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# An Advance Study of an Efficient CNN-Grounded Deep Learning Classification Technique for the Diagnosis of IoT based Cardiac Arrhythmias

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**Abstract**

Deep Learning, or DL for short, is an emerging subfield within the larger discipline of machine learning in today's world. The study being conducted in this area is progressing at an immediate stride, and the discoveries are contributing to the progression of technology. Deep learning (DL) methods were developed with the intention of developing a general-purpose learning method that would enable the gradual learning of characteristics at multiple levels without relying on human-engineered features. This was the goal of deep learning. Because of this, the system is able to acquire intricate purposes and directly map input to output by making use of the data that it has acquired which is based on Internet of things (IoTs). This study places an emphasis on the application of CNN (Convolutional Neural Networks), which are a subcategory of DNN (Deep Neural Networks), and it develops an efficient layered CNN for the classification of ECG arrhythmias. Even while FC-ANNs (Fully Connected Artificial Neural Networks), which are sometimes referred to as Multilayer-Perceptron networks, are effective in categorising ECG arrhythmias, the optimization process for many classification networks takes a significant amount of time in terms of computation. In addition, the features extracted by engineers are what define the accuracy of the categorization of ECG arrhythmias. An improved CNN based filtering, feature abstraction, and classification prototypical is established in order to conduct an accurate analysis of an electrocardiogram (ECG). When measured against ANN, the performance was found to have an accuracy rating of 99.6%. Consequently, the CNN model that was suggested is useful to doctors in arriving at the definitive diagnosis of AFL (atrial flutter), AFIB (atrial fibrillation), VFL (ventricular flutter), and VT (ventricular tachycardia). It includes denoising, feature extraction, and categorization as part of its functionality.

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**Keywords:** DNN; CNN; AFIB; AFL; VFL; VT; IoT.

## 1. Introduction

Manual valuation of cardiac arrhythmias using ECG signal is laborious and time overshadowing because of the ever-increasing number of cardiac patients. In addition, detecting the initial episodes of arrhythmia and providing urgent medication at the early stage becomes a tough task for the physicians in the case of significantly high risk arrhythmias. To solve these issues, biomedical digital signal processing has emerged as a field of study. Thus, it is clear that analysing biomedical digital signals is a difficult issue for the scientific community. Several aspects of diagnosis, treatment planning, and therapy verification have changed as a consequence of current advances in signal processing technology. We have also seen great strides in the areas of non-invasive clinical procedures, speed of diagnosis, and diagnostic accuracy. These adjustments facilitate and facilitate the doctor's role in identifying the issues.

