arrhythmic events [10]. However, manual analysis of long-term ECG recordings is time-consuming, error-prone, and challenging because arrhythmic events may be subtle, transient, and morphologically variable [11], [12]. Thus, automatic ECG beat classification has become an important research area of computer-aided arrhythmia detection [13], [14]. The ANSI/AAMI standard identifies five general types of ECG beats: Normal, Supraventricular, Ventricular, Fusion, and Unknown beats [15]. Recent CNN-based studies have reported strong results for five-class ANSI/AAMI classification using the MIT-BIH Arrhythmia Database [11], [16].

Despite these advances, current methods face three critical, often interrelated limitations. First, to achieve high classification accuracy, recent approaches frequently employ complex architectures, such as deep residual networks, hybrid CNN-LSTMs, transformer modules [17], [18], [19], [20], [21], [22] or meta-heuristic frameworks, which increase computational burden and hinder reproducibility [23], [24]. Second, morphological variations among patients make minority classes, particularly Supraventricular and Fusion beats, exceptionally difficult to distinguish from the Normal majority class [20], [25], [26]. Finally, many high-performing models evaluate performance using a heartbeat-level (intra-patient) data partition

[19], [20], [26]. This strategy allows heartbeats from the same patient to appear in both the training and testing sets, enabling the model to learn subject-specific characteristics rather than generalized arrhythmic features, thereby yielding an overly optimistic assessment of clinical viability. Therefore, a distinct research gap exists for a lightweight architecture capable of generalizing to unseen patients while dynamically handling extreme class imbalance. While inter-patient evaluation, separating complete subject groups, provides a stricter and more clinically relevant assessment [27], [28], [29], determining the true efficacy of a model requires assessing how performance shifts when the identical architecture is subjected to both intra-patient and inter-patient data partitions [30].

This study proposes an Efficient Channel Attention ECG Network, termed ECA-ECGNet, for automated ECG beat classification. ECG beats are segmented using R-peak-centered windows and classified into the five ANSI/AAMI categories. The proposed architecture integrates three Conv1D-based feature-extraction blocks with lightweight ECA modules to recalibrate informative channel features. To address the class imbalance affecting clinical use, the network is trained with categorical focal loss. ECA-ECGNet is evaluated under two settings. The intra-patient setting uses stratified heartbeat-level partitioning to facilitate comparison with previous beat-level studies. The inter-patient setting separates complete subject groups between model development and testing to assess generalization to unseen patients. Therefore, the primary goal of this research is to design a light and low-computation CNN model with channel attention and focal loss to classify 5 distinct AAMI classes of the heartbeat with strict patient-independent data partitioning. The specific contributions of this study are as follows: 1) developing ECA-ECGNet that combines lightweight ECA with categorical focal loss to boost patient-independent ECG classification; 2) quantifying performance inflation due to patient data overlap using a dual intra- and inter-patient evaluation framework; 3) empirical evidence quantifying the importance of strict patient separation and dynamic class-imbalance handling for robust ECG model evaluation; 4) empirical evidence demonstrating that combining ECA and categorical focal loss significantly improves the recognition of the minority classes in unseen patients.

This paper is organized as follows: Related work is reviewed in Section II. Section III presents the methodology. The experimental results are given in Section IV. Findings and limitations are discussed in Section V. Finally, Section VI concludes the paper.

II. Related Work

The classification of arrhythmias by ECG has attracted a lot of attention in recent years, especially as the field

of deep learning has evolved. The reported performance of these approaches is not only related to the model architecture but also to the classification task, preprocessing, and data-partitioning strategy. The MIT-BIH Arrhythmia Database has been used in several studies with CNNs. Xu and Liu [16] trained a CNN using 300 sample ECG segments and obtained 99.43% accuracy with a stratified split into heartbeats across five classes from the AAMI database. Raza et al. [31] designed a nine-layer CNN and achieved an accuracy of 99.68% on an identical assessment based on the level of heartbeat. The 12-layer fully connected 1D CNN with wavelet denoising proposed by Wu et al. [32] had an accuracy of 97.41%. These studies show that CNNs can be used to obtain morphological features from the ECG, but the evaluation was done on a heartbeat level, which does not explicitly exclude the possibility that the same heartbeats could be present in the training and testing sets.

Many studies have highlighted the critical need to determine and optimize the proper architecture of the neural network for the classification of medical data, since the structural configuration directly influences the features extracted by the model and the final diagnostic accuracy [33]. Therefore, more advanced architectures have been explored to further enhance classification performance. Hassan et al. [18] used CNN and bidirectional long short-term memory layers. Unlike most heartbeat-level studies, all patients were split into training, validation, and testing sets, with 98% of the patients in the testing set. To deal with the class imbalance issue, Khan et al. [19] proposed a residual 1D CNN combined with the Synthetic Minority Over-sampling Technique (SMOTE) and obtained an accuracy of 98.63% on average. Lamba et al. [26] used wavelet-based preprocessing, SMOTE, ACO, and Fully Convolutional Networks. Their ACoBiLSTM model gave an accuracy of 98.9%, and an accuracy of 99.1% was obtained by their ACoFCN model for the classification of five classes. Recurrent layers, residual connections, and multi-stage pre-processing procedures add to the architectural and computational complexity, despite their good performance.

To address the above issues, Zheng et al. [20] proposed a multi-input CNN that also leverages Squeeze-and-Excitation attention, multi-scale ECG segments, short-time Fourier transform representations, and Mixup augmentation. The model performed with 99.13% accuracy when the ratio of the two classes was set at 90:10 at the level of a single heartbeat. Guhdar et al. [21] proposed a 1D CNN with the combination of a Squeeze-and-Excitation attention mechanism, focal loss, regularization, mixed precision training, and an ensemble strategy. Their model achieved 99.48% accuracy for five MIT-BIH heartbeat classes using stratified cross-validation. However,

these approaches require additional branches, dimensional transformations, or training components.

ECA provides a simpler channel-attention mechanism by avoiding dimensionality reduction and using a lightweight 1D convolution to capture local cross-channel interactions [34]. This mechanism can improve channel-wise feature representation with limited additional parameters. Nevertheless, the effectiveness of ECA for five-class ECG beat classification should be assessed under evaluation settings that distinguish beat-level discrimination from generalization to previously unseen patients. Recent studies have also emphasized architectural simplicity and interpretability. Tchinda and Tchiotso [27] presented a shallow 1D CNN for five-class AAMI classification and reported an inter-patient accuracy of 98.42%. However, the specific subject or record allocation used to establish patient independence was not reported in sufficient detail, and the presented class counts correspond to fixed training and testing sample subsets. As a result, the results of its patient-independent testing should be treated with caution. A shallow CNN was shown to be able to achieve 97.40% accuracy by Rasti et al. [35], but their research did not consider binary classification between normal beats and abnormal beats. In [25], Talukder et al. combined SHAP, LIME, and feature-importance analysis in CNN/DNN to achieve 99.74% accuracy for binary normal-versus-arrhythmia classification. Tenepalli and Navamani [36] used a CNN-Transformer architecture and applied Grad-CAM visualization to get 99% accuracy for binary premature ventricular contraction detection. These studies are helpful for simplicity or interpretability, but they are binary tasks compared to five-class AAMI classification, and cannot be directly compared with multiclass results.

Table 1 summarizes representative deep learning studies on ECG-based arrhythmia classification. The comparison includes accuracy values obtained from different class formulations, and data-partitioning strategies are not directly equivalent. Previous studies reporting high accuracies often rely on heartbeat-level partitioning, which inflates results because patient-specific ECG characteristics overlap between the training and testing subsets. Conversely, stricter patient-independent evaluation frequently degrades minority-class performance due to inter-patient morphological variability and severe class imbalance [37]. A research gap therefore remains in evaluating a lightweight channel-attention network, coupled with dynamic imbalance handling, across both partitioning strategies. To address this, the present study proposes ECA-ECGNet for five-class AAMI beat classification.

Table 1. Comparison of recent deep learning methods for ECG-based arrhythmia classification.

