Asian Journal of
Science, Technology, Engineering, and Art

e-ISSN: 3025-4507
p-ISSN: 3025-5287

Index: Harvard, Boston, Sydney University, Dimensions, Lens, Scilit, Semantic, Google, etc

https://doi.org/10.58578/AJSTEA.v3i4.5905

Modified Cardiac Arrhythmia Classification from Electrocardiography Signals Using a Convolutional Neural Network Model

Sabo Abdulhafiz[1], Abdulsalam Ya'u Gital[2], Sani Sabo Mohammed[3], D. M. Nazif[4]
[1]Sa'adu Zungur University, Gadau, Nigeria; [2,3]Abubakar Tafawa Balewa University, Bauchi, Nigeria; [4]Federal Polytechnic Bauchi, Bauchi, Nigeria
kyawasabo@gmail.com

Article Info:

Submitted:	Revised:	Accepted:	Published:
Apr 17, 2025	May 15, 2025	May 28, 2025	Jun 2, 2025

Abstract

Manual classification of cardiac arrhythmias from electrocardiogram (ECG) signals is a labor-intensive and error-prone process due to the complex and variable nature of cardiac waveforms. Convolutional Neural Networks (ConvNets), widely recognized for their success in image classification, offer a promising solution for automating this task. This study proposes an enhanced ConvNet-based approach for the classification of cardiac arrhythmias, leveraging AlexNet as a feature extractor. The features obtained from the convolutional layers are input into a backpropagation neural network for final classification. The proposed model was evaluated on four distinct arrhythmia conditions using ECG waveforms from the MIT-BIH Arrhythmia Database. Comparative analysis against traditional models revealed the superior performance of the proposed ConvNet architecture, achieving high scores across multiple evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. The feature extractor demonstrated robust performance, with classification accuracies of 1.00 and 0.99 on training and testing datasets, respectively. These findings underscore the potential of

ConvNet-based models to serve as efficient, accurate, and fully automated tools for arrhythmia diagnosis, contributing significantly to advancements in cardiovascular disease detection and clinical decision support systems.

Keywords: Convolutional Neural Network; ECG Classification; Cardiac Arrhythmia; Cardiovascular Diseases; Deep Learning in Healthcare

Introduction

Electrocardiogram (ECG) is a widely utilized tool in clinical medicine for the evaluation of heart health due to its low cost, simplicity, and non-invasive nature making it a preferred method for diagnosing a variety of cardiac disorders, including cardiac arrhythmias (Dilaveris et al., 1998; Elgendi et al., 2014). The rhythm of the heart in terms of beats per minute (bpm) can be easily calculated by counting the R peaks of the ECG wave during one minute of recording. More importantly, rhythm and the morphology of the ECG waveform is altered by cardiovascular diseases and abnormalities such as the cardiac arrhythmias (Rangayyan, 1999), which their automatic detection and classification is the main focus of this research. Furthermore, the distinctive characteristics of ECG signals, along with the vast amount of ECG data accessible, make them suitable for analysis and application using machine learning (ML) techniques.

However, major drawback of this machine learning techniques heavily relies on hand-crafted features, which demand extensive domain knowledge to extract effectively, making the process time consuming (Wang et al 2019). Additionally, machine learning models often encounter significant issues with vanishing gradient and over fitting, which negatively impact the performance of the training model (Chen et al 2018).

In response to the challenges faced by sallow machine learning techniques mentioned earlier, a prominent approach in deep learning is the ConvNets have been developed to address the limitation of shallow machine learning techniques. ConvNet is a deep learning model commonly used for analyzing signals, recognizing images, processing pixel data, and natural language understanding. ConvNet are effective at detecting spatial hierarchies and patterns through small, trainable filters known as kernels (Zhou et al., 2020). These kernels are adept at extracting local details from ECG data, such as the shape and duration of heartbeats, which are crucial for diagnosing arrhythmias.

In this research we proposes a classification model based on ConvNet by fine-tuning the hyper parameters which significantly impact the performance of ConvNet to address the limitations of traditional electrocardiograms (ECG) in the diagnosis of arrhythmias, which can be affected by noise and randomness of events, leading to misdiagnosis and errors. The lack of such models or frameworks that incorporates three blocks, and each block comprises two ConvNet layers, a max-pooling layer, a dropout layer, and a batch-normalization layer motivated this research.

In current medical routine, traditional electrocardiograms (ECG) have performed well in classifying cardiac arrhythmias. These advantages have provided considerable commercial interests in the computer aided classification and diagnosis of the ECG signals in hospital and health community. However, major challenges of this traditional (ECG) techniques require visual and manual interpretations, which demand extensive domain knowledge to extract effectively, making the process time consuming (Wang et al 2019), especially in cases in which the real-time diagnosis is of matter. Therefore, in recent years, the use of automated computer-aided methods for diagnosis has been significantly increased and although several methods have been proposed, this matter still attracts the attention of researchers (Said et al 2020). Recently, deep learning algorithms such as convolutional neural networks (CovNet) as an automated computer-aided method have been frequently used for different biomedical tasks and yielded encouraging results (Tian et al 2020). A quick search in the literature shows diverse methods proposed for arrhythmia classification. The authors of (Hassan et al 2024) trained a CNN-BiLSTM to classify five types of cardiac arrhythmia from the MIT-BIH dataset; the model obtained 0.98 accuracy, 0.91 sensitivity and 0.91 specificity. The authors of (Kachuee et al 2023) proposed a CNN algorithm to classify heartbeats into five classes and achieved an overall accuracy of 0.96. A study (Xu et al 2022) proposed a network of CNN-ELM to categorize five ECG arrhythmias with a recognition accuracy of 0.95. (Singh et al 2021) proposed CAD prediction model using CNN. The proposed model can discriminate between arrhythmias with an accuracy of 0.93 for the two second model and 0.94 for the five-second model. Most of the methods are based on heavy deep learning methods that use a high number of layers to detect arrhythmias. The high number of layers decelerates the training phase and later the evaluation phase resulting in sacrificing the real-time goal. Therefore, there is a need to develop a lightweight CovNet model to classify ECG arrhythmias with high accuracy.

2.0 METHODOLOGY

The proposed CovNet model is suggested for classifying cardiac arrhythmia into four phases: data acquisition, data preprocessing, training of CovNet for classifying cardiac arrhythmias and performance evaluation. The proposed classification of cardiac arrhythmias based on CovNet algorithm is shown in Figure 1.