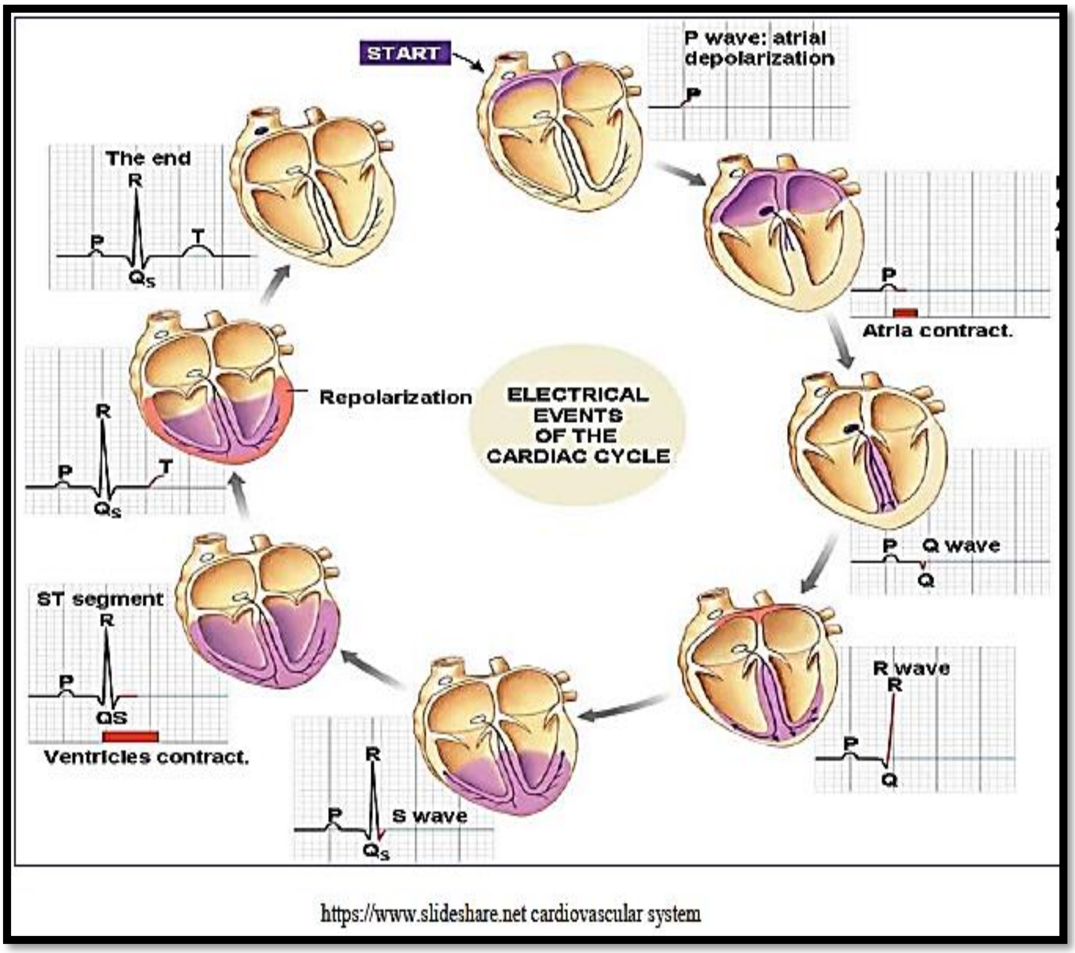


Figure 1: Electrical events of the Heart.

Deep learning techniques are aimed to create a general-purpose learning technique that would allow characteristics from different levels to be learned gradually without trusting on human-engineered topographies. This allows the scheme to study complex purposes and directly map input to output using the collected data. This paper emphasizes the usage of CNNs, a type of Deep Neural Network (DNN), and creates an effective 11-layered CNN for the categorization of ECG arrhythmias. Even while Multilayer-Perceptron networks, or ECG arrhythmias can be effectively classified using Fully Connected Artificial Neural Networks (FC-ANNs), however many of the classification networks take a long time to tune [1]. Furthermore, the accuracy with which ECG arrhythmias are categorised is dependent on the characteristic that human-powered engineers recover. A suitable feature vector that significantly discriminates between the classes must be chosen in order to increase the classifier's effectiveness. Long ECG sequences cannot be expeditiously analysed by FC-ANNs. To get beyond these obstacles offered by ANN, the implementation of CNNs for arrhythmia classification exceeds the use of traditional automated techniques. CNNs inherit numerous significant traits. CNN's ability to execute end-to-end knowledge that is, the incorporation of feature abstraction, feature selection, and combining various classification techniques into one algorithm. CNNs are representation-founded knowledge techniques that inevitably study topographies at various levels of concept and determine a plotting from input information to output information. Three layers comprise deep learning: a hidden layer, an input layer, and an output layer. Deep learning is a representation-based learning technique [2].

One of the most well-liked neural network methods that are effective in analysing big databases of ECG sequences is CNN [3].

An impenetrable layer in a convolution operation varies from a specialized layer in that the former studies global outlines in its global input interplanetary, whereas the latter learns local patterns in constrained two-dimensional windows. An image's edges, lines, colour dips, and other visual elements are among the features that a convolutional layer seeks to identify. This is a highly intriguing property since it allows it to learn a distinctive at one point in the image and later recognize it in any other area of the image [4].

Instead, if the pattern reappears in a different area of the image in a highly linked neural network, it must be learned again. Without employing any prior domain knowledge, CNNs are designed to learn challenging tasks and then classify the output by applying certain convolution filters.Since the turn of the twenty-first century, computers have effectively integrated CNN, assisting them in reaching the pinnacle of speech recognition, object identification, and handwriting digit recognition. It can be used to analyse medical images, X-rays, computed tomography (CT), magnetic resonance imaging (MR), and histology [5].