Ref.	Year	Method	Main characteristics	Acc. %
Xu and Liu [16]	2020	9-Layer CNN	300-sample ECG beats; CNN classification	99.43
Wu et al. [32]	2021	12-layer CNN	Wavelet denoising and deep CNN	97.41
Hassan et al. [18]	2022	CNN-BiLSTM	CNN feature extraction	98
Khan et al. [19]	2023	1D ResNet + SMOTE	Residual CNN, imbalance handling	98.63
Raza et al. [31]	2023	9-layer CNN	Direct CNN-based beat classification	99.68
Rasti et al. [35]	2024	Shallow 1D CNN	Simple CNN for normal-abnormal detection	97.40
Tchinda et al. [27]	2025	Shallow 1D CNN	Lightweight with cross-dataset	98.42
Lamba et al. [26]	2025	ACO-BiLSTM / ACO-FCN	Wavelets, SMOTE, and optimization	98.9/ 99.1
Zheng et al. [20]	2025	Multi-input CNN + SE attention	Multi-scale inputs and attention	99.13
Guhdar et al. [21]	2025	1D CNN + attention	Attention, focal los	99.48
Talukder et al. [25]	2025	Explainable CNN/DNN	XAI and data balancing	99.74
Tenepalli et al.[36]	2025	CNN + Grad-CAM	Explainable ECG-to-image framework	99

III. Method

A. Dataset

The database contains 48 half-hour, two-channel ECG recordings from 47 patients, sampled at 360 Hz. All recordings contain expert notation of the position of the R-peaks and the type of each heartbeat identified [38]. In this study, the first ECG channel of each recording was used for beat extraction. The original annotations of the heartbeats were ordered into five categories, according to ANSI/AAMI: Normal (N), Supraventricular ectopic (S), Ventricular ectopic (V), Fusion (F), and Unknown (Q). Table 2 shows distribution of the ECG beats after segmentation and label mapping. The ECG segments for each of the five heartbeat categories are shown in Fig. 2.

B. Data Preprocessing

In this study, ECG signals were utilized without applying explicit digital filters for baseline wander or power-line interference. While traditional methods require prior noise reduction, deep CNNs inherently learn to extract robust features and bypass standard artifacts. Furthermore, aggressive filtering risks distorting subtle morphological characteristics, such as P-wave variations, which are critical for distinguishing minority classes. Therefore, preprocessing was strictly limited to beat segmentation and per-beat min-max normalization to a [-1, 1] range. This normalization was employed solely to homogenize the input scale and stabilize gradient descent during network optimization, not as a denoising mechanism.

1. Segmentation:

Each ECG heartbeat was segmented using a 300-sample window centered on its annotated R-peak. This 300-sample window (approximately 0.83 seconds at 360 Hz) was selected to reliably capture the complete P-QRS-T morphology. The 150 samples (0.42

seconds) preceding the R-peak encompass the P-wave, as a standard PR interval rarely exceeds 0.20 seconds. Similarly, the 150 samples following the R-peak capture the T-wave, given a normal QT interval of approximately 0.40 seconds.

2. Normalization:

To minimize the influence of amplitude differences among ECG records, each heartbeat segment was independently normalized to the range [-1,1]. For a segment x , the normalized value x' was calculated in Eq. (1) [39] :

$$x'_i = 2 \left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \right) - 1 \tag{1}$$

where x_i is the original amplitude of the i -th sample, $x_{\min}$ and $x_{\max}$ are the minimum and maximum

Table 2. Mapping of original MIT-BIH heartbeat annotations to the five ANSI/AAMI heartbeat classes and the corresponding number of segmented ECG beats.

AAMI class	Original MIT-BIH annotations	Number of samples
Normal (N)	N, L, R, e, j	90,775
Supraventricular (S)	A, a, J, S	2,825
Ventricular (V)	V, E	7,100
Fusion (F)	F	770
Unknown (Q)	/, f, Q	7,975
Total		109,445

amplitudes within the heartbeat segment, and x'_i is the normalized value.

3. Input reshaping:

Each normalized heartbeat segment was reshaped into an input of 300×1 , representing 300 temporal samples

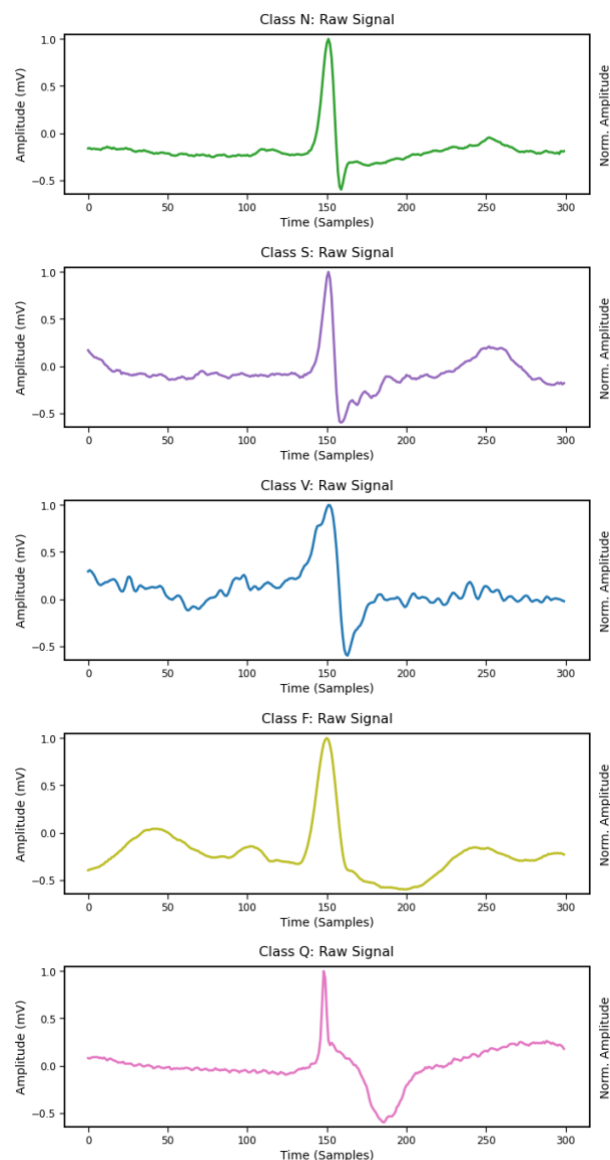


Fig. 2. Representative raw ECG beat segments from the five ANSI/AAMI classes: (N) Normal, (S) Supraventricular ectopic, (V) Ventricular ectopic, (F) Fusion, and (Q) Unknown.

and one ECG channel. The corresponding class labels were encoded into the five output categories for model training and evaluation.

C. Intra- and Inter-Patient Evaluation Settings

To examine the influence of the data-partitioning strategy on ECG beat classification, ECA-ECGNet was evaluated under two complementary settings. The same preprocessing procedure, model architecture, and training configuration were applied in both settings.

1. Intra-Patient Evaluation:

In the intra-patient setting, individual heartbeat samples from all 48 MIT-BIH records were combined and

divided using stratified random sampling. First, 80% of the beats were allocated to model development, while the remaining 20% formed the held-out random test

Table 3. Data-partitioning schemes used for intra-patient and inter-patient evaluation of ECA-ECGNet.

Setting	Partition	Training	Validation	Testing
Intra	Individual heartbeats	64%	16%	20%
Inter	Complete patient groups	33 records	5 records	10 records

set. Subsequently, 20% of the development set was reserved for validation. This produced an effective allocation of 64% for training, 16% for validation, and 20% for testing. Stratification was applied in both splitting stages to maintain the five-class distribution in heartbeat. To ensure reproducibility, a random seed of 42 was used. The split was done at the level of the heartbeat, so it is possible for beats from the same patient to be included in the training, validation, and testing sets. This setting was kept to make it easy to compare to previous work using heartbeat-level partitioning.