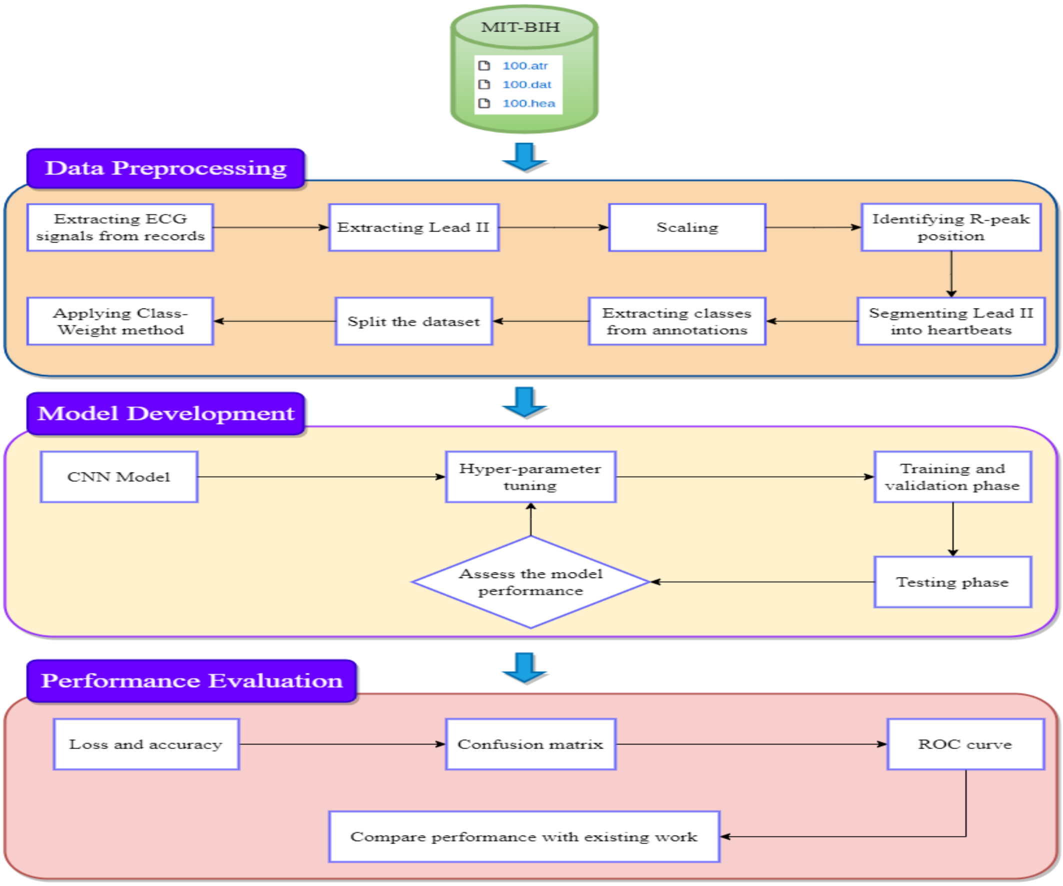


Figure 1: The proposed classification of cardiac arrhythmias based on CovNet model.

Dataset Description

In this research, the original and noise-attenuated ECG signals obtained from the MITBIH. (Moody et al, 2022) dataset are used as a data source to classify four arrhythmias according to the Association for the Advancement of Medical Instrumentation (AAMI) standard EC57 (2012). The MIT-BIH dataset contains 48 ECG recordings, thirty minutes long, obtained from 47 patients. Each record has two types of ECG signals:

LeadIIandLeadV5. There recordings were digitized across a 10 mV range at 360 Hz per channel in 11-bit resolution. In this experiment, ECGs Lead II have been extracted, scaled, and segmented into four types of arrhythmias to train and test the proposed CovNet model.

Dataset Prepossessing

The 48 ECG records were converted to NumPy arrays, and the signals from the leads II were extracted to train the model. NumPy arrays are multi-dimensional arrays used for scientific computing in Python (NumPy, 2023). They are homogeneous; meaning each element in the array must be of the same type. They are fixed-size at creation, unlike Python lists. It is a requirement that all elements in a NumPy array are of the same data type, and they are indexed by a tuple of non-negative integers. NumPy arrays are written mostly in C language and are stored in contiguous memory locations, which make them faster and more powerful than Python lists. Each extracted signal was scaled and segmented into heart beats with a window length of 180 features for each heartbeat centered around the R-peak. The steps of extracting the heartbeats from the ECG signal II are described in Figure 2.

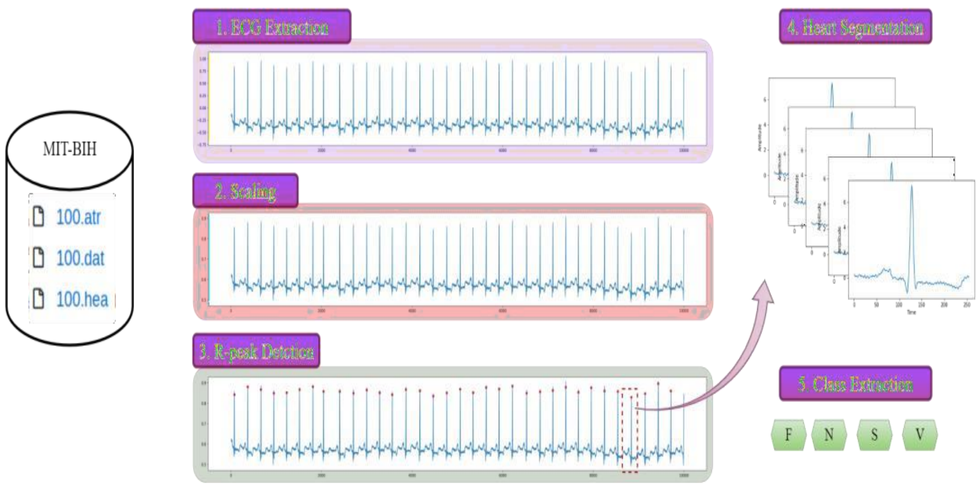


Figure 2: Heartbeat extraction pipeline.

Heartbeat Extraction

To extract the heartbeats from the MIT-BIT lead II, we propose a simple yet effective method (a visual representation is shown in Table 1) to extract heartbeats from signals. The main steps of the extraction method are described as follows:

- Extracting ECG lead II signals from the patient records and converting them into NumPy array.
- Scaling the extracted signals to ensure that all signals have the same mean and standard deviation, which helps classify several arrhythmias correctly.
- Detecting the R-peak position using XQRS from the WFDB library to segment the heartbeats.
- Segmenting the signal into heartbeat windows with a length of 180 features in each window centered around the R-peak position.
- Extract each heartbeat class from the annotations given by cardiologists in the dataset.

Table 1: Arrhythmia classes, related annotation and sample size of each class in the dataset

Class	**Annotation**	**Sample Size**
N	Normal Left/Right bundle branch block Atrial escape Nodal escape	89,649
S	Atrial premature Aberrant atrial premature Nodal premature Supra-ventricular premature	2114
V	Premature ventricular contraction Ventricular escape	6487
F	Fusion of ventricular and normal	779
	Total	99,774

Table 1 shows the categorization of the four types of ECG heart beats, which are divided into four classes according to (AAMI, 2012).

It is essential to high light that the proposed technique extracts all the key regions, such as QRS Complex, P-wave and T-wave that are generally used by cardiologists to identify arrhythmia. Moreover, all extracted beats contain exact window sizes, which is crucial to train the model.

