IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 8, April 2024

# ECG Arrhythmia Classification using Deep Learning

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**Abstract:** *An electrocardiogram (ECG) is a painless, noninvasive way to help diagnose numerous common heart problems. ECG plays an important role in diagnosing various Cardiac ailments. In recent years, Deep learning techniques have shown remarkable promise in achieving accurate and automated ECG arrhythmia classification. The primary goal of the system is to develop a robust and accurate system for the automated detection and classification of arrhythmias in electrocardiogram (ECG) data. By leveraging state-of-the-art techniques such as Convolutional Neural Networks (CNNs), we analyze pattern recognition within ECG signals to detect arrhythmias. Furthermore, we address the challenge of dataset scarcity by augmenting the data through nine different image cropping methods during the training phase. The implementation of techniques like Batch Normalization and data augmentation will further enhance the model's adaptability to diverse data sources, making it an invaluable tool for healthcare professionals. The CNN will be trained and tested using the ECG Dataset obtained from the MIT-BIH Database and from it, seven types of signals of arrhythmia will be classified. These seven signals are Premature Ventricular contractions (PVC), Paced beat (PAB), Right bundle branch block beat (RBB), Left bundle branch block beat (LBB), Atrial premature contraction (APC), Ventricular escape beat (VEB) and Normal beat. This system bridges the gap between advanced technology and healthcare, offering a transformative approach to ECG arrhythmia classification that has the potential to significantly improve patient outcomes and reduce the burden of manual diagnosis*

**Keywords:** Electrocardiogram · Arrhythmia · Convolutional neural network · MIT-BIH Database

## I. INTRODUCTION

Cardiovascular diseases (CVDs) constitute the leading cause of mortality globally, with over 17.7 million deaths recorded in 2017, accounting for 31% of all fatalities, particularly affecting low and middle-income nations. Among CVDs, arrhythmia, characterized by irregular heartbeats, poses a significant threat, encompassing various forms such as atrial fibrillation and ventricular tachycardia. While individual arrhythmias may seem benign, persistent irregular rhythms can lead to severe consequences. Regular monitoring of heart rhythms is thus pivotal in managing and preventing CVDs. Electrocardiogram (ECG) emerges as a pivotal diagnostic tool, non-invasively depicting heart status. Automatic detection of irregular heart rhythms from ECG signals represents a crucial endeavor in cardiology. Leveraging Deep Learning, ECG classification into seven categories, including normal and six arrhythmia types, is achieved using a deep two-dimensional CNN with grayscale ECG images. This novel approach obviates the need for noise filtering and feature extraction by transforming one-dimensional signals into two-dimensional images, ensuring comprehensive beat inclusion. Augmenting ECG images expands training data, enhancing classification accuracy. This innovation not only amplifies precision and speed in arrhythmia identification but also fosters early detection, thereby bolstering patient outcomes and reshaping cardiac healthcare. As technology progresses, the fusion of AI and cardio-logical diagnostics promises transformative advancements, heralding a brighter future for patient well-being.

The paper is organized as follows. Section II provides an overview of the literature survey and states findings from the literature survey. Section III highlights system design. Section IV details methodology VI demonstrates the results and the analysis.

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## II. LITERATURE SURVEY

This literature survey aims to provide an overview of recent advancements in ECG arrhythmia classification using deep learning techniques. By examining key studies, methodologies, and findings in this rapidly evolving field, we seek to identify current trends, challenges, and opportunities for further research. Through this comprehensive analysis, we aim to contribute to the ongoing efforts in improving the early detection and management of arrhythmias, ultimately enhancing patient outcomes and advancing the field of cardiac healthcare.

Ali Haider Khan et al. [1] made the system using Arrhythmia Classification Techniques using Deep Neural Networks. LSTM-based RNN for sequential ECG data, exhibit excellent performance in long-term monitoring. These methods yield high sensitivity, specificity, and accuracy, making them valuable tools in the early detection of irregular heart rhythms. However, there are concerns related to overfitting, emphasizing the need for robust model training and validation to ensure reliable results.

Arjon Turnip et al. [3]gave an approach that involves the training of an SVM model to differentiate between normal and abnormal heart rhythms based on features extracted from ECG data. This approach proves robust when handling noisy ECG signals, ensuring consistent performance in challenging conditions. However, it's worth noting that SVM may exhibit lower accuracy and sensitivity compared to more advanced models like Convolutional Neural Networks (CNNs). Nonetheless, SVM remains a valuable tool for arrhythmia detection, offering reliability in the face of signal noise, although with some trade-offs in classification accuracy.

