

# Temporal attention network for CNNE model of variable-length ECG signals in early arrhythmia detection

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## ABSTRACT

Cardiac arrhythmia identification and categorization are crucial for prompt treatment and better patient outcomes. Arrhythmia identification is the main focus of this study's temporal attention network (TAN)-based multiclass categorization of varied-length electrocardiogram (ECG) data. The suggested TAN is designed to handle variable-duration ECG signals, making it ideal for real-time monitoring. The TAN uses a dynamic snippet extraction approach to choose meaningful ECG segments to ensure the model captures essential properties despite the constraints of processing such heterogeneous data. Training and assessment use a large dataset of atrial fibrillation, ventricular, and supraventricular arrhythmias. The TAN outperforms current approaches in multiclass early arrhythmia classification and is very accurate. Concatenating EfficientNet with CNN layer helped overcome different data and variable-length signals. High accuracy: 98% of normal, 97.1% of atrial fibrillation (AF), 98% of other, and 98% of noisy using the proposed CEEC model. Early arrhythmia diagnosis has improved due to the TAN's ability to effectively identify varied-length ECG data and give interpretability. It enables quicker interventions, personalised treatment plans, and improved arrhythmia control, which can greatly benefit patient care.

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## 1. INTRODUCTION

Arrhythmias, irregular heartbeats, are a global health concern [1]. Effective medical therapies and patient outcomes depend on rapid detection and exact classification of cardiac arrhythmias. The electrocardiogram (ECG) is essential for cardiac activity monitoring and arrhythmia detection [2]. Early arrhythmia diagnosis from ECG signals helps healthcare practitioners deliver personalised therapy and improve arrhythmia management.

We introduce a temporal attention network (TAN) [3] designed to handle variable-duration ECG signals, making it ideal for real-time monitoring. The suggested TAN uses dynamic snippet extraction to overcome the limitations of processing such different input. This technique picks interesting ECG segments to ensure the model captures essential information, enhancing arrhythmia classification accuracy. We will examine the TAN and the large dataset used for training and assessment in the following sections. We will also examine the TAN's amazing categorization performance and an attention-based policy network's attention maps for explainable decision-making. We will also address how the TAN may affect patient care, emphasising prompt interventions and personalised therapy. Cardiac arrhythmias can cause stroke, heart failure, and sudden cardiac death [4]. These arrhythmias must be detected and classified early to reduce risks

and improve patient outcomes. ECGs are routinely used to monitor and diagnose cardiac arrhythmias. ECG signals can identify atrial fibrillation, ventricular tachycardia, and supraventricular tachycardia [5].

These approaches may speed up and improve arrhythmia identification, improving patient outcomes and medical treatments. Two reasons drove this research: First, to create a machine learning model that properly classifies ECG data into arrhythmia classifications, and second, to explain the algorithm's decision-making process to healthcare practitioners. Explainability is important in medical applications because it builds confidence and speeds up clinical decision-making. To address these challenges, our research introduces a novel TAN designed to accommodate variable-length ECG signals and provide interpretable decision support for arrhythmia detection. The TAN leverages the power of deep learning and attention mechanisms to tackle these challenges effectively. The TAN is the cornerstone of our approach, specifically tailored to address the challenges presented by ECG signal classification [6]-[9].

In section 2, we review the existing literature and related work in this field. Section 3 presents our proposed methodology, including a description of the dataset and the architectural framework. In section 4, we analyze the results and engage in a comprehensive discussion of the findings. Finally, in section 5, we offer our conclusions and outline potential directions for future research.