Data Preparation

After segmenting the signals into heartbeats, the total number of heartbeats is 99,774 for the 48 records. Each class contains a different number of heartbeat samples. The heartbeats are categorized into 89,694 for normal beats, 6487 for ventricular ectopic beats, 2814 for supraventricular ectopic beats, 779 for fusion beats, and 24 for unknown beats. The unknown beats have dropped because they contain unclassified beats and have a significantly lower number of instances (Gai et al 2023). The heartbeats were split into 75% (74,830 samples) for training and validation and 25% (24,944samples) for testing. We used the stratify parameter to ensure that all the classes had been split equally into the training and testing data. The utilization of the stratify parameter guarantees that the proportion of samples is maintained consistently across each class, for both the training and testing data. The training and validation dataset splits into 80% (59,864 samples) for training and 20% (14,966 samples) for validation.

Table 2 shows a significant imbalance among the four classes (i.e., class 'N' has 89,694, while class 'F' has only 779). An unbalanced dataset leads to a classification bias toward classes with more samples, which leads to deficient performance in classifying categories with fewer samples (Hosgungor et al, 2023). Therefore, estimating class-weight technique (Pedregosa et al, 2022) is applied to balance the datasets. The class-weight technique adjusts the model's cost function such that misidentifying an instance belonging to a minority class incurs a more significant penalty than misidentifying an example belonging to a majority class (Chou et al, 2020). This strategy can improve the model's accuracy by rebalancing the class distribution.

Training of Convolutional Neural Network (CovNet) for Classifying Cardiac Arrhythmia

Convolutional neural network (CovNet) is a deep learning network that can infer high level features from input features (Feng et al. 2022). A CovNet is conceptually comparable to a multilayer perceptron (MLP), where each neuron possesses an activation function that translates the weighted inputs into the outputs. CovNet consist of three main layers: the convolutional layer, the pooling layer, and the fully connected layer. With proper training, CovNet can be utilized in many applications, including speech recognition (Chan et al. 2022), structure engineering (Yu et al. 2022; samali et al. 2022), and image processing (Ding et al. 2021). Here are a few reasons why CovNet s are particularly well suited for signal data:

- Time-invariant feature learning: A CovNet is able to learn time-invariant features from a signal, meaning that it is able to extract features that are robust to small shifts in time. This is important for signal data because signals are often affected by noise, variations in the measurement scale, and non-stationary. With a CovNet, a network can learn to extract relevant features that are robust to these variations, resulting in improved performance.
- Local feature extraction: In CovNet, the convolutional layers are able to extract

local features from the signal, which are important for signal data, as signals are often composed of local patterns. These patterns could be variations, such as frequency, amplitude, or shape, which the CovNet is able to learn and extract.

- Translation invariance: CovNet s are also translation invariant, which means that they are able to detect the same pattern, regardless of its location in the signal. This is particularly useful for signals where the location of the pattern is not known. Multiscale feature learning: The combination of convolution and pooling operations in a CovNet allows the network to learn features at different scales and resolutions, which is useful for signal data because signals often have patterns at different scales. This property, along with the ability of CovNet to learn complex and abstract feature representations, makes them a good fit for signal data. Algorithm 1 shows an example of the basic structure of a CovNet algorithm in pseudo code

Algorithm1. The CovNet pseudo codes.

CovNet model architecture

```
Input: input_data, test_data, filter, kernel, blocks, cls_weight Output: Predictions
Start Algorithm (CovNet)
1      | model = Sequential ()
2      | For (block in blocks) do
3      | model. Add (Conv1D (filter, (kernel,), activation = 'relu')
4      | model. Add (Conv1D (filter, (kernel,), activation = 'relu')
5      | model. Add (MaxPooling1D (2))
6      | model. Add (Dropout (0.2))
7      | model. Add (Batch Normalization ())
8      | End; //For loop
9      | model. Add (Flatten ())
10     | model. Add (Dense (512), activation = 'relu')
11     | model. Add (Dropout (0.2))
12     | model. Add (Dense (4), activation = 'softmax') Phase 1, Compile the model
       |model. Compile (loss = 'sparse_categorical_crossentropy',
13     optimizer = Adam (learning_rate = 0.001, decay = 1e−6),
        metrics = ['accuracy'])
       Phase 2, Fit the model
       | model. Fit (input_data, batch_size = 512,
14     epochs = 500,
       validation_split = 0.20,
       class_weight = cls_weight)
       Phase 3, Predict   arrhythmias
       | Predictions = model. Predict (test_data)
        | Return Predictions
15     End;//Algorithm
```

This pseudocode assumes that the CovNet class has already been implemented with functions for applying filters and combining output and that the convolutional and fully connected layers are stored in lists within the CovNet object. The input data are passed through the convolutional layers, with each layer applying a set of filters to the input using 1D convolution and producing output data. The output data from the final convolutional layer is then passed through the fully connected layers, with each layer combining the output from the previous layer into a single set of predictions. The final set of predictions is then returned as the output of the CovNet.

Due to its compact and simple configuration performance, CovNet is also suitable for real-time applications and low-cost hardware implementations. Equation (1) represents a single convolution of a signal, $x^n_1 = [x_1, x_2, ...,x_n]$, in which n denotes the total number of points . (Malkhodari et al. 2021), h denotes the activation function, l denotes layer index, b denotes the bias of the j^{th} feature map, M denotes the kernel size, $W^j{}_m$ denotes the feature map's weight and mth denotes the filter index.

$$C^{lj}_i = h(b_j + \sum^M_{m=1} W^j_m \, x^j{}_{i+m-1}) \qquad (1)$$

This research developed a modified cardiac arrhythmia classification from ECG lead II using ConvNet. An intensive experiment was conducted to select the minimal model architecture with optimal parameters to improve the model performance. The architecture of the proposed model is represented in Figure 3.