Bishal Malla et al. [4] studied ECG signal classification which is approached using K Nearest Neighbors (k-NN) with an emphasis on feature selection for reduced feature engineering effort. While this method offers advantages in terms of simplicity and reduced feature engineering, it is sensitive to noisy data, potentially impacting accuracy. Evaluation metrics, including F1-score, accuracy, and a confusion matrix, provide insights into its performance. This approach aims to streamline the classification process, although it may trade off some accuracy, making it a suitable choice for scenarios where simplicity and efficiency are prioritized over precision.

C K Roopa et al. [5] gave The proposed method, "Robust Spatial Kernel Fuzzy C-Means," introduces an innovative approach to clustering ECG arrhythmia data. This technique eliminates the need for trained labels, enhancing its applicability. However, it's crucial to acknowledge the limitation that noise, artifacts, and interference in ECG signals can lead to morphological variations, affecting the accuracy of the clustering process. In assessing the performance of this method, key metrics like accuracy, sensitivity, specificity, andprecision play a vital role in evaluating its effectiveness.

Qiao Xiao et al. [16] gave A Systematic Review on Deep Learning Based ECG Arrhythmia Classification. This systematic review investigates various studies published in the literature focusing on deep learning-based approaches for ECG arrhythmia classification. The survey encompasses a diverse range of methodologies, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), hybrid models, and attention mechanisms, applied to different types of arrhythmias such as atrial fibrillation, ventricular tachycardia, and premature ventricular contractions. Evaluation metrics, datasets used, and performance outcomes are analyzed, revealing promising advancements in achieving high accuracy, sensitivity, and specificity, while also identifying challenges such as dataset heterogeneity, class imbalance, and interpretability concerns.

Zahra Ebrahimi et al. [20] gave a reviewthat explores deep learning methods in ECG arrhythmia classification, emphasizing the significance of lightweight CNN architectures and real-time inference capabilities. Key evaluation metrics include sensitivity, specificity, accuracy, and AUC, which underscore the effectiveness of these methods. Notably, scalability, achieved through larger datasets, enhances accuracy, but the consideration of computational complexity remains paramount for practical implementation.

Zou C, Muller et al. [21]reviewed the main purpose of the paper “Heartbeat Classification by Random Forest with a Novel Context Feature: A Segment Label”. which presents a novel approach for heartbeat classification using a Random Forest ensemble with a unique context feature. This method achieves high sensitivity, specificity, and positive predictive value, making it efficient 3 for real-time classification. However, it exhibits limited generalization across diverse patient demographics, warranting further research to enhance its applicability and accuracy.

Each of these research summaries explores different methodologies for ECG arrhythmia classification, ranging from deep learning techniques like CNNs and RNNs to traditional methods like SVM and clustering algorithms, highlighting their performance, advantages, and limitations.

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## III. SYSTEM DESIGN

**System Algorithm**

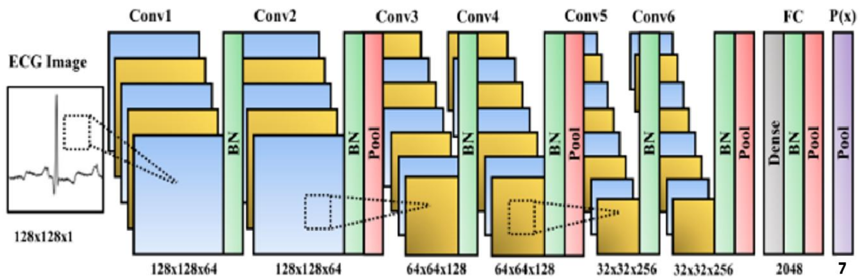


Fig. 1 CNN Algorithm [16]

Conv2D: This layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs. It applies 64 filters of size (3,3) to the input image. The strides=(1,1) argument specifies the stride of the convolution along the height and width of the input.

ELU: This layer applies the Exponential Linear Unit (ELU) activation function element-wise to the output. ELU is a type of activation function that helps the network learn complex patterns in the data.

Batch Normalization: This layer normalizes the activations of the previous layer at each batch, i.e., it applies a transformation that maintains the mean activation close to 0 and the activation standard deviation close to 1. This helps in faster convergence during training and reduces overfitting.

MaxPool2D: It is a layer used in neural networks to reduce the size of the input representation by selecting the maximum value within a defined window, typically set as (2,2) for both dimensions. This process effectively down-samples the input, retaining essential features while reducing computational complexity. The strides = (2,2) argument specifies the stride of the pooling operation.

Flatten: This layer flattens the input without affecting the batch size. It converts the output of the previous layer into a one-dimensional array, which is then fed into the dense layers.

Dense: This layer is a fully connected layer with 2048 neurons. It takes the flattened input and computes the dot product of the input and weight matrices, adding a bias term.

Dropout: The dropout layer applies dropout regularization, randomly setting a fraction of input units to 0 at each update during training. In this model, a dropout layer with a dropout rate of 0.5 is added to prevent overfitting.