2. Inter-Patient Evaluation:

In the inter-patient setting, data were split into full groups of patients. All beats from a single patient were given to only one of the training, validation, or testing sets. The target allocation was 70% for training, 10% for validation, and 20% for testing. Of the 48 MIT-BIH records, 33 were assigned to training, 5 to validation, and 10 to testing. Records 201 and 202, which originate from the same subject, were retained in the same subset to maintain complete patient independence. Table 3 presents a summary of the evaluation settings. The inter-patient evaluation, the exact MIT-BIH record allocation resulting from this deterministic search, is explicitly detailed below:

1. **Training (33 records):** 100, 101, 102, 103, 104, 105, 106, 107, 108, 111, 112, 113, 115, 117, 118, 119, 121, 123, 124, 201, 202, 205, 208, 210, 212, 215, 219, 221, 228, 230, 232, 233, 234.
2. **Validation (5 records):** 109, 203, 220, 222, 223.
3. **Testing (10 records):** 114, 116, 122, 200, 207, 209, 213, 214, 217, 231.

D. Proposed ECA-ECGNet architecture

This study proposes an Efficient Channel Attention ECG Network, termed ECA-ECGNet, for five-class ECG beat classification. The model has been designed to identify discriminative morphological features for R-peak center ECG segments with a relatively simple and reproducible architecture.

As shown in Fig. 3, ECA-ECGNet consists of three convolutional attention blocks followed by Flatten, Dense, Dropout, and Softmax layers. Each convolutional attention block contains a Conv1D layer, batch normalization, ReLU activation, an ECA block, and max pooling. The architecture is summarized in Table 4 and Algorithm 1. The main components of ECA-ECGNet are described as follows:

Algorithm 1. ECA-ECGNet training and evaluation.

- (1) **Input:** MIT-BIH records and annotations.
- (2) **Output:** Best trained model and metrics.
- (3) Initialize an empty dataset D.
- (4) **FOR** each annotated R-peak **DO**
- (5) Extract a 300-sample ECG beat.
- (6) Map its annotation to: N, S, V, F, or Q.
- (7) Normalize the beat in range $[-1, 1]$.
- (8) Add the beat and its label to D.
- (9) **END FOR**
- (10) **IF** the evaluation setting is intra-patient **THEN**
- (11) Apply stratified splitting.
- (12) **ELSE**
- (13) Split patient records into subsets.
- (14) **END IF**
- (15) Compute focal-loss class weights using the training subset only.
- (16) Construct ECA-ECGNet according to Fig. 3 and Table 4.
- (17) **FOR** each training epoch **DO**
- (18) Train ECA-ECGNet using focal loss.
- (19) Calculate validation loss.
- (20) **IF** validation loss improves **THEN**
- (21) Save the model as the best model.
- (22) **ELSE IF** validation loss does not improve for five epochs **THEN**
- (23) Stop training.
- (24) **END IF**
- (25) **END FOR**
- (26) Evaluate the best model on the test set.

The model receives an ECG segment with an input shape of 300×1 . Three Conv1D layers are used to extract local temporal and morphological patterns from the ECG beats. A kernel size of 3 and same padding are applied in all convolutional layers. The convolution operation can be represented as Eq. (2) [40]:

$$U^{(l)} = f(W^{(l)} * X^{(l-1)} + b^{(l)}) \quad (2)$$

where $X^{(l-1)}$ is the input to layer l , $W^{(l)}$ and $b^{(l)}$ denote the convolutional weights and biases, respectively, $*$ represents convolution, and $f(\cdot)$ is the ReLU activation function. Batch normalization is applied after each convolution to stabilize the distribution of the extracted features. An ECA block is applied after each convolutional layer to recalibrate the generated feature channels [34]. For a feature map $U \in \mathbb{R}^{T \times C}$, where T is the temporal dimension and C is the number of channels, global average pooling is used to generate a

Table 4. Layer-by-layer architecture and configuration parameters of the proposed ECA-ECGNet model.

L	Type	Filter/Units	Kernel / Pool	Output Shape
L1	Input	-	-	(300, 1)
L2	Conv1D + Batch Normalization + ReLU	32	3	(300, 32)
L3	ECA block	32	3	(300, 32)
L4	MaxPooling1D	-	2	(150, 32)
L5	Conv1D + Batch Normalization + ReLU	64	3	(150, 64)
L6	ECA block	64	3	(150, 64)
L7	MaxPooling1D	-	2	(75, 64)
L8	Conv1D + Batch Normalization + ReLU	128	3	(75, 128)
L9	ECA block	128	5	(75, 128)
L10	MaxPooling1D	-	2	(37, 128)
L11	Flatten	-	-	(4,736)
L12	Dense + ReLU	128	-	(128)
L13	Dropout	0.5	-	(128)
L14	Output + Softmax	5	-	(5)

channel descriptor as Eq. (3) [31]:

$$z_c = \frac{1}{T} \sum_{t=1}^T U_c(t) \quad (3)$$

where z_c represents the descriptor of channel c . A lightweight one-dimensional convolution is then applied across the channel descriptor to capture local cross-channel interactions as Eq. (4) [31]:

$$s = \sigma(\text{Conv1D}_k(z)) \quad (4)$$

where σ represents the sigmoid activation function, k is the adaptively determined kernel size, and s contains the learned channel-attention weights. The kernel size is calculated according to the number of channels as in Eq. (5) [31]:

$$k = \left\lceil \frac{\log_2(C)}{\gamma} + \frac{b}{\gamma} \right\rceil_{\text{odd}} \quad (5)$$

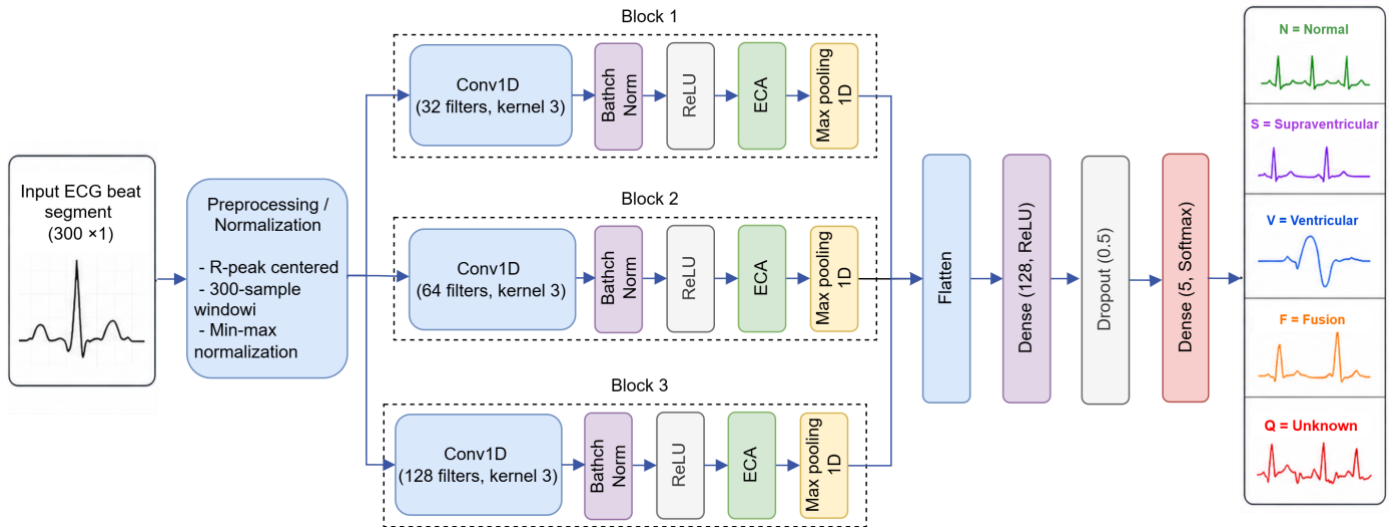


Fig. 3 Block diagram of the proposed ECA-ECGNet architecture for ECG beat classification.