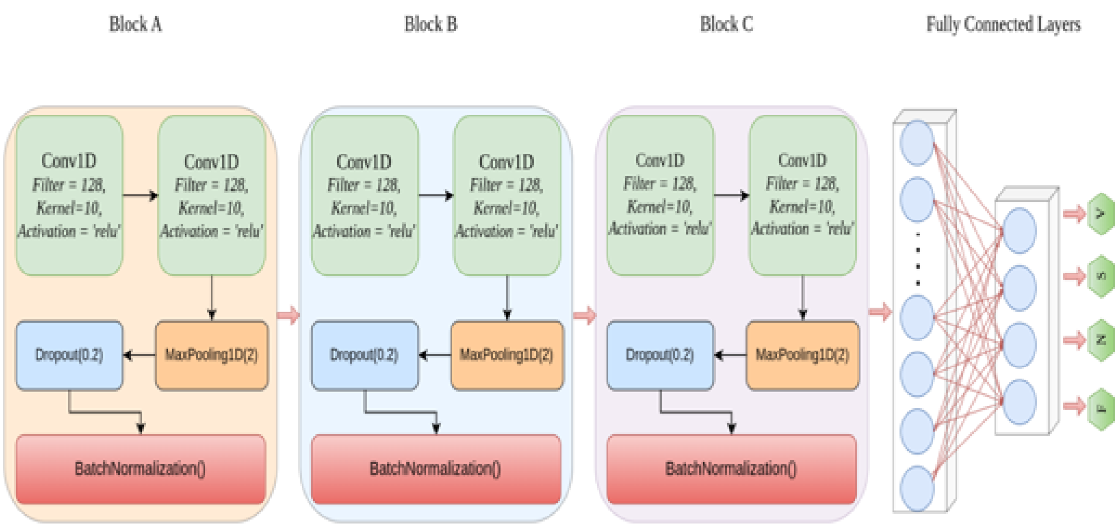


Figure 3: The proposed CovNet model architecture

Figure 3 shows that the model consists of three convolution blocks (A, B, C). Each block contains two 1D-CNN layers, a max-pooling layer, a dropout layer, and a batch normalization layer. Each CovNet layer contains 128 filters with a kernel-window size of 10 for each filter. Each layer of a CovNet is activated using the rectified linear unit (ReLU) function. Activation functions are crucial to increase the expressiveness of neural networks and enhance the approximation capability between the network's different layers (Zheng et al. 2020).

The max-pooling layer is applied after the CovNet with a pooling size of two to highlight the most present feature by calculating the largest value in each patch. To accelerate the learning speed of the model structure, max-pooling down-samples the input representation by selecting the largest value inside a spatial region (Zheng et al. 2020). The setting of the network hyper parameters was determined through an empirical approach, involving experimentation with different values to find the optimal configuration.

As shown in Table 3, to reduce the over fitting, a dropout layer of 0.20 and the normalization layer were applied (Kiranyaz et al. 2021). During the training period, the dropout layer randomly sets the inputs at each step with zero frequency. Dropout regularization reduces interdependence between layers by probabilistically dropping some of the nodes in the same layer.

Table 2: Parameter tuning of the proposed model.

Parameter	Value
Filter	128
Kernel size	10
Dropout	0.2
Learning rate	0.001
Decay	$1\times10-6$
Batch size	512
Epoch	500

The normalization of CovNet layers accelerates model convergence during training and prevents gradient growth (Jason et al. 2022). In addition, the batch-normalization layer guarantees that the transformation of the various batches remains within a specified range, stabilizing the learning process and accelerating the parameters' convergence (Zheng et al. 2020).

The fully connected layer combines the information from the preceding layers to create the final output. In the flatten layer, the preceding layer's output is transformed into a single vector to be implemented as input for the dense layer. Each neuron in the dense layer gets the outputs of all neurons in the layer underneath it and conducts matrix-vector multiplication. Table: 4 illustrate the proposed structure of the CovNet model. The first dense layer has 512 nodes and an activation function of ReLU, followed by a 0.20 dropout layer. The second dense layer consists of four nodes, each representing a class, and a Soft Max activation function to classify the output into four arrhythmia types. The model was fitted with sparse cross-entropy as the loss function and the Adam optimizer with a learning rate of 0.001 and a decay factor of 1×10−6 as the optimization function. The model fits the training and validation datasets with 512-epoch batches and 500 iterations.

Experimental Results

Performance Matrices

The confusion matrix and AUC-ROC curve, frequently used to assess machine learning models, were used to assess the model performance. Specifically, the model is evaluated using accuracy, precision, recall (sensitivity), f1 score, specificity, and ROC curve, which are described below

Accuracy: how often the model is correct. The TP and TN denote true positive and true negative, respectively, whereas FP and FN denote false positive and false negative, respectively

$$Accuracy = \frac{TP+TN}{TP + FP + FN + TN} \tag{2}$$

Precision: how often the model predicts a class as positive relative to the total number of positives in all classes.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Recall: how many times the model correctly predicts the class to be positive.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Specificity: Specificity is defined as the proportion of true negatives correctly identified by the model. It is also referred to as the true negative rate (TNR) or selectivity. It measures the ability of the model to accurately identify negative examples.

$$Specificity = \frac{TN}{FP + TN} \tag{5}$$

Sensitivity: The ratio of the prediction of abnormal or cardiac arrhythmia class is called the sensitivity of the model and can be determined using Equation (11).

$$Sensitivity, S_E = \frac{TP}{TP + FN} \tag{6}$$

F1-score describes the weighted average of recall and precision.

$$F1_{score} = \frac{2 * recall * precision}{recall + precision} \tag{7}$$

AUC-ROC Curve: The Area Under Curve (AUC) is a measure of the thresholds between true and false-positive rates. The Receiver Operating Characteristic curve (ROC) visually illustrates the trade-off between sensitivity and specificity, where the *x*-axis represents the false-positive rate, and the *y*-axis represents the true-positive rate. The AUC evaluates the capability of the ROC curve to distinguish between classes. The larger the AUC number, the better the performance.

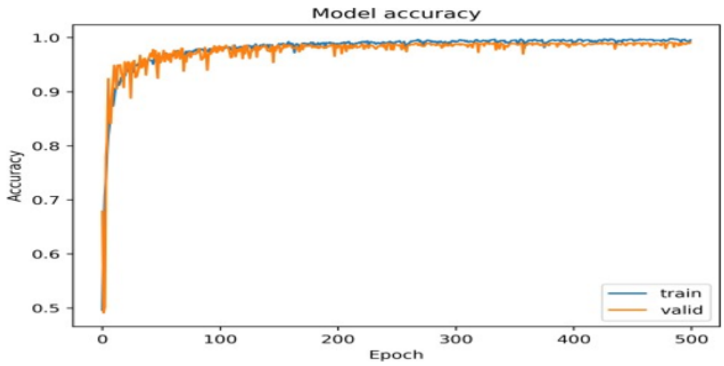
$$AUC = \frac{1}{2}\frac{TP}{TP+FN} + \frac{TN}{TN+FP} \tag{8}$$

Performance of the Proposed Method

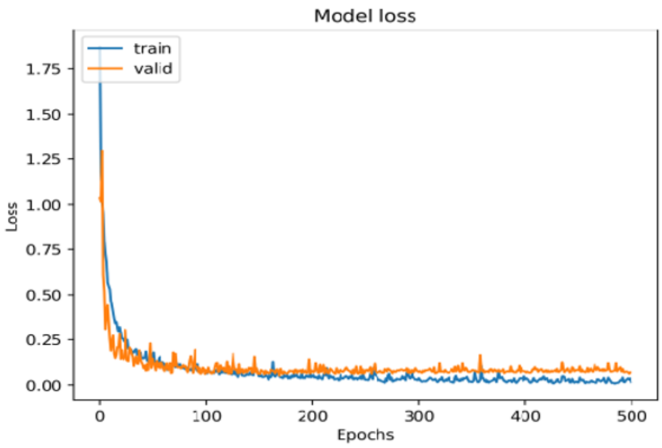
The experimental dataset used in this work is from the MIT-BIH, which is currently used in a lot of ECG research and contains accurate and thorough expert annotation (Boursalie et al 2015); (Zhang et al 2022). As discussed in Section 3, the ECG lead II signals of the 47 patients have been extracted, scaled, and segmented into heartbeats. The working environment for training the model consisted of one NVIDIA GeForce GTX 1070 GPU with 16 GB of RAM.