Dense: This is the final output layer with 7 neurons, each representing a class in the classification task. The activation function 'softmax' is used to convert the raw scores into probabilities, making it suitable for multi-class classification problems.

Compilation: The compile method configures the model for training. It specifies the loss function ('categorical_crossentropy'), the optimizer ('adam'), and the metrics to monitor during training ('accuracy').

The algorithm commences with a Convolutional Neural Network (CNN) model, an architecture well suited for image-based data. The model is initialized with a 3x3 convolutional layer consisting of 64 filters, aiming to capture essential patterns in the input data. An Exponential Linear Unit (ELU) activation function introduces non-linearity into the model. Batch normalization follows, which standardizes the inputs, aiding in faster and more stable training.

This pattern of convolutional, ELU activation, and batch normalization layers is repeated for multiple stages. The subsequent layers, which involve 128 and 256 filters, progressively enhance the model's ability to capture complex features within the ECG images. Max-pooling layers are strategically inserted to down sample and reduce dimensionality, allowing efficient extraction of dominant patterns.

After the convolutional layers, the model employs a Flattened layer to transition from a 2D convolutional representation to a 1D feature vector. The fully connected layers follow, beginning with a dense layer of 2048 units. ELU activation and batch normalization are applied to the dense layers, introducing nonlinearity and aiding in training stability. A dropout layer is introduced to mitigate overfitting, and the final dense layer comprises 7 units, with multi-class classification for the arrhythmia types.

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**ECG arrhythmia classifier**

In our system, we utilized the softmax function as the final classifier in our ECG arrhythmia classification system. The softmax function provided us with a probabilistic interpretation of the output, assigning each ECG signal pattern a probability score corresponding to each arrhythmia class. This approach enabled us to not only classify the ECG signals but also to quantify the confidence of the classification. The use of softmax in our classification system aligns with our objective of achieving accurate and interpretable ECG arrhythmia classification, ensuring that our model's predictions are both reliable and clinically meaningful.

**Data acquisition**

The ECG arrhythmia data for this study was sourced from the MIT-BIH arrhythmia database. It contains 48 half hour long ECG recordings collected from 47 patients of different age group (25 men aged 32 to 89 years, and 22 women aged 23 to 89 years). The ECG signal is captured at 360 readings per second. The MIT-BIH arrhythmia database comprises approximately 110,000 ECG beats encompassing 15 distinct categories, including normal sinus rhythm. By using the MIT-BIH database we will be classifying into 7 types such as normal beat (NOR), premature ventricular contraction (PVC), paced beat (PAB), right bundle branch block beat (RBB), left bundle branch block beat (LBB), atrial premature contraction (APC), and ventricular escape beat (VEB).

Table 1. Summary of standard databases for arrhythmia classification and detection[19]

| Databases | Records | Time |
|---|---|---|
| The Creighton University Ventricular Tachyarrhythmia Database (CUDB) | 35 records | 8 mins each |
| MIT-BIH Noise Stress Test Database (NSTDB) | 12 records | 30 mins each |
| St Petersburg INCART 12-lead Arrhythmia Database (INCARTDB) | 32 records | 30 mins each |
| Long-Term AF Database (LTAFDB) | 84 records | 24-25 h each |
| MIT-BIH Supraventricular Arrhythmia Database (SVDB) | 78 records | 30 mins each |
| Sudden Cardiac Death Holter Database (SCDDB) | 23 records | 24-48 h each |
| Normal Sinus Rhythm RR Interval Database (NSRDB) | 18 records | 24 h each |
| Georgia 12-Lead ECG Challenge Database (GA12ECG) | 20,672 records | 5-10 s each |
| Apnea-ECG Database | 70 records | 7-10 h each |
| MIT-BIH Arrhythmia Database | 48 records | 23-48 s each |
| PTB Diagnostic ECG Database | 549 records | 10 s each |
| European ST-T Database | 90 records | 2 h each |
| The PhysioNet Computing in Cardiology Challenge 2017 (AFDB) | 12,186 records | 30-60 s each |

**System Architecture**

The proposed algorithm for ECG arrhythmia classification is based on a Convolutional Neural Network (CNN) architecture and involves a series of well-defined steps to effectively classify ECG signals into various arrhythmia types. The foundational stages of this algorithm encompass ECG data preprocessing and the ECG arrhythmia classifier. For the training and testing of the CNN model, we employed the MIT BIH arrhythmia database, a widely recognized dataset in the field of arrhythmia research. To enable the CNN model to process the ECG signals effectively, a crucial pre-processing step is applied. This pre-processing phase involves a significant transformation, wherein ECG signals are converted into ECG images. This transformation is essential because CNN models are designed to work with two-


DOI: 10.48175/IJARSCT-17968

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dimensional images as their input data. By converting ECG signals into images, the algorithm ensures that the data format is compatible with the neural network architecture, allowing for seamless integration into the classification process.