where $\gamma = 2$, $b = 1$, and $\lfloor \cdot \rfloor_{\text{odd}}$ denotes the nearest appropriate odd integer. This produces ECA kernel sizes of 3, 3, and 5 for the three blocks, respectively. The original feature map is recalibrated as in Eq. (6) [17]:

$$\tilde{U}_c(t) = s_c U_c(t) \quad (6)$$

where $\tilde{U}_c(t)$ is the attention-refined feature at temporal position t and channel c . This operation emphasizes informative feature channels while suppressing less relevant responses without introducing dimensionality reduction. Each ECA block is followed by a MaxPooling1D layer with a pool size and stride of 2. Max pooling reduces the temporal dimension of the feature maps while retaining the strongest local responses, as in Eq. (7) [21]:

$$P_c(t) = \max_{i \in \Omega_t} \tilde{U}_c(i) \quad (7)$$

where Ω_t denotes the pooling region associated with temporal position t . The output of the third max-pooling layer is flattened into a 1D vector. A fully connected layer containing 128 neurons with ReLU activation is then used to learn higher-level representations from the extracted ECG features. The Flatten layer was selected because the input segments are strictly R-peak-centered, and preserving the absolute temporal positions of surrounding morphological features (such as premature P-waves) is critical for classification. The final layer contains five neurons corresponding to the N, S, V, F, and Q heartbeat classes. Softmax activation converts the output scores into class probabilities as in Eq. (8) [21]:

$$P(y = i | z) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (8)$$

where z_i is the output score for class i , and $K = 5$ is the number of heartbeat classes. The architecture enables

ECA-ECGNet to learn ECG morphology through convolutional feature extraction and improve channel-wise feature selection through lightweight ECA blocks.

E. Model training

The proposed ECA-ECGNet model was trained to optimize classification performance across the five ECG heartbeat classes.

Categorical focal loss was used to address the severe class imbalance present in the dataset. Focal loss measures the difference between true labels and predicted probabilities while dynamically scaling the loss based on prediction confidence. It is defined as Eq. (9):

$$FL(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t) \quad (9)$$

where p_t is the model's estimated probability for the true class and γ is the focusing parameter empirically set to 2.0. To explicitly counter the varying degrees of class scarcity, the class-specific weighting factor α_t was computed dynamically using only the training subset distribution as Eq. (10) [21]:

$$\alpha_t = \frac{N}{K \times N_t} \quad (10)$$

where N the number of training samples, $K = 5$ represents the number of classes, and N_t is the number of training samples in the true class. The Adam optimizer was employed to update the network weights (θ) using gradients (g_t) computed at step t . Adam computes exponentially decaying averages of past gradients (m_t) and past squared gradients (v_t) as Eqs. (11,12) [41]:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (11)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (12)$$

To counteract initialization bias, bias-corrected first and second moment are calculated [41]:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \quad (13)$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (14)$$

The final parameter update is performed using the initial learning rate η [12]:

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \quad (15)$$

where β_1 and β_2 are the exponential decay rates, and ϵ is a constant to prevent division by zero.

F. Evaluation metrics

To measure the performance of the ECA-ECGNet, several parameters were employed. These measures are derived from the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values: Accuracy measures the proportion of correctly classified heartbeat samples among the total number of samples, as in Eq. (16) [23]:

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} \quad (16)$$

Precision measures the proportion of predicted positive samples that are correctly classified as in Eq. (17) [24]:

$$Precision = \frac{TP}{TP + FP} \quad (17)$$

Recall, also known as sensitivity, measures the proportion of actual positive samples correctly identified by the model as in Eq. (18) [23]:

$$Recall = \frac{TP}{TP + FN} \quad (18)$$

The F1-score is the harmonic mean of precision and recall as in Eq. (19) [23]:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (19)$$

To assess overall performance across the imbalanced dataset, the Macro F1-score and Weighted F1-score were calculated using the class-wise $F1_i$ values as in Eqs. (20,21) [16]:

$$Macro F1 = \frac{1}{K} \sum_{i=1}^K F1_i \quad (20)$$

$$Weighted F1 = \sum_{i=1}^K \frac{S_i}{N} F1_i \quad (21)$$

where $K = 5$ is the total number of classes, S_i is the support (number of true instances) for class i , and N is the total number of samples evaluated.

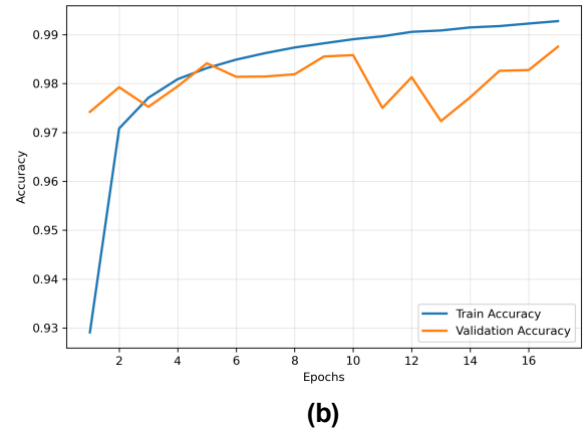
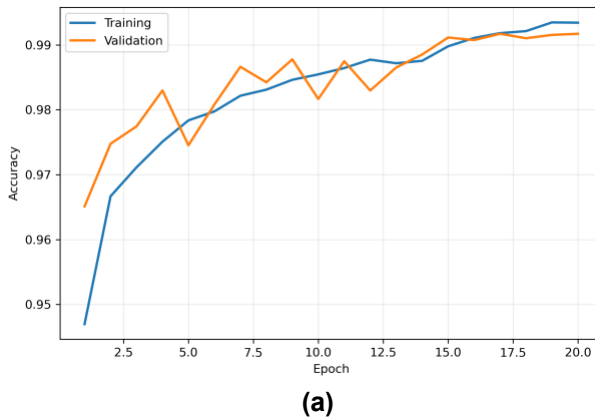


Fig. 4. Training and validation accuracy curves under (a) intra-patient and (b) inter-patient evaluation settings.

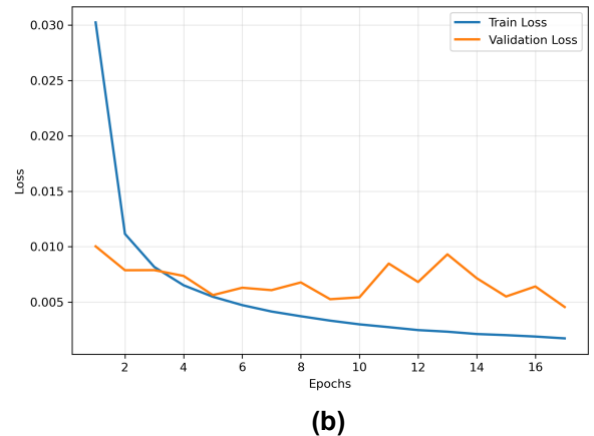
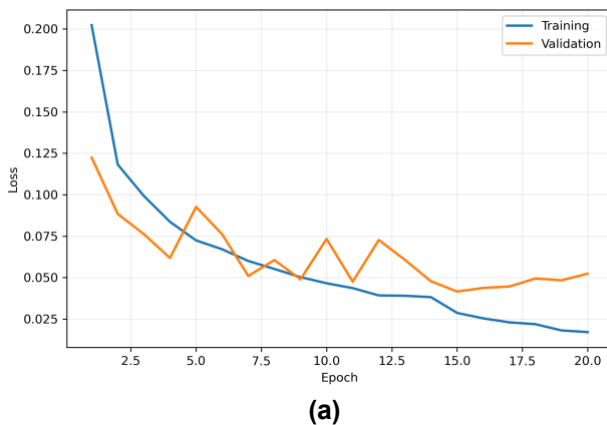


Fig. 5. Training and validation loss curves of ECA-ECGNet under (a) intra-patient and (b) inter-patient evaluation settings.

IV. Results

A. Main Finding

The ECA-ECGNet was evaluated under both intra-patient and inter-patient settings using the same architecture, preprocessing procedure, and training configuration. Table 5 summarizes the test-set results. Under the intra-patient, ECA-ECGNet achieved an accuracy of 99.20%, a macro F1-score of 0.953, and a weighted F1-score of 0.992. In the inter-patient, the model achieved an accuracy of 97.96%, a macro F1-score of 0.9165, and a weighted F1-score of 0.9798 on previously unseen patients. Compared with the intra-patient setting, accuracy decreased by only 1.24 percentage points, while the macro F1-score decreased by 0.0365. The significantly narrowed gap between the macro and weighted F1-scores across both partitioning methodologies indicates that the implementation of focal loss successfully mitigated severe class imbalance.