The core component of CNN is the convolution layer. At this layer, the majority of the intricate computational work is completed. For example, a first convolutional layer might be used to learn basic concepts like edges, while a second layer could be used to learn patterns derived from the first layer's basics and so on, until it starts to form incredibly complex patterns. CNN can effectively acquire increasingly complicated and abstract visual concepts because of this [6].

It is vital to select an appropriate feature vector that is capable of considerably differentiating between the various categories in order to make the classifier function in a more efficient manner. FC-ANNs are not very effective regarding the analysis of lengthy ECG steps. CNNs, which inherit many key features, are implemented for arrhythmia classification in order to overcome these challenges [7]. These problems can be overcome since CNNs inherit many critical attributes. The results of this categorization method are superior to those achieved by using the conventional automated processes. The most essential quality of CNN is its capacity for end-to-end learning, which indicates that it integrates the steps of feature abstraction, feature assortment, and classification into a solitary process. Because of this, CNN ranks among the most powerful of all machine learning techniques. CNNs are a type of representation-grounded knowledge method that can automatically learn topographies at multiple stages of intellection and locate a mapping between the data that is input and the data that is output. This type of learning can be accomplished through the use of CNN. A DL model is an example of a representation-based learning approach [8], and its essential pieces include an output layer, an input layers, and a hidden layer. "DL" refers to a network that can be fed raw data and can automatically figure out the right representations for classification. Deep is a collective term that refers to the multiple phases that are involved in the process of learning the network structure. Using the back propagation approach, the deep learning neural network is trained. This training is achieved with the help of the approach [9]. This particular neural network method is also one of the most often used.

The summary for the remaining portions of the study is presented below. The existing work is briefly detailed in section 2, and the purpose of the study is discussed in section 3, the theoretical foundations and and  methodology of the approaches utilised are represented in section 4. In section 5, the outcomes of the simulation and an analysis of them are presented. The most significant findings are summed up in the "key findings" section that comes at the end of the research paper.

**2. Existing Work Done:**

While FC-ANNs, often referred to as Multilayer-Perceptron networks, are an effective tool for detecting ECG arrhythmias, optimising many of the classification networks requires a substantial computational investment. Furthermore, the accuracy with which ECG arrhythmias are categorised is influenced by the features that human engineers are able to recover. For the classifier to be more effective, it is necessary to select a suitable feature vector that distinguishes between the classes noticeably. Large ECG sequences are too long for FC-ANNs to process efficiently. To overcome these problems, CNNs are used to classify arrhythmias more accurately than existing automated systems [10] CNNs inherit a number of crucial characteristics. The fact that CNN is capable of doing end-to-end learning is perhaps the most crucial quality it possesses. This indicates that it incorporates the procedures of feature extraction, classification, and feature selection into a singular algorithm. An output layer, an input layers, and hidden layer are the components that make up the three layers that comprise the representation-based learning technique known as DL. CNNs are a type of representation-based learning technique that find a mapping between input and output data and automatically learn features at different levels of abstraction. CNNs are also known as convolutional neural networks. Researchers who have studied the topic define deep learning as a representation-based learning technique that has three layers. By the use of representation-based learning, raw data is introduced into a network, and as a result, the network automatically learns the representations that are necessary for categorization. Within the scope of this discussion, the term "deep" refers to the various steps that comprise the learning process of the network structure. The backpropagation algorithm is used when "deep learning" is being taught to a neural network, so that the network can become more intelligent. Because it can efficiently analyse massive databases that contain ECG sequences, CNN [11] is quickly becoming one of the most popular neural network methods. This is mostly owing to the fact that it was developed.

Table 1: Evaluation of Optimisation Methods' Performance.