The initial phase of the experiments involved dividing the dataset into 75% (74,830 samples) for training and validation and 25% (24,944 samples) for testing. The model was trained for 500 epochs with a batch size of 512 per epoch. The accuracy and loss curves of the conducted experiment are illustrated in Figure 8. The loss function in CovNet quantifies the discrepancy between the expected outcome and the outcome produced by the CovNet algorithm. It is used to measure how far an estimated value is from its true value (Heaton et al 2018). In this experiment, the sparse categorical cross entropy loss function is used for our multiclass classification task. This loss function computes the logarithm of the output index, which is indicated by the ground truth. This means that the loss is computed only once per instance and the summation is omitted, leading to better performance (Heaton et al 2018). The formula for the sparse categorical cross entropy loss is as follows:

$$J(w) = -log\, \hat{y}_y$$



(a) Accuracy Curve



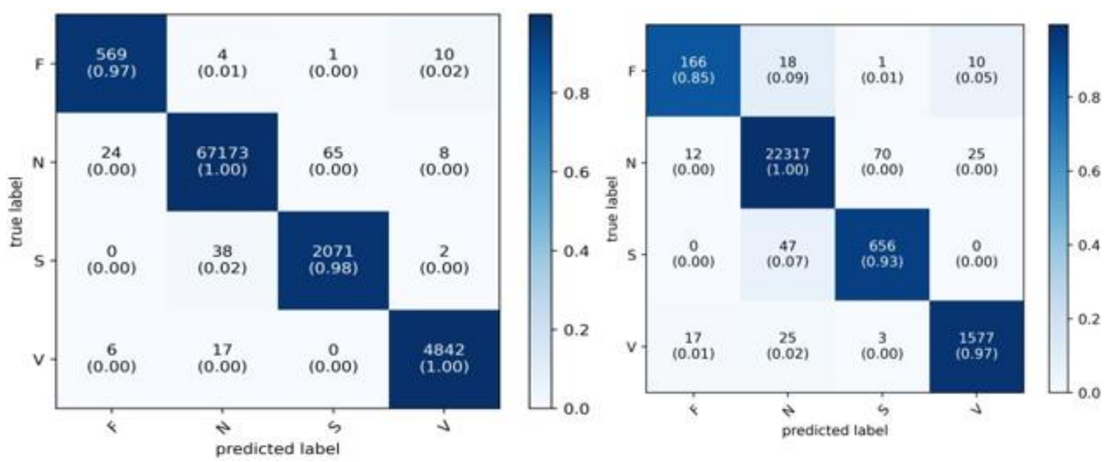
(b) Loss Curve

Figure 4: Accuracy and loss curves of the CovNet model.

Figure 4 shows that both the training and validation curves increased in a stable manner. Furthermore, the proposed model achieved remarkable precision, recall, f1-score, AUC, average accuracy, and loss in the training and testing datasets. Table 4 shows the performance matrices used to evaluate the model in the training and testing datasets. It is worth mentioning that all the numbers in the manuscript have been rounded to 2 decimal numbers. The average in the table refers to the mathematical mean of all classes in a particular measurement without considering the proportion of each class in the dataset. For example, in the training dataset, the model scores an average of 0.99 per cent in recall, and 0.98 per cent in precision and f1-score, respectively. Amongst the four classes, class N and class V secure perfect results of 1.00 in all matrices, whereas class F scores the worst, with 0.95, 0.97, and 0.96 in precision, recall and f1-score, respectively. Figure 5 presents the number of correctly and incorrectly classified samples in the training and testing dataset, along with their percentages.

Table 3: Confusion matrix report of CovNet model.

Matrix	**Training Dataset**					**Testing Dataset**				
	F	**N**	**S**	**V**	**Average**	**F**	**N**	**S**	**V**	**Average**
Precision	0.95	1.00	0.97	1.00	0.98	0.85	1.00	0.90	0.98	0.93
Recall	0.97	1.00	0.98	1.00	0.99	0.85	1.00	0.93	0.97	0.94
F1-score	0.96	1.00	0.98	1.00	0.98	0.85	1.00	0.92	0.98	0.93
AUC	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00
Accuracy			1.00					0.99		
Loss			0.02					0.06		

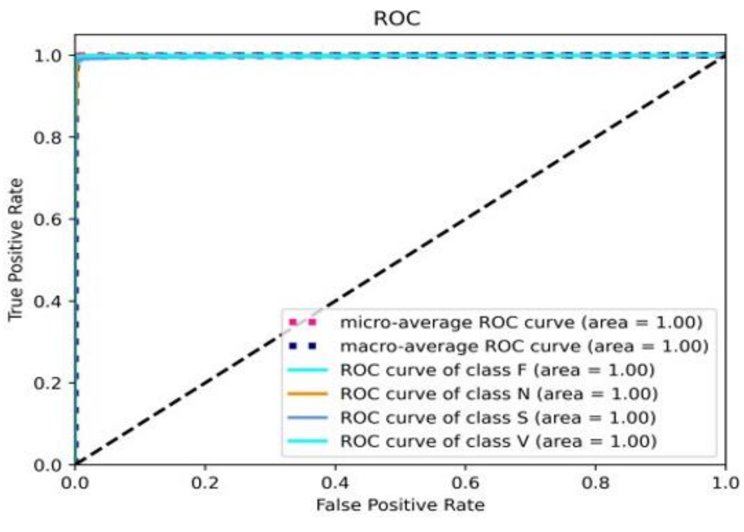


(a) Training-based confusion matrix. (**b**) Testing-based confusion matrix.

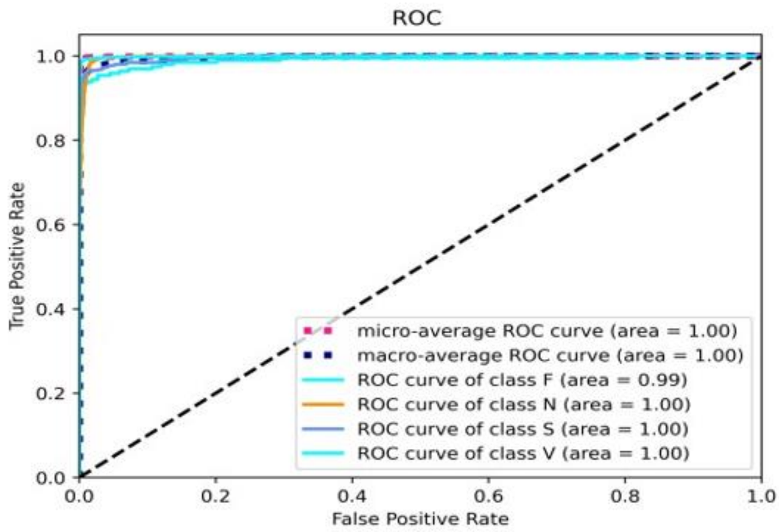
Figure 5: Confusion matrix of the CovNet model for arrhythmia categorization.