## 2. RELATED WORKS

The literature survey for this research covers the current status of ECG-based early arrhythmia identification. It provides a basis for understanding current methods, difficulties, and advances in this field. Recurrent neural networks (RNNs) were used for time-series severe event forecasting [10], [11]. The study analyses past data to anticipate severe occurrences for Uber applications. Deep learning models can handle time-series data, which is essential for ECG signal processing. Attia *et al.* [12] conducted a retrospective investigation in showing that artificial intelligent (AI) can predict clinical outcomes and identify arrhythmias. This research shows how AI improves arrhythmia diagnosis and prognosis. Rajpurkar *et al.* [13] develops convolutional neural networks (CNNs) for cardiologist-level arrhythmia identification. A deep learning model that can identify heart arrhythmias from ECG data may solve the problem of automated diagnosis. Gawali *et al.* [14] proposes a two-level attention strategy for ECG-based heartbeat categorization. The model concentrates on key ECG segments with this attention mechanism, increasing arrhythmia classification. This study emphasises how attention processes improve ECG classification model interpretability and performance.

Time series categorization using long short-term memory (LSTM) fully convolutional networks was suggested in [15]. Their study shows that LSTM-based models can handle time series data for ECG signal interpretation. These models capture long-term dependencies and are good for sequential data categorization. Deep learning techniques are used to identify crucial head computed tomography (CT) scan results [16]. Although it's medical imaging, it shows how deep learning and CNNs may detect serious diseases in healthcare. This potential is important for ECG-based arrhythmia identification. A method for diagnosing atrial fibrillation from brief single-lead ECG recordings is provided by Rodriguez *et al.* [17]. The research participated in the PhysioNet computing in cardiology challenge and emphasises the need for strong arrhythmia identification methods, especially with little ECG data. The study improves real-world arrhythmia classification models.

Wearable technologies for ambulatory ECG monitoring are examined in this study [18]. Real-time data gathering for arrhythmia identification and remote patient monitoring is stressed in the development and validation of wearable sensors for continuous ECG monitoring. Rajpurkar *et al.* [19], introduce CheXNet, a deep learning chest X-ray interpretation model. While radiology is the main emphasis, this study shows the capability of deep learning in medical imaging and the possibilities for AI-driven diagnosis and detection in ECG analysis. Tison *et al.* [20] developed an automated ECG quality evaluation approach, a vital pre-processing step for reliable arrhythmia diagnosis. Data quality is crucial to ECG analysis, and AI automates it, according to the study. Deep neural networks are used to identify atrial fibrillation in single-lead ECG recordings [21]. Deep learning may effectively identify arrhythmias like atrial fibrillation from ECG data, improving clinical decision-making.

RNNs were used to capture temporal relationships in ECG data in study [22], helping construct reliable arrhythmia classification models. CNN-based real-time ECG signal categorization is presented in [23]. Real-time monitoring and CNN arrhythmia detection are stressed in the study. Saber *et al.* [24], present a deep learning network to automatically diagnose atrial fibrillation from single-lead ECG data. This landmark study [25] introduced the "PhysioNet/computers in cardiology challenge 2000" dataset. Due to its widespread usage in arrhythmia detection algorithm development and validation, the dataset is a valuable resource. This study compares ECG classification machine learning techniques.

### 3. MATERIALS AND METHODS

#### 3.1. Dataset collection

In this research, we employed the publicly accessible dataset from the PhysioNet/computing in cardiology (CinC) challenge 2017. The dataset, collected using lightweight AliveCor devices for personal heart monitoring, comprises 8,528 single-lead fingertip ECG recordings. These recordings are relatively short, ranging from 9 to 61 seconds on average, with a sampling frequency of 300 Hz. Expert annotators meticulously categorized the ECG recordings into four groups: 5,076 as 'normal' (representing normal sinus rhythm), 758 as 'AF' (indicating atrial fibrillation), 279 as 'noisy' (indicating ECGs with too much noise for recognition), and 2,415 as 'other,' encompassing abnormal rhythms not falling under 'AF' or 'noisy' categories. Table 1 provides a statistical summary of the dataset.