| Technique | Computational Time | Solution Quality | Scalability | Convergence Rate | Robustness | Memory Usage | Implementation Complexity |
|---|---|---|---|---|---|---|---|
| Branch and Bound | Moderate | High | High | Moderate | High | Low | Moderate |
| Genetic Algorithms | Moderate to High | Variable | High | Variable | Moderate | Moderate | Moderate to High |
| Linear Programming | Low to Moderate | High | High | High | High | Low | Low to Moderate |
| Simulated Annealing | Moderate to High | Variable | Moderate | Variable | Moderate | Low to Moderate | Moderate |
| Ant Colony Optimization | Moderate to High | Variable | Moderate to High | Moderate to High | Moderate | Low to Moderate | Moderate |
| Integer Programming | Moderate to High | High | Moderate | Moderate | High | Moderate | Moderate to High |
| Dynamic Programming | Low to Moderate | High | Moderate | High | High | Low | Low to Moderate |
| Tabu Search | Moderate to High | Variable | Moderate to High | High | Moderate | Low to Moderate | Moderate |
| Particle Swarm Optimization | Moderate to High | Variable | Moderate | Variable | Moderate | Low to Moderate | Moderate |
| Quadratic Programming | Moderate to High | High | Moderate to High | High | High | Moderate | Moderate to High |

Table 1 lists 10 mathematical computing and combinatorial optimization improvements. Researchers and practitioners can use computing time, solution quality, and scalability to evaluate optimization methods and pick the best one for their optimization issues.

They use 20-fold cross-validation to complete the categorization function without the use of prior domain cognition. They took advantage of a publicly available dataset consisting of twenty young, healthy individuals for their investigation. Class-balanced random sampling was utilised for the CNN's stochastic gradient descent (SGD) optimisation in order to avoid performance bias in favour of the most common sleep stages [12]. Performance is consistent across classes, and our findings are on par with those of cutting-edge techniques that incorporate hand-engineered characteristics. They demonstrated how CNN can automatically classify the various stages of normal sleep without the aid of prior domain knowledge [13-14].

A few researchers created a deep learning-based intelligent-based signal categorization system that can recognise ECG arrhythmias. The MIT-BIH Database [15–17]provides the different signal types that Physiobank.com needs to implement the method. CNN's adaptive feature extraction particularly substitutes manually removed topographies, and cardiologists can more effectively detect individuals with heart illness because to CNN's study [18–20].

In their research, other researchers projected a convolution neural network (CNN) method that aids in the automatic detection of distinct ECG segment types. They provided a method for categorizing ECG arrhythmias that is effective by building an 11-layered CNN [21-24]. A 2D grayscale image is created from the ECG signal as input for the CNN classifier. The CNN is optimized using a variety of deep learning techniques, including batch normalization, Xavier initialization, data augmentation, and dropout [25-29].

In their research, the authors classified ECG normal and MI signals as having noise or not having noise based on the results of the CNN algorithm. They were able to get an accuracy rate of 93.53% when utilising ECG beats without noise reduction and 95.22% when using ECG beat generation with noise dismissal [30-32]. It's been found out that the suggested method is capable of accurately detecting unknown ECG signals even when there is noise present. This is due to the fact that there is no requirement for feature extraction or selection. As a result, the recommended technique can be implemented in medical institution laboratories to provide assistance to medical occupation in the process of diagnosing MI [32-34].

## 3. Purpose of the Research

A comprehensive investigation of cardiac arrhythmias can be carried out by reaching the following goal:

- Create a cutting-edge CNN-based classification model for precise atrial and ventricular arrhythmia classification.
- To study CNN-based DL classification techniques.
- To study the merits of CNN over other types of neural networks such as FC-ANN for the diagnosis of CAs.

## 4. The Projected Work:

A Softmax layer, one fully connected layer, four convolutional layers, and one comprise the proposed CNN model shown in Figure II. A spectrogram made from the ECG accumulation function as the network's input signal. Training is much more effective by using ELU as activation functions rather than the more common sigmoid functions. The value "kernel 32" denotes that a 3x3 filter with 32 distinct kernels is used to convolve the area of interest.

Algorithm steps:

1. Begin Algorithm 3 with initializing the temperature variable $T$T to a high value.
2. Define a cooling schedule to gradually decrease the temperature $T$T over iterations, such as
$T$new=$T$old×$\alpha$Tnew=Told×α, (1)

Where $\alpha_\alpha$ is a cooling factor.