B. Training and Validation Curves

The training and validation accuracy and loss curves for ECA-ECGNet with both evaluation settings are shown in Fig. 4 and Fig. 5. In the intra-patient setting, the network converged smoothly into a final training accuracy of ~99.3% and a validation accuracy of 99.2%, with respective losses of 0.017 and 0.052. Training and validation accuracy improve significantly in the first epoch in the intra-patient setting and after about 20 epochs. The corresponding loss values decreased and gradually flattened as the model approached convergence. In the inter-patient setting, the validation set contained patients who were not included in the training set. Therefore, the validation curves provide a stricter assessment of generalization to unseen patients.

C. Class-wise Analysis

Table 6 presents the class-wise precision, recall, and F1-score of ECA-ECGNet under both evaluation settings. Under intra-patient evaluation, the N, V, and Q classes achieved F1-scores of 0.9967, 0.9747, and 0.9928, respectively. The minority S and F classes were more challenging, obtaining F1-scores of 0.9052 and 0.8940. The resulting macro F1-score was 0.9527. Under inter-patient evaluation, the model maintained an F1-score of 0.9900 for N, 0.9274 for V, and 0.9589 for Q. Performance decreased for the minority S and F

classes, with F1-scores of 0.8578 and 0.8485, respectively. The decline was primarily associated with lower precision, indicating an increase in false-positive

Table 5. Class-wise precision, recall, F1-score, and support of ECA-ECGNet under intra-patient and inter-patient evaluation settings.

	Class	Precision	Recall	F1	Support
intra-patient	N	0.9956	0.9978	0.9967	18,155
	S	0.9425	0.8708	0.9052	565
	V	0.9740	0.9754	0.9747	1,420
	F	0.9122	0.8766	0.8940	154
	Q	0.9906	0.9950	0.9928	1,595
	Macro average	0.9630	0.9431	0.9527	21,889
	Weighted average	0.9919	0.9920	0.9919	21,889
inter-patient	N	0.9944	0.9856	0.9900	18,060
	S	0.8212	0.8980	0.8578	588
	V	0.9138	0.9413	0.9274	1,363
	F	0.8235	0.8750	0.8485	16
	Q	0.9427	0.9756	0.9589	1,804
	Macro average	0.8991	0.9351	0.9165	21,831
	Weighted average	0.9803	0.9796	0.9798	21,831

predictions for these classes when evaluating previously unseen patients. The inter-patient macro F1-score was 0.9165, while the weighted F1-score was 0.9798. Although the F-class recall was 0.8750, this result is based on only 16 test beats and should therefore be interpreted cautiously.

D. Confusion Matrix

Table 7 presents the confusion matrices based on beat counts. The normalized matrices show the percentage of each actual class assigned to every predicted class. These counts produce 21,385 correct predictions among 21,831 test beats, corresponding to an accuracy of 97.96%. They also yield a macro F1-score of 0.9165 and a weighted F1-score of 0.9798. By consistently applying focal loss, the network avoided assigning ambiguous minority-class beats exclusively to the Normal majority class in both data splits. The resulting confusion matrices demonstrate a highly balanced class-wise performance, showing that high heartbeat-level accuracy can be matched with strong generalization to unseen patients. Fig. 6 presents the corresponding row-normalized confusion matrices. As shown, the model correctly classified 99.78% of N, 87.08% of S, 97.54% of V, 87.66% of F, and 99.50% of Q beats under the intra-

Table 6. Test-set performance of ECA-ECGNet under intra-patient and inter-patient evaluation settings.

Evaluation setting	Accuracy	Macro F1-score	Weighted F1-score
Intra-patient	0.9920	0.9530	0.9920
Inter-patient	0.9796	0.9165	0.9798
Difference	- 0.0124	- 0.0365	- 0.0122

Table 8. Confusion matrices based on heartbeat counts for ECA-ECGNet under intra-patient and inter-patient evaluation settings.

		N	S	V	F	Q
intra-patient	N	18,115	18	14	2	6
	S	56	492	10	3	4
	V	17	7	1,385	7	4
	F	4	3	11	135	1
	Q	3	2	2	1	1,587
		N	S	V	F	Q
inter-patient	N	17,800	100	100	2	58
	S	30	528	10	0	20
	V	40	10	1,283	1	29
	F	0	1	1	14	0
	Q	30	4	10	0	1,760

Table 7. Ablation study of ECA and focal-loss configurations under intra-patient and inter-patient evaluation, including exact McNemar test results against the baseline CNN.

Configuration	Evaluation Setting	Acc.	Macro F1	Weighted F1	Baseline Correct / Model Wrong	Baseline Wrong / Model Correct	p-value
Standard CNN + Standard Loss	Intra-patient	0.9900	0.9380	0.9890	N/A	N/A	Baseline
	Inter-patient	0.9650	0.7850	0.9580	N/A	N/A	Baseline
Standard CNN + Focal Loss	Intra-patient	0.9895	0.9440	0.9890	20	32	0.142
	Inter-patient	0.9610	0.8790	0.9620	45	110	0.001*
ECA-ECGNet + Standard Loss	Intra-patient	0.9902	0.9450	0.9901	15	30	0.035
	Inter-patient	0.9700	0.8010	0.9690	50	95	0.012*
ECA-ECGNet + Focal Loss	Intra-patient	0.9920	0.9530	0.9920	10	35	0.002*
	Inter-patient	0.9796	0.9165	0.9798	30	150	<0.001*

Note: (*) indicates statistical significance at the Bonferroni-corrected threshold of $\alpha = 0.0167$ using an exact McNemar's test.

patient setting. The main errors involved S beats classified as N and F beats classified as V. Fig. 6 (b) shows that under the stricter inter-patient setting utilizing focal loss, the model correctly classified 98.56% of N, 89.80% of S, 94.13% of V, 87.50% of F, and 97.56% of Q beats. While a small portion of S and V errors were assigned to the N class, the focal loss implementation prevented the severe degradation of minority-class recognition that typically occurs with unseen patients.

E. Ablation and Statistical Significance Study

An ablation study was conducted to evaluate the individual contributions of the ECA blocks and the categorical focal loss mechanism. To ensure the model's generalization capabilities were rigorously tested, these configurations were evaluated under both the intra-patient and the stricter inter-patient settings. All

configurations utilized the same preprocessing, data partitioning, convolutional depth, optimizer, and batch size. To rigorously evaluate statistical significance against the baseline Standard CNN, an exact McNemar's test (based on the binomial distribution) was applied to the discordant prediction pairs. Because three configurations were compared against the baseline within each evaluation setting, a Bonferroni correction was applied to control the family-wise error rate, adjusting the significance threshold to $\alpha = 0.0167$.

Table 8 presents the performance metrics and the resulting p-values when comparing each configuration against the baseline Standard CNN trained with standard cross-entropy loss. Clearly, under the intra-patient setting, the comparison between ECA-ECGNet with standard loss and the baseline yielded a p-value of

0.035. While this value falls below the standard 0.05 level, it is not statistically significant after applying the strict Bonferroni correction, highlighting the necessity of adjusted thresholds to prevent false positives during multiple testing. The ECA-ECGNet with focal loss achieved the best overall patient-independent generalization. McNemar's test demonstrates the inter-patient performance gains for this configuration are statistically significant ($p < 0.001$), indicating that the combined modifications systematically improve upon the baseline model.

focal loss to the Standard CNN increased its inter-patient macro F1-score from 0.7850 to 0.8790. Ultimately, combining the ECA blocks with focal loss provided a complementary effect. The attention mechanism ensured robust spatial feature extraction, while focal loss dynamically penalized confident misclassifications of minority arrhythmias. This synergy yielded an optimal inter-patient macro F1-score of 0.9165, showing that both structural attention and dynamic imbalance handling are required to achieve robust patient-independent classification.