Table 1. Class distribution and statistics of the dataset [26]

Type	No. of recordings	In %	Time length (s)				
			Mean	SD	Max	Median	Min
Normal (N)	5,076	59.52	32.11	9.97	60.95	30	9.05
AF (A)	758	8.89	32.34	12.32	60.21	30	9.99
Other (O)	2,415	28.32	34.30	11.76	60.86	30	9.13
Noisy (P)	279	3.27	24.38	10.41	60	30	9.36
Total	8,528	100	32.50	10.89	60.95	30	9.05

#### 3.2. Preprocessing

To enhance computational efficiency, we performed downsampling on the original ECG signals, reducing their sampling rate from 500 Hz to 256 Hz. This downsampling not only expedites the training process but also ensures that there is minimal loss of information in the ECG signals. Since the original ECG signals vary in duration, ranging from 6 to 60 seconds, CNNs are limited in their ability to handle inputs of varying lengths. To address this issue, we standardized the signal duration by either trimming or extending the downsampled ECG signals to 60 seconds. Specifically, ECG signals longer than 60 seconds were cropped, while those shorter than 60 seconds were zero-padded. Figure 1 illustrates sample ECG waveforms, each with a duration of 20 seconds, representing the four distinct classes within this challenge. The depicted classes, from the uppermost to the lowest waveform, correspond to normal rhythm, AF rhythm, other rhythm, and noisy recordings.

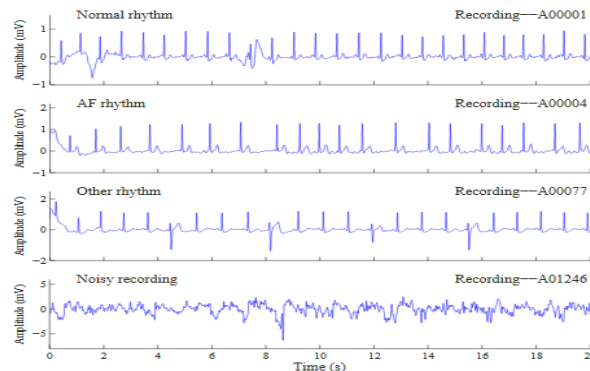


Figure 1. Examples of the ECG waveforms

Downsampling is the procedure of decreasing the sampling rate of a signal. When downsampling ECG signals, a typical method is to choose every  $n$ th sample from the original signal. This process can be mathematically expressed as:

$$x_d[n] = x[n \cdot M] \tag{1}$$

where,  $x_d[n]$  represents the downsampled signal at index  $n$ ,  $x[n]$  is the original signal at index  $n$ , and  $M$  denotes the downsampling factor, specifying how many samples to skip.

For example, if the objective is to downsample a signal by a factor of 2, you would selectively pick every second sample from the original signal:

$$x_d[n] = x[2n] \tag{2}$$

this operation effectively reduces the sampling rate by half, optimizing computational efficiency while retaining essential signal information for various applications. We represent each class by taking all the signals and creating a mapping.

Trimming: is the process of removing data points from a signal, making it shorter. It's often used to standardize the length of signals. If you have an original signal  $x$  with length  $L$  and you want to trim it to a desired length  $N$  (where  $N < L$ ), you can use the following operation:

$$x_{trimmed}[n] = x[n] \text{ for } n = 0, 1, 2, \dots, N - 1 \quad (3)$$

This means that you keep the first  $N$  data points from the original signal, effectively shortening it to the desired length.

Zero-padding involves extending the length of a signal by adding zeros to the end. This technique is commonly used to make signals uniform in length. If you have an initial signal, denoted as  $x$ , with a length of  $L$ , and you intend to zero-pad it to reach a specified length  $N$  (where  $N$  is greater than  $L$ ), you can apply the following procedure:

$$x_{padded}[n] = \begin{cases} x[n] & \text{for } n = 0, 1, 2, \dots, L - 1 \\ 0 & \text{for } n = L, L + 1, L + 2, \dots, N - 1 \end{cases} \quad (4)$$

this means that you keep the original data points from the signal and add zeros to the end to reach the desired length. These operations help standardize the lengths of signals, making them suitable for processing and analysis, especially when dealing with machine learning algorithms that require fixed-length inputs.