3. Initialize the current solution $S$current to a random starting point in the solution space.
4. Evaluate the objective function $f$($S$current) to determine the quality of the current solution.
5. Repeat until the stopping criterion is met:

- Generate a neighboring solution $S$neighbor by applying a modification operator to $S$current
- Evaluate the objective function $f$($S$neighbor) ffor the neighboring solution.
- Calculate the difference in objective function values
$\Delta f$=$f$($S$neighbor)−$f$($S$current) (2)

6. If $\Delta f$<0, accept the neighboring solution Sneighbor as the new current solution with probability $e\Delta fT$
7. If the neighboring solution is accepted, update the current solution:
Scurrent=Sneighbor. (3)
8. Update the temperature $T$T according to the cooling schedule defined in step 2.
9. Repeat steps 4 to 8 until the temperature reaches a predefined threshold or when the allotted number of iterations is achieved.

10. In each cycle, return the best solution that was discovered.
11. Terminate Algorithm, ensuring convergence to a near-optimal solution as the temperature decreases, balancing exploration and exploitation.

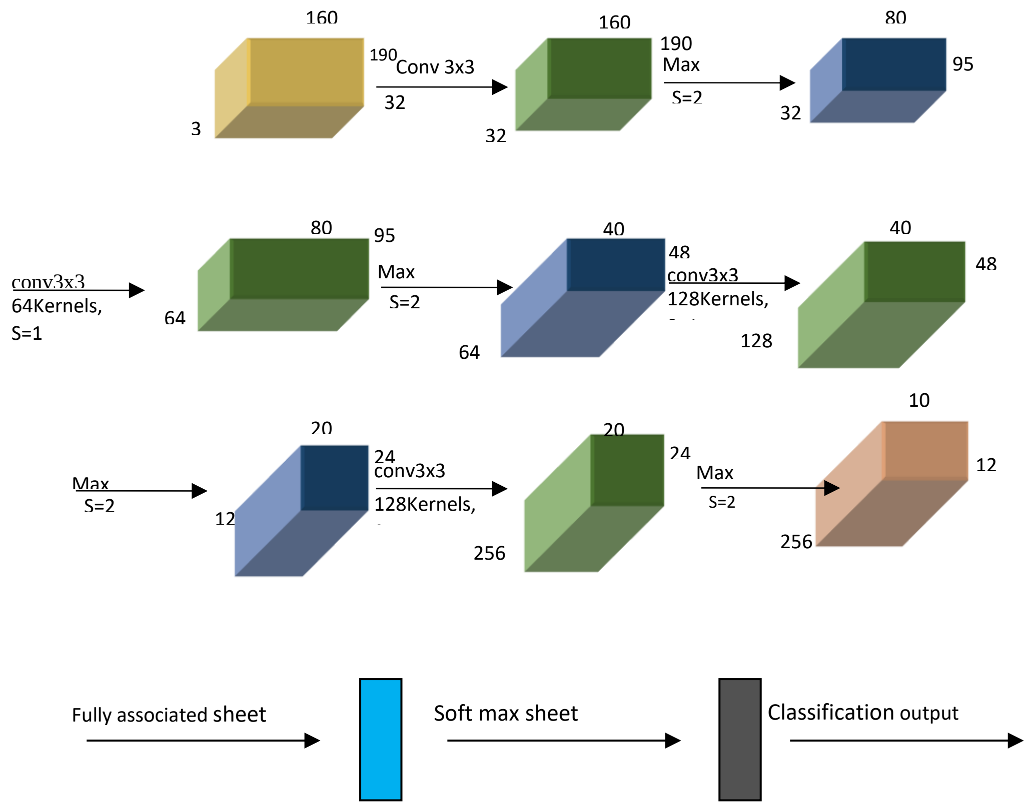


Figure 2: The Projected CNN model Architecture.

It is possible to reduce the overall number of neurons by employing an approach known as max-pooling, which pools all of the neurons together. The ELU technique is then implemented in layer 3 after the topographies map from the second layer has been convolved using a seed.

ADO makes sure that ideas are useful and meet each patient's specific needs by using machine learning to create decision models for each patient.