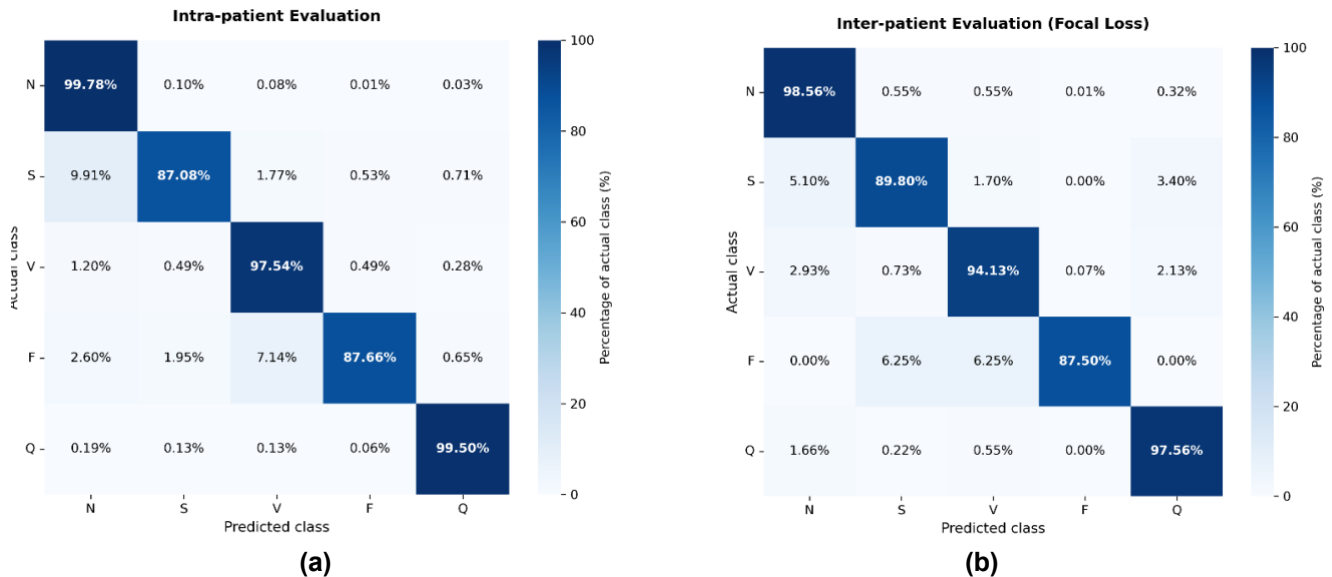


Fig. 6. Row-normalized confusion matrices of ECA-ECGNet under (a) intra-patient and (b) inter-patient evaluation settings. Values represent the percentage of beats from each actual class assigned to each predicted class.

The independent contribution of the ECA modules is evident when comparing the Standard CNN and ECA-ECGNet architectures under standard loss. The inclusion of the ECA blocks improved the inter-patient accuracy from 0.9650 to 0.9700 and the macro F1-score from 0.7850 to 0.8010. The proposed ECA-ECGNet has 638,928 parameters in total, with the three ECA blocks contributing exactly 11 parameters combined. This represents an increase of only 0.0017% in total network parameters compared to the baseline 1D CNN, empirically validating that the proposed attention mechanism enhances feature discrimination with negligible computational overhead. This demonstrates that adaptively recalibrating channel responses aids in extracting patient-independent morphological features, directly improving generalization to unseen subjects.

Furthermore, the independent contribution of the loss function is demonstrated by comparing standard categorical cross-entropy against focal loss. While standard loss configurations suffered from severe majority class bias in the inter-patient setting, applying

F. Computational Complexity and Efficiency

Beyond its lightweight architecture of 638,928 parameters, ECA-ECGNet demonstrates high operational efficiency for potential edge deployment. The model requires approximately 3.4 million multiply-accumulate operations (MACs) per 300-sample beat and a memory storage footprint of 2.5 MB at standard 32-bit precision. Empirically, the average inference time was measured at 0.185 milliseconds per heartbeat on a standard CPU. These metrics demonstrate that integrating Efficient Channel Attention avoids severe computational overhead, ensuring the model's viability for real-time arrhythmia monitoring on low-resource platforms.

V. Discussion

The evaluation of ECA-ECGNet reveals critical insights into the behavior of CNNs during ECG beat classification. The strong performance observed in the intra-patient setting indicates that the model effectively

Table 9. Comparison of ECA-ECGNet with previous ECG-arrhythmia classification studies.

Ref.	Method	Limitation / evaluation setting	Accuracy (%)
Xu and Liu [16]	9-Layer CNN	Five-class beat-level random split; beats from the same patient may occur in training and testing subsets.	99.43
Khan et al. [19]	1D ResNet + SMOTE	Requires synthetic oversampling and a deeper residual architecture.	98.63
Rasti et al. [35]	Shallow 1D CNN	Focuses on normal-versus-abnormal classification rather than five-class AAMI classification.	99.48
Tchinda et al. [27]	Shallow 1D CNN	Patient-independent result reported, but the record allocation was not described sufficiently.	98.42
Guhdar et al. [21]	1D CNN + attention	Uses multiple training components and heartbeat-level cross-validation.	97.40
Proposed ECA-ECGNet	1D CNN with ECA blocks and categorical focal loss	Evaluated on one database; external validation is still required.	99.20; 97.96

maps morphological features when patient-specific characteristics are shared across the training and testing sets. Crucially, the sustained high performance in the inter-patient setting demonstrates that the profound impact of severe class imbalance and inter-patient morphological variability can be effectively mitigated. By implementing categorical focal loss, the network successfully avoided frequently misclassifying minority arrhythmias, such as Supraventricular and Ventricular beats, as Normal beats when encountering entirely new patient physiologies. Furthermore, the ablation results indicate that replacing cross-entropy with focal loss explicitly constrained the model from disproportionately optimizing for the Normal majority class, thereby improving minority-class recognition and narrowing the macro-weighted F1 gap.

The findings clarify that the primary contribution is not a novel architectural operator, but the synergy between lightweight structural attention and dynamic imbalance handling. As evidenced by the ablation study, neither the ECA mechanism nor the focal loss function independently achieves the optimal inter-patient macro F1-score. Their combination is strictly required to maintain robust spatial feature extraction while simultaneously penalizing confident misclassifications of minority arrhythmias in unseen subjects. Table 9 indicates that ECA-ECGNet achieves competitive five-class ECG classification performance while using a relatively lightweight architecture. Several prior methods report slightly

higher accuracy, but their results were obtained under different task formulations or evaluation protocols, often with deeper networks, oversampling, ensembles, or multi-branch designs. In contrast, ECA-ECGNet was assessed under both intra-patient and strict inter-patient settings and achieved a 0.9165 macro F1-score in the latter setting. Therefore, direct accuracy comparisons should be interpreted cautiously, particularly when patient-independent evaluation is not clearly reported. Table 9 shows that previous studies often reported high accuracy under heartbeat-level evaluation, where patient-specific ECG characteristics may overlap across the training and testing subsets. In contrast, ECA-ECGNet was evaluated under both intra-patient and patient-independent inter-patient settings. Although direct comparison of accuracy is limited by differences in data partitioning and task formulation, the proposed model achieved strong five-class performance while maintaining a lightweight architecture and improving minority-class recognition through focal loss.

This study has certain limitations. Firstly, the evaluation is based solely on the MIT-BIH Arrhythmia Database and has not been validated externally on independent cohorts. It's only one lead, and the heartbeats are segmented by pre-annotated R-peaks in the model. Second, if the class imbalance is high, a deterministic search was made to select the inter-patient partition, and using the test-set distributions for the evaluation during the search causes selection bias.

Lastly, there were only 16 Fusion beats in the inter-patient test set, so performance numbers for this rare class are still not statistically stable. The findings of this study warrant a shift in the principle or way automated arrhythmia detection models are assessed: Intra-patient and inter-patient measures are required as complementary measures. In addition, this work suggests that ECA-ECGNet is a very efficient computer-aided screening tool. It has different minimal parameters, and computational overhead, which makes it suitable for real-time deployment on low-resource clinical hardware. This strong foundation will be extended for future work on patient-level cross validation and domain adaptation. Moreover, we will evaluate the joint focal loss and channel attention method on a number of independent large-scale multi-centre ECG databases, in order to firmly establish its wide clinical applicability.