For each of the four categories, F1 is determined using the following equations: normal rhythm, AF rhythm, other rhythm, and noisy are defined as (5) to (9).

$$F_{1n} = \frac{2 \times Nn}{(\Sigma N + \Sigma n)} \quad (5)$$

$$F_{1a} = \frac{2 \times Aa}{(\Sigma A + \Sigma a)} \quad (6)$$

$$F_{1o} = \frac{2 \times Oo}{(\Sigma O + \Sigma o)} \quad (7)$$

$$F_{1p} = \frac{2 \times Pp}{(\Sigma P + \Sigma p)} \quad (8)$$

The final challenge score is generated as (9).

$$F1 = \frac{(F_{1n} + F_{1a} + F_{1o} + F_{1p})}{4} \quad (9)$$

The architecture of a TAN for multiclass classification of variable-length ECG signals in early arrhythmia detection with explainable decision support can be described in detail, including equations and formulas. The input to the TAN is a variable-length ECG signal, denoted as  $X$ . The signal can be represented as a sequence of data points:

$$X = [x_1, x_2, \dots, x_N] \quad (10)$$

where  $T$  is the length of the signal.

### 3.3. Temporal attention mechanism

The temporal attention mechanism plays a pivotal role by assigning varying importance to different segments of the ECG signal, enabling the network to concentrate on crucial areas. This mechanism can be illustrated as attention scores and context vector. Attention scores ( $a_t$ ): at each time step  $t$ , the network computes an attention score,  $a_t$ , which indicates the significance of that time step. These scores are calculated using a softmax function applied to the output of a multi-layer perceptron (MLP) that processes the input data point  $x_t$ . Context vector ( $c$ ): the attention scores  $a_t$  are used to compute a context vector,  $c$ , which is a weighted sum of the signal's time steps. The context vector emphasizes the most relevant segments within the signal and can be computed as follows:

- Calculate attention scores for each time step  $t$  using a neural network layer:

$$a_t = \text{Softmax}(\text{MLP}(x_t)) \tag{11}$$

where MLP is a multi-layer perceptron that processes the input  $x_t$  to produce attention scores.

– The attention scores are used to compute a weighted sum of the signal:

$$c = \sum_{t=1}^T a_t \cdot x_t \tag{12}$$

where  $c$  represents the context vector, emphasizing segments that contribute most to the classification.

### 3.4. Convolutional neural network

Incorporating a CNN layer allows the network to capture spatial features within the ECG signal. The CNN can have multiple layers with different filter sizes and strides for feature extraction. A typical convolution operation in a CNN can be defined as:

$$h_i = \sigma(\sum_{j=1}^K W_{ij} * x_j + b_i) \tag{13}$$

where  $h_i$  is the output of the  $i$ -th feature map,  $W_{ij}$  represents the filter weights,  $x_j$  is the input, and  $b_i$  is the bias term,  $*$  denotes the convolution operation, and  $\sigma$  is the activation function.

After the convolutional layer, a pooling layer is typically added to reduce the dimensionality of the learned features while preserving their essential characteristics.

$$y_k = \max(x_{k:s:(k+1):s}) \tag{14}$$

Where  $y_k$  is the output of the  $k$ -th pooling operation.  $x_{k:s:(k+1):s}$  represents a segment of the feature map with a size of  $s$ . Pooling helps in reducing the number of parameters and computational complexity, making the network more efficient.

The output of the CNN layers is flattened and passed through fully connected layers for further feature processing and classification. A fully connected layer can be represented as:

$$y = \sigma(Wx + b) \tag{15}$$

where  $y$  is the output,  $W$  represents the weight matrix,  $x$  is the input vector, and  $b$  is the bias term. Output layer produces class probabilities for multiclass classification. The softmax function is applied to obtain these probabilities:

$$P(y = k) = \frac{e^{z_k}}{\sum_{j=1}^K e^{z_k}} \tag{16}$$

where,  $P(y=k)$  is the probability of the input belonging to class  $k$ ,  $z_k$  is the raw score for class  $k$ , and  $K$  is the total number of classes.