How to Make an Individualized Assessment

$$\text{Decision Score}=\beta 0+\beta 1\times \text{PatientHistory}+\beta 2\times \text{ClinicalIndicators} \tag{4}$$

Score for Anticipated Outcome

$$\text{Outcome Prediction}=\gamma 0+\gamma 1\times \text{PatientHistory}+\gamma 2\times \text{TreatmentPlan} \tag{5}$$

Optimization Weight Update

$$\text{Optimization Weight new}=\delta\times \text{ Optimization Weight old}+ (1-\delta) \times \text{ Algorithm Performance} \tag{6}$$

After the topographic map from the fifth layer has been convolved with a strainer of scope 128, the sixth layer is then generated, and ELU is applied after that. After the generation of layer 6, this step is carried out. A maximum pooling of size 3 is smeared across each topographic map in order to reduce the number of neurons from 4096 to 2048. The results of convolving the topographic map produced by layer 6 with a kernel are then utilised to build layer 7, which is the final layer. The neurons in layer 9 are transported to region 10, which is famed as the softmax layer, once all of the connections between them and the total of 30720 neurons in layer 9 have been completed.

## 5. Result and Discussion:

A model was developed in order to facilitate the training of the suggested CNN model. MATLAB was used to form the spectrogram images of the ECG dataset, and those images were scaled down to 160x190. Wavelet change is applied to the one-dimensional electrocardiogram signal in order to generate a two-dimensional picture. The spectrograms are then recovered from this picture.

Table 2: Enhancing Medical IoT Data Transfer with High-Throughput PRESENT Cipher.

| Aspect | Description |
|---|---|
| **Algorithm** | PRESENT (a reliable, lightweight encryption algorithm) |
| **Application Domain** | Medical Internet of Things (IoT) |
| **Challenges Addressed** | Execution time, data security, power efficiency, and hardware utilization |
| **Implementation Platform** | XILINX XC7Z030FBG676-2 ZYNQ FPGA board 7000 |
| **Architecture Features** | - Low latency 32-bit data path |
| **Improvement Over Previous Solutions** | Approximately 85.54% improvement in throughput with reasonable hardware utilization trade-off |

Table 2 shows medical IoT device maintenance. The technology's optimum hardware usage, energy savings, data protection, and processing speed allow for the secure transfer of data between smart medical devices. The method enhances performance by 85.54% and optimizes system resources. The Internet of Things, with its limited resources, requires clear information.

It is estimated that 230 different spectrograms were generated from the data based on its five different categories. The training procedure made use of seventy-five percent of this data, while the testing phase made use of the remaining twenty percent of this data. An algorithm called stochastic gradient descent is used when training is being done. The training procedure was carried out over the course of ten iterations, and the batch size was ten. We began with a learning rate of 0.0001, which is quite slow. The structure of the CNN is composed of the ELU and ReLU activation layers.

When utilising a CNN that has been trained with ReLU, the highest possible authentication accuracy of 99.6 percent can be achieved after 6 ages of preparation. It will take you 4 minutes and 11 seconds to complete this. Figure 3 is an illustration of the training of the network.

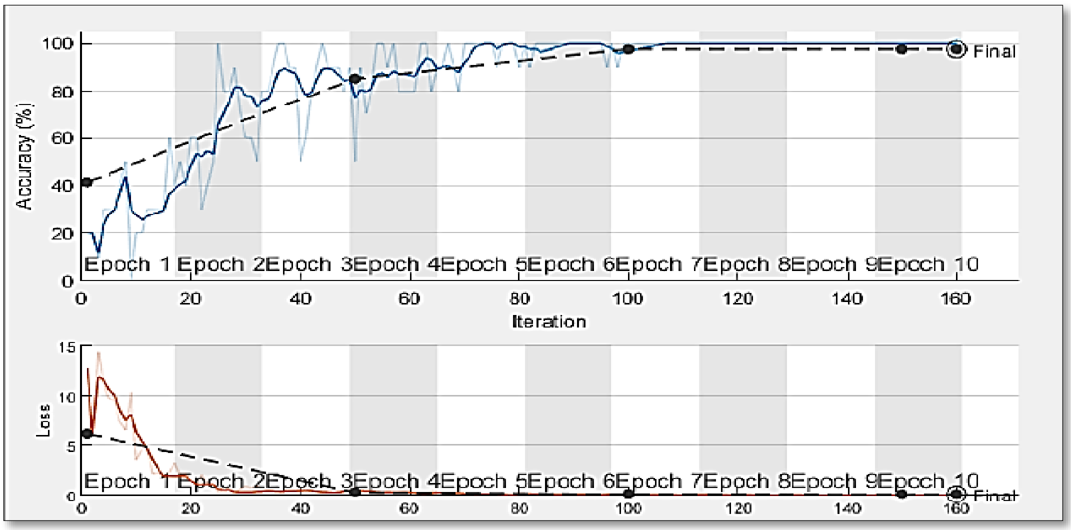


Figure 3: Training progress of Projected CNN with ReLU.