In the test dataset, the average of all classes decreased by 0.5 per cent in all classes compared to the training dataset, with overall 0.93, 0.94, and 0.93 precision, recall and f1-score, respectively. Class N is still in the lead with a perfect score in all performance matrices, while class V dropped 0.02 per cent in precision and f1-score and 0.03 per cent in recall. Class S dropped 0.07 per cent in precision, 0.05 per cent in recall and 0.06 per cent in F1-score. Even though the class weight technique has been applied to adjust the cost function of the model, class F is still the worst class, with 0.85 per cent in all classes with a 0.10 per cent drop. We can relate the low score of class F to the sample size, which only has 584 and 195 samples; among them, only 15 and 29 samples were misclassified in the training and testing datasets, respectively.

AUC is another measurement score to evaluate the model's performance in discriminating between classes. It measures the trade-off between the true-positive and false-positive rates, which can graphically represent using the ROC curve. Figure 8 shows the ROC curve on the training and testing datasets. The figure shows a perfect score in all classes in the training and testing datasets except class F in the testing set with 0.99 per cent.



(a) Training-based ROC curve



(b)Testing-based ROC curve

Figure 6: ROC curve of the CovNet model for arrhythmia classification.

Micro-average and macro-average are two ways of summarizing the information of the multiclass ROC curves. Micro-averaging aggregates the contributions from all the classes to compute the average metrics as follows:

$$TPR = \frac{sum(TP_c)}{sum(TP_c+FN_c)}; \qquad FPR = \frac{sum(FP_c)}{sum(TP_c+TN_c)} \tag{9}$$

Macro-averaging requires calculating the metric individually for each class and then averaging the results, hence treating all classes equally a priori.

Comparison of the Proposed Method to Other Previous Works

Further comparison with existing work in the literature showed that our proposed network scores superior performance in distinguishing different classes exceeding traditional and deep learning models. Furthermore, the experiment in this research achieved excellent accuracy compared to existing works in the literature, with total training and testing dataset accuracy of 1.00 and 0.99 per cent, respectively. Compared to traditional machine learning models such as (Acharya et al 2019; Hosseini et al 2021; marinho et al) the proposed CovNet model exceeds them in terms of accuracy with an estimate of 0.05 to 0.02 percent. Moreover, machine learning models tend to apply feature engineering to select high-weight features to reduce complexity. For instance, (Xie et al 2021) used Fourteen features from ECG signals to train SVM and DTs to diagnose cardiac arrhythmia. The authors of (Midani et al., 2023) trained a Naïve Bayes model using only four features. Using such an approach in ECG signals might cause losing important features and break up the temporal relationships between features (Cui J et al. 2021). Moreover, feature engineering requires additional processes to choose the feature selection method and the best number of features to train the model. On the other hand, the deep learning approach automatically reduces feature complexity while training the model. CNN, for instance, can automatically learn the unique relationships between features. Therefore, CNN is commonly used with spatially related data due to its ability to effectively model spatial localities using shared weights for the filters (Huang et al. 2022). Table 4 summarizes selected state-of-the-art studies and compares them to our work. It is worth mentioning that all the existing work in Table 4 used the MIT-BIH dataset.

Table 4: Existing work for arrhythmia classification from ECG signals

Author	Classifier Recall	Classes	Accuracy	Sensitivity	Specificity
(Xie et al 2021)	CNN	5	0.92	0.82	0.96
(Yong et al. 2021)	XDM	4	0.93	0.47	0.94
(Cui J et al. 2021)	FFBPNN	2	0.88	0.92	0.83
(Peimankar and Puthusserypady 2022)	CNN-LSTM	5	0.93	0.93	0.92
(Yuanlu et al. 2022)	CNN	4	0.96	0.69	0.95
(Ojha et al., 2022)	CNN-SVM	2	0.98	0.96	0.97
(Huang et al. 2022)	2D-CNN	5	0.94	0.77	0.98
(Hassan et al. 2023)	CNN-BiLSTM	5	0.97	0.91	0.91
(Midani et al., 2023)	CNN + BiLSTM	4	0.98	0.94	0.98
(Ahmed et al. 2023)	1D-CNN	12	0.95	0.96	0.97
Our work	CovNet	**4**	**0.99**	**0.94**	**0.99**

Compared to CovNet models such as (Ahmed et al. 2023), the proposed model exceeds in terms of accuracy with an estimate of 0.04 per cent, respectively. Moreover, our model scores higher specificity with an estimate of 0.02 per cent. Similarly, (Huang et al. 2022) developed a model with thirteen layers of 2D CNN to predict five types of arrhythmias and achieved less than our model with an estimate of 0.05 and 0.01 in accuracy and sensitivity. Compared to hybrid models that combine two architectures such as (Hassan et al. 2023), our CovNet model surpasses them by at least 0.02 per cent in accuracy and sensitivity and 0.08 per cent in specificity. In (Ojha et al., 2022) a deep learning model combining CNN and SVM is developed to classify the normal and abnormal beats from ECG signals. Our model scores better in accuracy sensitivity and specificity with 0.01, 0.03, and 0.02, respectively. In (Hassan et al. 2022), a CNN-BiLSTM model is developed to classify five types of arrhythmias and scored 0.01 less than our model in accuracy and specificity.

Conclusion

In clinical routine, computer aided diagnosis of cardiac arrhythmias can reduce the workload of cardiologists dramatically enabling them to focus more on treatment rather than diagnostics. In this research, an efficient transferred deep learning-based ECG classification system is realized to carry out automatic ECG arrhythmia diagnostics by classifying patient ECG's into corresponding four different cardiac conditions; normal beats, ventricular ectopic beats, supraventricular ectopic beats and fusion beats. After the ECG records are acquired from the online MIT-BIH arrhythmia database, they are filtered from noises and QRS waves are detected to extract R-T segments of the ECG. Pre-trained AlexNet, is transferred and used as a feature extractor for the ECG classification task in hand. The extracted features are fed into a simple back propagation neural network to classify the input ECG R-T segments into one of the four cardiac conditions. The proposed CovNet model has demonstrated its efficiency in predicting four arrhythmia classes with an outstanding performance. Additionally, transferring a pre-trained deep CovNet eliminates the need for high expertise and computational power required for training a deep convolutional neural network from scratch. The distribution of categories in the MIT-BIH dataset we used for training and testing was quite unbalanced. Even though we have addressed the imbalance with the class weight approach, the imbalance of the data still has some impact on the model generalization. Furthermore, cardiac arrhythmias can vary greatly between patients; therefore, a larger dataset is needed to train deep learning models to handle such variability and to better generalize new cases, which will be our aim in future work.