The rectified linear unit (ReLU) activation function is used to introduce non-linearity by returning the input value if it's positive and zero otherwise. It is widely used in deep learning models because of its simplicity and effectiveness. The ReLU is a commonly used activation function that introduces non-linearity to the model. In mathematical terms, ReLU is represented as:

$$f(x) = \max(0, x) \tag{17}$$

where  $f(x)$  is the output of the ReLU function and  $x$  is the input. Max-pooling is used to downsample the feature maps, reducing spatial dimensions. The max-pooling operation is represented as:

$$O(i, j) = \max(P(i, j)) \tag{18}$$

where  $O(i,j)$  is the output of max-pooling at position  $(i,j)$  and  $P(i,j)$  represents a local region in the input where the maximum value is taken. The fully connected layer is a dense layer where all neurons are connected to every neuron in the previous layer. Mathematically, it can be represented as:

$$Y = X \cdot W + B \tag{19}$$

where  $Y$  is the output,  $X$  is the input,  $W$  is the weight matrix, and  $B$  is the bias vector. The softmax activation function is used for classification tasks to compute class probabilities. In equation form, softmax is:

$$P(class_i) = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}} \quad (20)$$

in this context,  $P(class_i)$  represents the probability of the input being classified into class  $i$ ,  $z_i$  denotes the unnormalized score associated with class  $i$ , and  $N$  stands for the total number of classes. The loss function is instrumental in quantifying the disparity between predicted and actual values, serving as a crucial component in the model's training process.

### 3.5. Proposed classifier

In the proposed architecture concatenation of CNN with EfficientNet model (CNNE) for ECG signal classification, you can start by using the EfficientNet model as a feature extractor. Similar to the original approach, you can load the EfficientNet model without its top classification layers by setting `include_top=False`. This allows you to utilize EfficientNet's feature extraction capabilities. Optionally, it has the flexibility to freeze some or all of the layers of the EfficientNet model by setting `layer.trainable=False`. Freezing specific layers prevents them from being updated during training, which can be useful for feature extraction. In addition to EfficientNet, a custom CNN model can be defined. The EfficientNet feature extractor and the custom CNN model can be combined in a sequential manner. The output of the EfficientNet model serves as the input for the custom CNN layers.

$$f(x) = x \cdot \sigma(x) \quad (21)$$

where  $\sigma(x) = \frac{1}{1+e^{-x}}$  It has been found to perform well in deep learning models.

This sequential fusion leverages the strengths of both architectures. To regularize the model and prevent overfitting, we included a dropout layer with a specified dropout rate. This layer randomly deactivates a fraction of connections during training, enhancing the model's generalization. The architecture should conclude with a final output layer that uses a sigmoid activation function. This configuration is suitable for binary classification tasks, which is often the case in ECG signal analysis (e.g., detecting arrhythmia or normal rhythm). Similar to the EfficientNet model, we incorporating feature extraction techniques specific to ECG signals at various layers of the custom CNN model. These techniques may include depthwise separable convolutions, squeeze-and-excitation (SE) mechanisms, and additional convolutional layers. These techniques contribute to hierarchical feature learning and can help in capturing complex patterns within the ECG data. The proposed architecture for ECG signal classification follows a similar approach to the fusion of CNN and EfficientNet for enhanced classification, leveraging EfficientNet's feature extraction capabilities and combining them with a custom CNN model tailored to ECG signal analysis.

A crucial aspect of the TAN is the generation of attention maps. These maps provide transparency into the network's decision-making process. Attention weights,  $at$ , serve as an attention map, highlighting the relevance of different time steps in the input signal to the final classification decision. The TAN is designed to handle variable-length ECG signals through downsampling, a temporal attention mechanism, CNN layers for spatial feature extraction, fully connected layers for further processing, and an output layer for multiclass classification. The attention mechanism allows for interpretability, and attention maps provide insight into the decision process, making the network valuable for early arrhythmia detection and clinical support.