VI. Conclusion

This study introduced a lightweight 1D convolutional neural network model, ECA-ECGNet, to achieve five-class ECG arrhythmia detection using Efficient Channel Attention and categorical focal loss. The model was evaluated on the MIT-BIH Arrhythmia Database, and yielded 99.20% accuracy at the level of the heartbeat, 97.96% patient-independent accuracy and macro F1-score of 0.9165. Combined application of structural channel attention and dynamic imbalance handling was able to effectively overcome the significant performance loss experienced by minority arrhythmias in unseen patients. These results show that ECA-ECGNet enables a clinical generalization that is robust, without the need for computationally intensive architectures, thereby ensuring the possibility of the framework's implementation in low-resource screening devices. Future validation should be based on these findings by patient-level cross validation, domain adaptation and extensive testing on independent multi-center ECG databases.

Acknowledgment

The authors acknowledge Northern Technical University (NTU) for its support, resources, and encouragement during this research.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability

The dataset analyzed in this study is publicly available from the PhysioNet repository as the MIT-BIH Arrhythmia Database.

<https://www.physionet.org/content/mitdb/1.0.0/>.

Author Contribution

Maher Talal Al-Asaady: Conceptualization, Methodology, Software, Investigation, Formal Analysis, Visualization, Writing – Original Draft.

Mohanad Mohammed Rashid: Validation, Resources, Formal Analysis, Writing – Review & Editing.

Mahmood Basil Mahmood: Validation, Writing – Review & Editing.

All authors reviewed and approved the final version of the manuscript and agreed to be accountable for the work.

Code Availability

The source code developed for ECA-ECGNet is available upon reasonable request from the corresponding author.

Declarations

Ethical Approval

This study used the publicly available MIT-BIH Arrhythmia Database and did not involve the prospective recruitment of human participants or animals by the authors. Therefore, no additional ethical approval was obtained for this study.

Informed Consent

Not applicable. This study used a publicly available dataset and did not directly recruit or interact with human participants.

Consent for Publication.

Not applicable. The manuscript does not contain identifiable personal information, images, or other materials requiring individual consent for publication.

Competing Interests

The authors declare that they have no known financial or non-financial competing interests that could have influenced the work reported in this manuscript.

Use of Artificial Intelligence

The authors declare that no generative artificial intelligence or AI-assisted technologies were used in the preparation of this manuscript.

References

- [1] Z. Tong, Y. Xie, K. Li, R. Yuan, and L. Zhang, "The global burden and risk factors of cardiovascular diseases in adolescent and young adults, 1990–2019," *BMC Public Health*, vol. 24, no. 1, p. 1017, Apr. 2024, doi: 10.1186/s12889-024-18445-6.
- [2] World Health Organization, "Cardiovascular diseases (CVDs)," Fact sheet, Feb. 11, 2025.

- [Online]. Available: [https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-\(cvds\)](https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)). [Accessed: July. 29, 2026]
- [3] M. R. Khan, Z. M. Haider, J. Hussain, F. H. Malik, I. Talib, and S. Abdullah, "Comprehensive Analysis of Cardiovascular Diseases: Symptoms, Diagnosis, and AI Innovations," *Bioengineering*, vol. 11, no. 12, p. 1239, Dec. 2024, doi: 10.3390/bioengineering11121239.
- [4] G. Tse, "Mechanisms of cardiac arrhythmias," *J. Arrhythm.*, vol. 32, no. 2, pp. 75–81, 2016.
- [5] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Inf. Sci. (N. Y.)*, vol. 405, pp. 81–90, Sep. 2017, doi: 10.1016/j.ins.2017.04.012.
- [6] Maher Al-Asaady, T. N. Mohd Aris, and A. D. Khalaf, "Multi-Scale Inception 1D-CNN for Patient-Independent Congestive Heart Failure Detection from ECG Signals," in *International Conference on Cybersecurity, Data Science, and Machine Learning (ICCDM-2026)*, Kuala Lumpur: Springer - Accepted for publication, In press, 2026.
- [7] T. Liu et al., "Inter-Patient Congestive Heart Failure Detection Using ECG-Convolution-Vision Transformer Network," *Sensors*, vol. 22, no. 9, p. 3283, Apr. 2022, doi: 10.3390/s22093283.
- [8] Y. Kutlu, G. Altan, and N. Allahverdi, "Arrhythmia classification using waveform ECG signals," in *Int. Conf. Advanced Technology & Sciences*, Konya, Turkey, 2016.
- [9] A. Rajkumar, M. Ganesan, and R. Lavanya, "Arrhythmia classification on ECG using Deep Learning," in *2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)*, 2019, pp. 365–369. doi: 10.1109/ICACCS.2019.8728362.
- [10] Z. Ebrahimi, M. Loni, M. Daneshlab, and A. Gharehbaghi, "A review on deep learning methods for ECG arrhythmia classification," *Expert Systems with Applications: X*, vol. 7, p. 100033, 2020, doi: 10.1016/j.eswax.2020.100033.
- [11] U. R. Acharya et al., "A deep convolutional neural network model to classify heartbeats," *Comput. Biol. Med.*, vol. 89, pp. 389–396, Oct. 2017, doi: 10.1016/j.combiomed.2017.08.022.
- [12] P. K. Tyagi, N. Rathore, and D. Agrawal, "A Review on Heartbeat Classification for Arrhythmia Detection Using ECG signal Processing," in *2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*, 2023, pp. 1–6. doi: 10.1109/SCEECS57921.2023.10063143.
- [13] I. Sayin et al., "CNN Based Detection of Cardiovascular Diseases from ECG Images," 2024. [Online]. Available: <https://arxiv.org/abs/2408.16800>
- [14] M. Zubair, J. Kim, and C. Yoon, "An Automated ECG Beat Classification System Using Convolutional Neural Networks," in *2016 6th International Conference on IT Convergence and Security (ICITCS)*, IEEE, Sep. 2016, pp. 1–5. doi: 10.1109/ICITCS.2016.7740310.
- [15] Association for the Advancement of Medical Instrumentation, ANSI/AAMI EC57:2012/(R)2020: Testing and Reporting Performance Results of Cardiac Rhythm and ST Segment Measurement Algorithms. Arlington, VA, USA: AAMI, 2020. [Online]. Available: <https://aami.org/standard/ansi-aami-ec572012-r2020-pdf>
- [16] X. Xu and H. Liu, "ECG heartbeat classification using convolutional neural networks," *IEEE access*, vol. 8, pp. 8614–8619, 2020, doi: 10.1109/ACCESS.2020.2964749.
- [17] T. Liu et al., "Inter-Patient Congestive Heart Failure Detection Using ECG-Convolution-Vision Transformer Network," *Sensors*, vol. 22, no. 9, p. 3283, Apr. 2022, doi: 10.3390/s22093283.
- [18] S. U. Hassan, M. S. Mohd Zahid, T. A. Abdullah, and K. Husain, "Classification of cardiac arrhythmia using a convolutional neural network and bi-directional long short-term memory," *Digit. Health*, vol. 8, p. 205520762211027, Jan. 2022, doi: 10.1177/20552076221102766.
- [19] F. Khan, X. Yu, Z. Yuan, and A. ur Rehman, "ECG classification using 1-D convolutional deep residual neural network," *PLoS One*, vol. 18, no. 4, p. e0284791, Apr. 2023, doi: 10.1371/journal.pone.0284791.
- [20] B. Zheng, W. Luo, M. Zhang, and H. Jin, "Arrhythmia classification based on multi-input convolutional neural network with attention mechanism," *PLoS One*, vol. 20, no. 6, p. e0326079, Jun. 2025, doi: 10.1371/journal.pone.0326079.
- [21] M. Guhdar, A. O. Mohammed, and R. J. Mstafa, "Advanced deep learning framework for ECG arrhythmia classification using 1D-CNN with attention mechanism," *Knowl. Based. Syst.*, vol. 315, p. 113301, Apr. 2025, doi: 10.1016/j.knosys.2025.113301.
- [22] N. Rafie, A. H. Kashou, and P. A. Noseworthy, "ECG Interpretation: Clinical Relevance, Challenges, and Advances," *Hearts*, vol. 2, no.