References

Acharya, U.R.; Oh, S.L.; Hagiwara, Y.; Tan, J.H.; Adam, M.; Gertych, A.; San Tan, R. (2017). *A deep convolutional neural network model to classify heartbeats*. Comput. Biol. Med, 89, 389–396. [CrossRef]

Amanullah MA, Habeeb RAA, Nasaruddin FH, Gani A, Ahmed E, Nainar ASM, Imran M (2020). *Deep learning and big data technologies for IoT security*. Compute Commun. https://doi.org/10.1016/j. comcom.2020.01.016.

Ansari, M. Y., Abdalla, A., Ansari, M. Y., Ansari, M. I., Malluhi, B., Mohanty, S., et al. (2022a). *Practical utility of liver segmentation methods in clinical surgeries and interventions.* BMC Med. imaging 22, 97–17. doi:10.1186/s12880-022-00825-2

Banerjee R, Ghose A, Khandelwal S (2019). *A Novel Recurrent Neural Network Architecture for Classification of Atrial Fibrillation Using Single-lead ECG.* Paper presented on the 27th European Signal Processing Conference (EUSIPCO)

Boursalie, O.; Samavi, R.; Doyle, T.E. M4CVD (2015): *Mobile machine learning model for monitoring cardiovascular disease.* Procedia Comput. Sci., 63, 384–391. [CrossRef]

Butun, E.; Yildirim, O.; Talo, M.; Tan, R.S.; Acharya, U.R. (2019) *1D-CADCapsNet: One dimensional deep capsule networks for coronary artery disease detection using ECG signals*. Phys. Med., 70, 39–48. [CrossRef]

Cai W, Chen Y, Guo J, Han B, Shi Y, Ji L, Luo J (2020). *Accurate detection of atrial fibrillation from 12-lead ECG using deep neural net-work.* Comput Biol Med 116:103378

Chandrasekar, V., Ansari, M. Y., Singh, A. V., Uddin, S., Prabhu, K. S., Dash, S., et al. (2023). *Investigating the use of machine learning models to understand the drugs permeability across placenta*. IEEE Access 11, 52726–52739. doi:10.1109/access.2023.3272987

Chang K-C, Hsieh P-H, Wu M-Y, Wang Y-C, Chen J-Y, Tsai F-J, Huang T-C (2020). *Usefulness of Machine-Learning-Based Detection and Classification of Cardiac Arrhythmias with 12-Lead Electrocardiograms.* Canadian Journal of Cardiology

Chan, W.; Park, D.; Lee, C.; Zhang, Y.; Le, Q.; Norouzi, M. SpeechStew: (2022) Simply Mix All Available Speech Recognition Data to Train One Large Neural Network.arXiv, arXiv:2104.02133. Available online: Http://arxiv.org/abs/2104.02133

Chou, Y.H.; Hong, S.; Zhou, Y.; Shang, J.; Song, M.; Li, H. Knowledge-shot learning (2020): *An interpretable deep model for classifying imbalanced electrocardiography data*. Neuro computing, 417, 64–73. [CrossRef]

Chuanqi Han, Peng Wang, RuoranHuang, and Li Cui, "HCTNet (2022): An experience-guided deep learning network for inter-patient arrhythmia classification on imbalanced dataset," Biomedical Signal Processing and Control, vol. 78, pp. 1039.

Ding, K.; Ma, K.; Wang, S.; Simoncelli, E.P. (2021) *Comparison of Full-Reference Image Quality Models for Optimization of Image Processing Systems*. Int. J. Comput. Vis., 129, 1258–1281. [CrossRef]

Diker A, Engin A (2019). *Feature extraction of ECG signal by using deep feature.* Paper presented at the 7th International Symposium on Digital Forensics and Security (ISDFS)

Elgendi, M, Eskofier, B, Dokos, S, Abbott, D (2014). *Revisiting QRS detection methodologies for portable, wearable, battery-operated, and wireless ECG systems*. PLoS ONE, e84018. [CrossRef]

E. Essa and X. and Xie (2021) "*An Ensemble of Deep Learning-Based Multi-Model for ECG Heartbeats Arrhythmia Classification,"* IEEE Access, vol. 9, pp. 103452-103464.

Feng, S.H.; Xu, J.Y.; Shen, H.B. (2022) *Artificial intelligence in bioinformatics: Automated methodology development for protein residue contact map prediction*. In Biomedical Information Technology; Academic Press: Cambridge, MA, USA, pp. 217–237. Available online: https://www.sciencedirect.com/science/article/pii/B9780128160343000079

Gai, N.D. (2023): *ECG beat classification using machine learning and pre-trained convolutional neural networks*. arXiv, arXiv: 2207.06408. Available online: Http://arxiv.org/abs/2207.

Gite, S.; Mishra, A.; Kotecha, K. (2022). *Enhanced lung image segmentation using deep learning. Neural Comput.* Appl., 1–15. [CrossRef]

Hassan, S.U.; Zahid, M.S.M.; Husain, K. Performance comparison of CNN and LSTM algorithms for arrhythmia classification. In Proceedings of the (2020). *International Conference on Computational Intelligence (ICCI), Bandar Seri Iskandar, Malaysia*, 8–9 October 2020; pp. 223–228. Available online: https://ieeexplore.ieee.org/abstract/document/9247636/.

Hu, H.; Zhang, Z.; Xie, Z.; Lin, S. Local relation networks for image recognition (2022). *In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV),* Seoul, Korea, 27 October–2 November 2019; pp.3464–3473. Availableonline:http://openaccess.thecvf.com/content_ICCV_2019/

Hong, S., Zhou, Y., Shang, J., Xiao, C., and Sun, J. (2020). *Opportunities and challenges of deep learning methods for electrocardiogram data: A systematic review.* Comput. Biol. Med. 122, 103801. doi:10.1016/j.compbiomed.2020.103801

Hosgungor,E."HowtoHandleImbalanceDataandSmallTrainingSetsinML.(2023)"*TowardsDataScience,Medium*, Available online: https://towardsdatascience.com/how-to-handle-imbalance-data-and-small-training-sets-in-ml-989f8053531d.

Jason, B. (2022). *A Gentle Introduction to Batch Normalization for Deep Neural Networks—Machine Learning Master.* Available online: https://machinelearningmastery.com/batch-normalization-for-training-of-deep-neural-networks.