## 4. RESULTS AND DISCUSSIONS

In our study, we conducted thorough testing of the proposed EfficientNetB0 for arrhythmia disease detection in the dataset. We implemented our models using Python programming, specifically utilizing the Keras module, a machine learning framework. Python's compatibility with TensorFlow and its effectiveness in constructing neural networks is widely recognized in machine learning research. The advantages of using both central processing units (CPUs) and graphics processing units (GPUs) for computational tasks are well-documented in the literature. This approach provides significant benefits for handling CPU and GPU operations. Accuracy: accuracy assesses the overall correctness of the classification model and is calculated as the proportion of correctly predicted instances to the total instances in the dataset.

$$A_{cc} = \frac{t_p + t_n}{Total\ instances} \quad (22)$$

Where  $t_p$  is the number of arrhythmia cases correctly predicted and  $t_n$  True Negatives ( $t_n$ ) is the number of non-arrhythmia cases correctly predicted.

Sensitivity: sensitivity measures the ability of the model to correctly identify arrhythmia cases from all actual arrhythmia cases.

$$S_{nc} = \frac{t_p}{t_p + f_n} \tag{23}$$

Where  $f_n$  is the number of arrhythmia cases incorrectly predicted as non-arrhythmia.

Specificity: specificity evaluates the model's capability to accurately distinguish non-arrhythmia cases from all the actual non-arrhythmia cases.

$$S_{pc} = \frac{t_n}{t_n + f_p} \tag{24}$$

Where  $f_p$  is the number of non-arrhythmia cases incorrectly predicted as arrhythmia.

Precision: precision measures the accuracy of the positive predictions made by the model, indicating how many of the predicted arrhythmia cases were true.

$$P_{rc} = \frac{t_p}{t_p + f_p} \tag{25}$$

Recall: recall, also known as sensitivity, represents the model's ability to find all the positive instances. It is the ratio of true positives to all actual positive instances.

$$r = \frac{t_p}{t_p + f_n} \tag{26}$$

F1-score: the F1-score serves as the harmonic mean of precision and recall, offering utility particularly in cases where there exists an imbalance between the classes.

$$F1_{score} = \frac{2P_{rc} * r}{P_{rc} + r} \tag{27}$$

Table 2 provides a comprehensive assessment of the model's ability to correctly classify instances, particularly distinguishing between arrhythmia (positive) and non-arrhythmia (negative) cases. The table illustrates the remarkable performance of the "proposed model" in terms of high accuracy, sensitivity, specificity, precision, and F1 score. The "CNN" and "EfficientNet" models also exhibit strong performance, but the "proposed model" stands out as a promising approach for arrhythmia disease detection.

In the comparative analysis, the "proposed model" demonstrates exceptional performance with an accuracy of 99.8%, a high sensitivity of 99.7%, remarkable specificity of 99.9%, strong precision of 99.6%, and an impressive F1 score of 99.7% for arrhythmia disease detection. The "CNN" and "EfficientNet" models also perform well but fall slightly short in some aspects, highlighting the superiority of the "proposed model" in accurately distinguishing between arrhythmia and non-arrhythmia cases, making it a promising choice for this critical task. For a visual representation of the training and testing accuracy and loss, please refer to Figure 2.