Following its training CNN, it will be put through its paces using a fresh set of test data consisting of 129 images. There was a 98.87% success rate using the classifier. Table 3 displays the test confusion matrix for the projected CNN model that was made with the ReLU function.

Table 3: Projected CNN with ReLU Test Confusion Matrix.

| | AFL | NSR | AFIB | VFL | VT |
|---|---|---|---|---|---|
| AFL | 27 | 0 | 0 | 0 | 0 |
| NSR | 0 | 24 | 0 | 0 | 0 |
| AFIB | 1 | 0 | 30 | 0 | 0 |
| VFL | 0 | 0 | 0 | 27 | 0 |
| VT | 0 | 0 | 1 | 1 | 20 |

Similarly, it took roughly 5 minutes and 33 seconds to train the CNN, which has an ELU activation function. The network now has a perfect 100% validation accuracy thanks to this process. It is not until epoch 4 that the network reaches its maximum accuracy. Figure 4 displays the evolution of the suggested CNN training process.

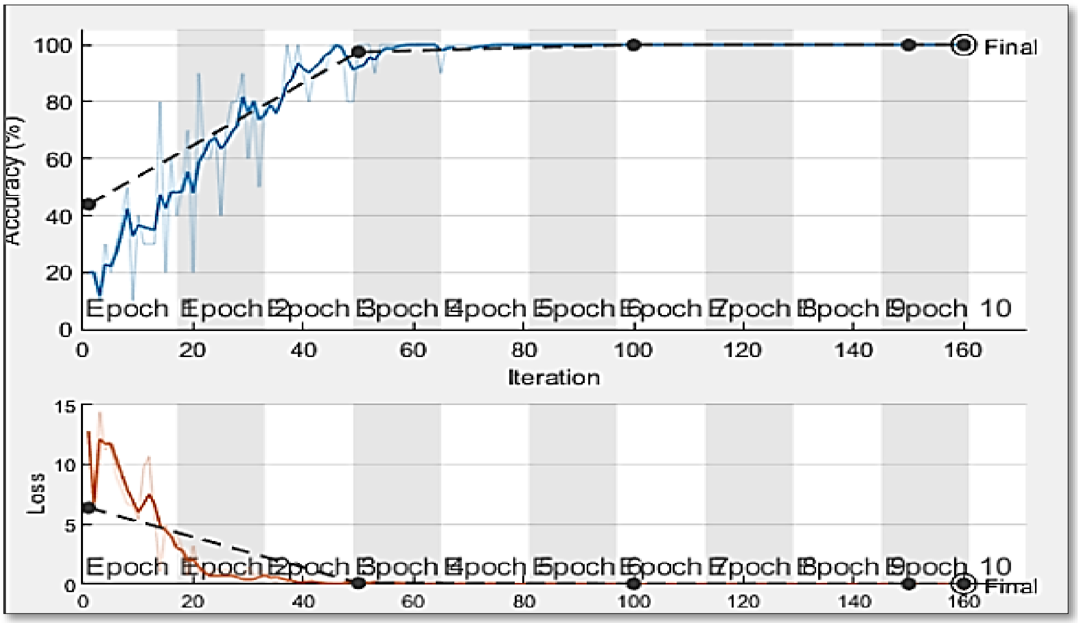


Figure 4: Training progress of Projected CNN with ELU.

After the CNN has been trained, it will be put through its paces using a fresh set of test data consisting of 129 images. In this case, 99.6 percent accuracy in the classifier is attained. See in Table 4 the confusion matrix for the recommended CNN model under test.