Jianfeng Cui, Lixin Wang, Xiangmin He, Victor Hugo C. De Albuquerque, Salman A. AlQahtani and Mohammad Mehedi Hassan (2021): *"Deep learning-based multidimensional feature fusion for classification of ECG arrhythmia," Neural Computing and Applications.*

Kiranyaz, S.; Avci, O.; Abdeljaber, O.; Ince, T.; Gabbouj, M.; Inman, D.J. 1D (2021) *convolutional neural networks and applications:* A survey. Mech. Syst. Signal Process, 151, 107398. [CrossRef]

Kiranyaz,S.; Ince, T.; Gabbouj, M. (2022). *Personalized monitoring and advance warning system for cardiac arrhythmias.* Available online:https://www.nature.com/articles/s41598-017-09544-z [CrossRef] [PubMed]

Koppad, D. (2021). *Arrhythmia classification using deep learning: A review.* WSEAS Trans. Biol. Biomed. 18, 96–105. doi:10.37394/23208.2021.18.11

Latif, G.; al Anezi, F.Y.; Zikria, M.; Alghazo, J. (2020). *EEG-ECG Signals Classification for Arrhythmia Detection using Decision Trees*. In Proceedings of the 4th International Conference on Inventive Systems and Control, ICISC, TamilNadu, India, 8–10 January 2020; pp. 192–196. [CrossRef]

MAlkhodari, M.; Fraiwan, L. (2021). *Convolutional and recurrent neural networks for the detection of valvular heart diseases in phonocardiogram recordings*. Comput. Methods Programs Biomed. [CrossRef]

Midani, W., Ouarda, W., and Ayed, M. B. (2023). *DeepArr: an investigative tool for arrhythmia detection using a contextual deep neural network from electrocardiograms (ECG) signals*. Biomed. Signal Process. Control 85, 104954. doi:10.1016/j.bspc.2023.104954

NumPy. NumPy Array Objects. NumPy18 December (2023). *Available online: https://numpy.org/doc/stable/reference/arrays.html.*

Nurmaini, S., Tondas, A. E., Darmawahyuni, A., Rachmatullah, M. N., Partan, R. U., Firdaus, F., et al. (2020b). *Robust detection of atrial fibrillation from short-term electrocardiogram using convolutional neural networks*. FutureGener.Comput. Syst. 113, 304–317. doi:10.1016/j.future.2020.07.021

Ojha, M. K., Wadhwani, S., Wadhwani, A. K., and Shukla, A. (2022). *Automatic detection of arrhythmias from an ECG signals using an auto-encoder and SVM classifier.* Phys. Eng. Sci. Med. 45, 665–674. doi:10.1007/s13246-022-01119-1

P. Singh and A. Sharma, (2022): *"Interpretation and Classification of Arrhythmia Using Deep Convolutional Network,"* IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 2518512.

Peimankar, A., and Puthusserypady, S. (2021).DENS-ECG: *A deep learning approach for ECG signals delineation*. Expert Syst. Appl. 165, 113911. doi:10.1016/j.eswa.2020.113911

Pedregosa,F.;Varoquaux,G.;Gramfort,A.;Michel,V.;Thirion,B.;Grisel,O.;Blondel,M.;Prettenhofer, P.; Weiss, R.; Dubourg, V. Scikit-learn: (2020) *Machine learning in Python*. J. Mach.Learn.Res2825–2830.Availableonline:https://www.jmlr.org/papers/volume12/pedregosa11a/pedregosa11a.pdf? ref=https://githubhelp.com

Ribeiro AH, Ribeiro MH, Paixão GM, Oliveira DM, Gomes PR, Canaz-art JA, Wagner M Jr (2020). *Automatic diagnosis of the 12-lead ECG using a deep neural network*. Nat Commun 11(1):1–9

Shadhon Chandra Mohandas, Mohammod Abdul Motin, Dinesh Kant Kumar, (2022) *"Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model,*" Sensing and Bio-Sensing Research, vol. 37, pp. 100502.

Shaker AM, Tantawi M, Shedeed HA, Tolba MF (2020). *Generalization of Convolutional Neural Networks for ECG Classification Using Generative Adversarial Networks*. IEEE Access 8:35592–35605

Sun, J.-Y., Shen, H., Qu, Q., Sun, W., and Kong, X.-Q. (2021). *The application of Deep Learning in electrocardiogram:* where we came from and where we should go? *Int. J. Cardiol.* 337, 71–78. doi:10.1016/j.ijcard.2021.05.017

Srivastava, N.; Hinton, G.; Krizhevsky, A.; Sutskever, I.; Salakhutdinov, R. Dropout (2023): *A simple way to prevent neural networks from overfitting.* J. Mach. Learn. Res. 2014, 15, 1929–1958. Available online: http://www.jmlr.org/papers/volume15/srivastava14a/

srivastava14a.pdf?utm_content=buffer79b43&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer.

Wani, A., Ahmad, F., Saduf, B., Asif, A., & Khan, I. (2020). *Advances in Deep Learning,* Singapore: Springer Nature

Wang, L.; Sun, W.; Chen, Y.; Li, P.; Zhao, L. (2018). *Multimode Data Fusion Based Remote Healthcare Framework. In Proceedings of the International Conference on Big Data Engineering and Technology, Chengdu, China*, 25–27, Association for Computing Machinery: New York, NY, USA.

Xu, X.; Jeong, S.; Li, J. (2020) *Interpretation of Electrocardiogram (ECG) Rhythm by Combined CNN and BiLSTM.* IEEE Access, 8, 125380–125388. [CrossRef]

Yu, Y.; Liang, S.; Samali, B.; Nguyen, T.N.; Zhai, C.; Li, J.; Xie, X. (2022) *Torsional capacity evaluation of RC beams using an improved bird swarm algorithm optimised 2D convolutional neural network*. Eng. Struct, 273, 115066. [CrossRef]

Yu, Y.; Samali, B.; Rashidi, M.; Mohammadi, M.; Nguyen, T.N.; Zhang, G. (2022) Vision-based concrete crack detection using a hybrid framework considering noise effect. J. Build. Eng., 61, 105246. [CrossRef]

Yuanlu Li, Renfei Qian, Kun Li, (2022). *"Inter-patient arrhythmia classification with improved deep residual convolutional neural network,"* Computer Methods and Programs in Biomedicine, vol. 214, pp. 106582.

Yong-Yeon Jo, Joon-myoung Kwon, Ki-Hyun Jeon, Yong-Hyeon Cho, Jae-Hyun Shin, Yoon-Ji Lee, Min-Seung Jung, Jang-Hyeon Ban, Kyung-Hee Kim, Soo Youn Lee, Jinsik Park, Byung-Hee Oh (2021) *"Detection and classification of arrhythmia using an explainable deep learning model," Journal of Electrocardiology*, vol. 67, pp. 124-132, July–August.

Zheng, Z.; Chen, Z.; Hu, F.; Zhu, J.; Tang, Q.; Liang, Y. (2020): *An automatic diagnosis of arrhythmias using a combination of CNN and LSTM technology*. Electronics, [CrossRef]

Zhou, S.; Tian, B. (2020). *Electrocardiogram soft computing using hybrid deep learning CNN-ELM*.Appl.SoftComput.,86,105778.Availableonline:https://www.sciencedirect.com/science/article/pii /S1568494619305599. [CrossRef]

Zhou Z, Zhai X, Tin C (2020). *Fully Automatic Electrocardiogram Classification System based on Generative Adversarial Network with Auxiliary Classifier.arXiv preprint arXiv:2004.04894*