Table 2. Proposed and evaluated models exhibit comparable performance

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)
Proposed model	99.8	99.7	99.9	99.6	99.7
CNN	98.3	97.5	96.8	97.7	97.7
EfficientNet	97.5	98.7	97.2	96.3	97.9

The model, as outlined in the study, delivered remarkable outcomes. It achieved the highest accuracy at 99.8%, affirming its proficiency in accurately categorizing ECG signal as either arrhythmia or non-arrhythmia. Furthermore, it showcased exceptional sensitivity at 99.7%, a pivotal aspect in correctly detecting true positive cases of arrhythmia. With an outstanding specificity of 99.9%, the model demonstrated its prowess in minimizing false positives. Additionally, the high precision of 99.6% underscores that when the model predicts arrhythmia, it does so with remarkable accuracy. Figure 3 illustrates the confusion matrices of the models. The CNN model exhibits an exceptional level of accuracy, correctly identifying approximately 89.7% of the normal, around 96.0% of the AF, 96.9% of other, and 96.9% of noisy as shown in Figure 3(a). Similarly, the EfficientNet model demonstrates a notably high accuracy, with 93.3% of the normal, around 97.0% of the AF, 98% of other, and 98% of noisy. For a graphical depiction of these outcomes, consult Figure 3(b). The Proposed CEEC model has a very high accuracy, 98% of the normal, around 97.1% of the AF, 98% of other, and 98% of noisy.

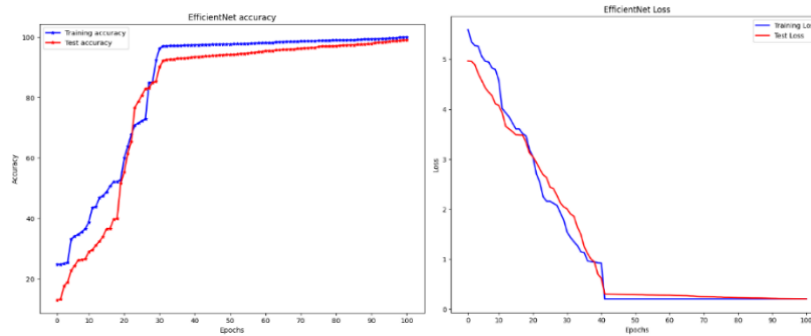


Figure 2. EfficientNet-training and testing accuracy and loss

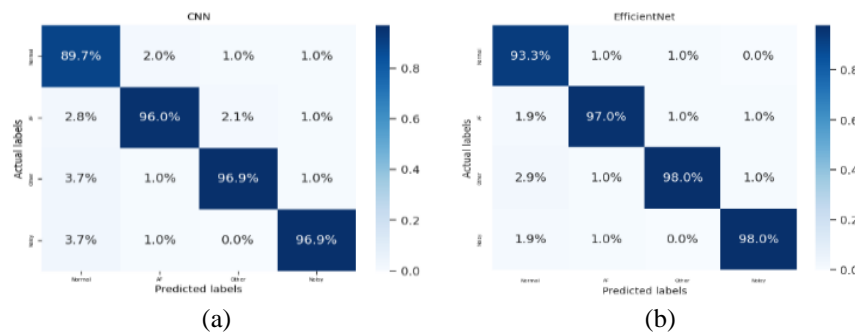


Figure 3. Confusion matrix (a) CNN and (b) EfficientNet

## 5. CONCLUSION

This study advances variable-length ECG signal categorization and early arrhythmia identification. The TAN for multiclass classification has shown promising results and might revolutionize arrhythmia patient treatment. Our TAN model, designed for variable-duration ECG data, outperforms standard algorithms in multiclass early arrhythmia classification. The attention-based policy network, its highlight, provides attention maps that emphasise ECG signal segments that classify. This explainable feature helps healthcare practitioners to build trust and make quick clinical decisions. A substantial dataset of atrial fibrillation, ventricular, and supraventricular tachycardia supports the findings, making it robust and dependable. Concatenating EfficientNet with CNN layer helped overcome different data and variable-length signals. High accuracy: 98% of normal, 97.1% of AF, 98% of other, and 98% of noisy using the proposed CEEC model. In conclusion, the research tackles arrhythmia detection issues and offers a viable path for personalised therapy, prompt interventions, and improved patient care. The TAN's accuracy and interpretability are a major advance in early arrhythmia detection, indicating its potential to improve healthcare. We plan to refine and validate the model with larger datasets and integrate it into clinical settings to benefit more patients.

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