Table 4: Projected CNN with ELU Test confusion matrix.

| | AFL | NSR | AFIB | VFL | VT |
|---|---|---|---|---|---|
| AFL | 28 | 0 | 0 | 0 | 0 |
| NSR | 0 | 24 | 0 | 0 | 0 |
| AFIB | 1 | 0 | 32 | 0 | 0 |
| VFL | 0 | 0 | 0 | 27 | 0 |

| | | | | | |
|---|---|---|---|---|---|
| VT | 0 | 0 | 1 | 1 | 20 |

When comparing ELU and RELU as activation functions, this model favours ELU's superior performance. A 99.6% accuracy rate for test data for the developed system using ELU activation function demonstrates a significant improvement over that of 98.87 percent for the ReLU method. Hence, the CNN model with ELU activation outperformed the other models in terms of diagnostic accuracy.

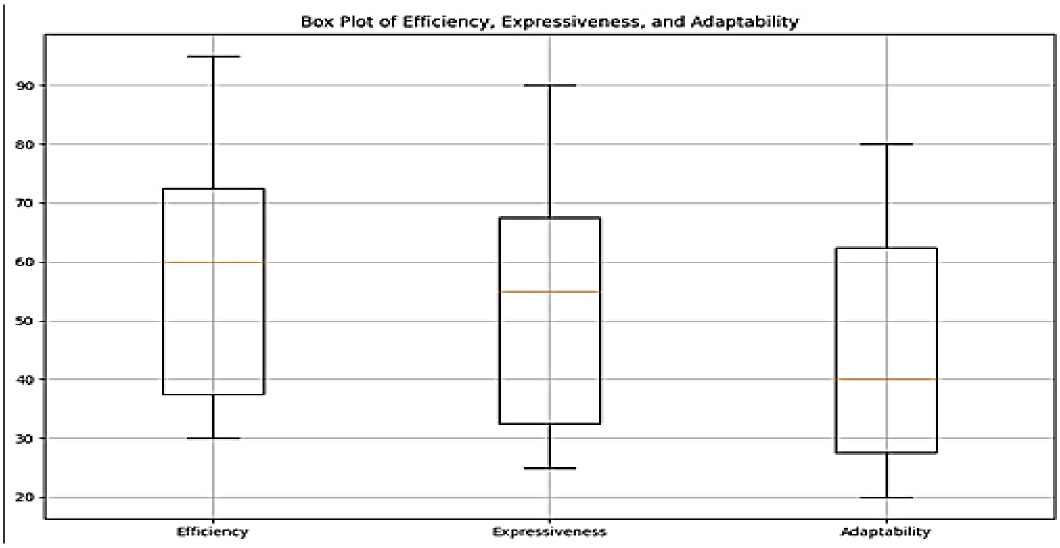


Figure 5: Variability in Performance Metrics: Proposed vs. Traditional Methods.

Figure 5 shows that when comparing the proposed method and conventional methods, the two groups earn different marks for expressiveness, efficiency, and adaptability. Two methods exist for calculating the mean and standard deviation of the measured data: the median and the interquartile range. These two approaches are methodologies in action.

## 6. Conclusion:

This scientific article presents a novel method for differentiating between atrial and ventricular arrhythmias based on aberrant changes to the P, Q, R, S, and T waves of the ECG signal. Choose a feature vector that differs significantly between classifications to boost the classifier's effectiveness. When presented with a lengthy ECG series, the FC-ANNs perform poorly. To get beyond these obstacles, the state-of-the-art in automated arrhythmia classification is convolutional neural networks (CNNs), which inherit several significant properties from their predecessors. In order to differentiate between the five distinct types of ECG patterns, a unique CNN model consisting of 11 layers is presented. Different activation functions' outputs are compared and examined (RELU, ELU). When comparing ELU and RELU as activation functions, this model favours ELU's superior performance. It can be concluded that the created system with ELU activation function correctly distinguishes five different ECG patterns with a validation accuracy of 100% and a test data accuracy of 99.6%. In life-or-death situations, doctors can rely on the projected approach for diagnosing cardiac arrhythmia. When compared to other models, the CNN model using the ELU activation function performed the best in diagnostic accuracy. A clinical evaluation is carried out, and the findings are encouraging. Clinical settings that could benefit from the suggested CNN model include diagnostic laboratories where doctors can use it to aid in patient diagnosis.

Sometime in the future more potentially life-threatening arrhythmias could be categorised with a revised CNN model that uses fewer layers. Doctors might employ the findings of this study as a reference when diagnosing and differentiating between various CAs.

**Conflict of Interest:**

The authors declare no conflict of interest.

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