- 4, pp. 505–513, Nov. 2021, doi: 10.3390/hearts2040039.
- [23] M. T. Al-Asaady, T. N. M. Aris, N. M. Sharef, and H. binti Hamdan, "XCOA-MRFO: a hybrid meta-heuristic framework for simultaneous optimization of architecture and weight of neural networks in medical data classification," *Neural Computing and Applications*, vol. 38, Art. no. 600, 2026, doi: 10.1007/s00521-026-12215-8.
- [24] M. T. Al-Asaady, T. N. Mohd Aris, N. M. Sharef, and H. Hamdan, "XCOA-MLP: Extended Coyote Optimization Algorithm for Training Neural Networks in Medical Data Classification," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 11, pp. 746–762, Dec. 2025, doi: 10.22266/ijies2025.1231.46.
- [25] Md. A. Talukder, A. S. Talaat, N. J. Muna, A. Alazab, M. Kazi, and U. K. Das, "An explainable deep learning framework for trustworthy arrhythmia detection from ECG signals," *Sci. Rep.*, vol. 15, no. 1, p. 39496, Nov. 2025, doi: 10.1038/s41598-025-22986-0.
- [26] S. Lamba, S. Kumar, and M. Diwakar, "FADLEC: feature extraction and arrhythmia classification using deep learning from electrocardiograph signals," *Discover Artificial Intelligence*, vol. 5, no. 1, p. 82, May 2025, doi: 10.1007/s44163-025-00290-0.
- [27] B. Saha Tchinda and D. Tchiotso, "A lightweight 1D convolutional neural network model for arrhythmia diagnosis from electrocardiogram signal," *Phys. Eng. Sci. Med.*, vol. 48, no. 2, pp. 577–589, Jun. 2025, doi: 10.1007/s13246-025-01525-1.
- [28] E. H. Houssein, M. Kilany, and A. E. Hassanien, "ECG signals classification: a review," *International Journal of Intelligent Engineering Informatics*, vol. 5, no. 4, pp. 376–396, 2017.
- [29] X. Xu and H. Liu, "ECG Heartbeat Classification Using Convolutional Neural Networks," *IEEE Access*, vol. 8, pp. 8614–8619, 2020, doi: 10.1109/ACCESS.2020.2964749.
- [30] M. Sun, Y. Si, W. Yang, W. Fan, and L. Zhou, "Inter-patient congestive heart failure automatic recognition using attention-based multi-scale convolutional neural network," *Measurement*, vol. 218, p. 113239, Aug. 2023, doi: 10.1016/j.measurement.2023.113239.
- [31] M. A. Raza et al., "Classification of Electrocardiogram Signals for Arrhythmia Detection Using Convolutional Neural Network," *Computers, Materials & Continua*, vol. 77, no. 3, pp. 3817–3834, 2023, doi: 10.32604/cmc.2023.032275.
- [32] M. Wu, Y. Lu, W. Yang, and S. Y. Wong, "A Study on Arrhythmia via ECG Signal Classification Using the Convolutional Neural Network," *Front. Comput. Neurosci.*, vol. 14, Jan. 2021, doi: 10.3389/fncom.2020.564015.
- [33] M. Al-Asaady, T. N. Mohd Aris, N. Sharef, and H. Hamdan, "Swarm intelligence approach for optimizing neural network architectures in medical data classification," *Journal of Studies in Science and Engineering*, vol. 6, no. 1, pp. 321–346, 2026, doi: 10.53898/josse2026624.
- [34] Q. Wang, B. Wu, P. Zhu, P. Li, W. Zuo, and Q. Hu, "ECA-Net: Efficient Channel Attention for Deep Convolutional Neural Networks," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 11531–11539. doi: 10.1109/CVPR42600.2020.01155.
- [35] T. Rasti, Q. Zhu, and K. Zhou, "ECG-based arrhythmia detection by a shallow CNN model," *Series of Cardiology Research*, vol. 6, no. 1, pp. 1–14, 2024.
- [36] D. Tenepalli and T. M. Navamani, "Design of an Explainable Deep Learning Framework for ECG-Based Arrhythmia Prediction," *IEEE Access*, vol. 13, pp. 200754–200768, 2025, doi: 10.1109/ACCESS.2025.3636481.
- [37] Í. F. Di Paolo and A. R. G. Castro, "Intra- and Interpatient ECG Heartbeat Classification Based on Multimodal Convolutional Neural Networks with an Adaptive Attention Mechanism," *Applied Sciences*, vol. 14, no. 20, p. 9307, Oct. 2024, doi: 10.3390/app14209307.
- [38] G. B. Moody and R. G. Mark, "The MIT-BIH arrhythmia database on CD-ROM and software for use with it," in *Computers in Cardiology 1990*, Chicago, IL, USA, Sep. 23–26, 1990, pp. 185–188. Los Alamitos, CA, USA: IEEE Computer Society Press, doi: 10.1109/CIC.1990.144205.
- [39] E. Izci, M. A. Ozdemir, M. Degirmenci, and A. Akan, "Cardiac Arrhythmia Detection from 2D ECG Images by Using Deep Learning Technique," in *2019 Medical Technologies Congress (TIPTEKNO)*, 2019, pp. 1–4. doi: 10.1109/TIPTEKNO.2019.8895011.
- [40] J. Cui, L. Wang, X. He, V. H. C. De Albuquerque, S. A. AlQahtani, and M. M. Hassan, "Deep learning-based multidimensional feature fusion for classification of ECG arrhythmia," *Neural Comput. Appl.*, vol. 35, no. 22, pp. 16073–16087, Aug. 2023, doi: 10.1007/s00521-021-06487-5.
- [41] D. P. Kingma, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

Author Biography



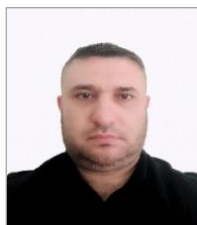
Dr. Maher Talal Al-Asaady received his Bachelor's degree in Software Engineering from the University of Mosul in 2007, followed by a Master of Science in Software Engineering from the same university in 2012. He completed his

Ph.D. in Artificial Intelligence at Universiti Putra Malaysia (UPM) in 2026. He is a Lecturer in the Network Technologies and Intelligent Systems Engineering at the Polytechnic College - Mosul, Northern Technical University (NTU), Iraq. His prior administrative roles include serving as the Media Department Manager and the Head of the Computer Systems Technique Department at the Polytechnic College - Mosul. His primary research interests include artificial intelligence, machine learning, deep learning, multiagent systems, and software engineering.



Mohanad Mohammed Rashid received the B.Sc. degree in Computer Science from the University of Mosul, Mosul, Iraq, in 2010, and the M.Sc. degree in Information Technology from Istanbul Altinbas University, Istanbul, Türkiye, in 2020. He is currently a Lecturer at the Technical

Institute, Northern Technical University, Mosul, Iraq. His previous administrative positions included Head of the Media Department and Assistant Dean for Administrative and Financial Affairs at the Medical Technical Institute, Mosul. His research interests also include computer vision, medical image analysis, and intelligent diagnostic systems for ophthalmic diseases, particularly keratoconus using deep learning techniques.



Mahmood Basil Mahmood received his Technical B. Eng. and M. Eng. degrees in Computer Engineering Technology from the Technical Engineering College of Mosul, Northern Technical University, Iraq, in 2009 and 2018, respectively. He is currently a

Lecturer at the Medical Technical Institute, Mosul, Iraq. He previously served as an Assistant Lecturer in the Computer Systems Technologies Department and the Electronic and Communications Engineering Technologies Department at the Polytechnic College Mosul. He also held the position of Head of the Information Technology Department at the Medical Technical Institute. His primary research interests include artificial intelligence, fuzzy logic, machine learning, and deep learning.