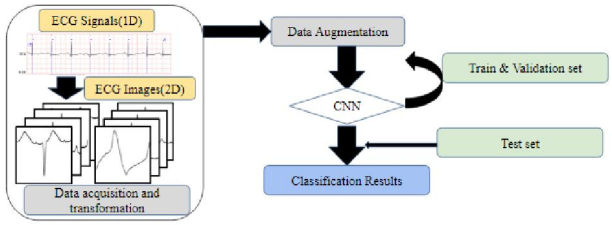


Fig. 2 System Architecture

Once the ECG signals have been successfully transformed into ECG images, the CNN classifier steps into action. This critical stage is where the actual classification of ECG arrhythmia types takes place. Leveraging the unique features extracted from the ECG images, the CNN classifier is trained to distinguish and categorize ECG signals into Seven distinct arrhythmia types. Through its extensive training on the MIT-BIH arrhythmia database, the CNN model adopts at making accurate predictions and classifications, thereby serving as a valuable tool for arrhythmia diagnosis and monitoring. This algorithm showcases the power of deep learning and image-based classification in the realm of ECG arrhythmia analysis, offering the potential for enhanced diagnostic accuracy and clinical utility.

## IV. IMPLEMENTATION

For ECG arrhythmia classification using deep learning, a Convolutional Neural Network (CNN) architecture can be employed. Initially, raw ECG signals are preprocessed to remove noise, normalize amplitudes, and segment into fixed-length windows. These segments are then fed into the CNN model, typically consisting of multiple convolutional layers followed by pooling layers to extract hierarchical features from the ECG signals. The model is trained using labeled data, employing techniques like cross-entropy loss and stochastic gradient descent to optimize parameters. Validation is performed on a separate dataset to monitor performance and prevent overfitting, while hyper-parameter tuning may be conducted to optimize the model's architecture. Once trained, the CNN can classify new ECG signals into different arrhythmia classes with high accuracy, facilitating clinical diagnosis and patient monitoring.

**Cost and optimizer function**

During neural network training, the cost function quantifies the discrepancy between the network's predictions and the desired outputs for each training sample. Minimizing this cost function, often achieved through optimizer algorithms, guides the network towards optimal performance. In deep learning, the cross-entropy function is a popular choice for cost function due to its effectiveness in various tasks.

$$C = -1/n \sum[y\ln a+(1-y)\ln(1- a)] \quad \text{--------Eq 1}$$

Where n is the number of training data (or the batch size), y is an expected value, and a is an actual value from the output layer.

Our CNN model utilized the Adam optimizer function with an initial learning rate of 0.0001. To optimize training, we employed an exponential learning rate decay with a decay rate of 0.95 after every 1,000 steps.

$$\text{Learning Rate} = \text{LearningRate}_0 * 095^{(\text{GlobalStep}/1000)} \text{ ------Eq 2}$$

## V. RESULT & ANALYSIS

Evaluation Parameters: We have used accuracy, precision, Recall and F-score for evaluating performance of the system as depicted below.

Precision: Precision measures the proportion of correctly predicted positive instances among the total predicted positives.

$$\text{Precision} = \text{True positives}/ (\text{True positives} + \text{False positives}) = TP/(TP + FP) \text{ -----Eq 3}$$

Recall: Recall is a measure that indicates the proportion of actual positive instances that were correctly identified by a model, out of all the positive instances that exist in the data.

Recall = True Positives / (True Positives + False Negatives) =TP/(TP+FN) ------Eq 4

F1 Score: The F-score, also referred to as the F1 score or F-measure, serves as a metric for assessing the performance of a Machine Learning model by combining precision and recall into a single score.

F-score = 2 * (precision * recall) / (precision + recall) ------Eq 5

Table 2 shows confusion matrix for implemented CNN model classified into 7 categories of Arrhythmia.

Table 2: Confusion Matrix of CNN model

**Actual**

| **Predicted** | NOR | PVC | PAB | RBB | LBB | APC | VEB |
|---|---|---|---|---|---|---|---|
| NOR | 74726 | 151 | 2 | 15 | 18 | 110 | 0 |
| PVC | 149 | 6947 | 1 | 3 | 7 | 11 | 0 |
| PAB | 19 | 13 | 6991 | 2 | 1 | 1 | 0 |
| RBB | 83 | 3 | 2 | 7159 | 1 | 9 | 2 |
| LBB | 82 | 32 | 1 | 0 | 7957 | 1 | 1 |
| APC | 186 | 17 | 0 | 5 | 1 | 2337 | 0 |
| VEB | 6 | 1 | 0 | 0 | 0 | 0 | 99 |

Table 3: Precision, Recall, F1 score and accuracy for each class

| | Precision | Recall | F1 Score | Accuracy |
|---|---|---|---|---|
| NOR | 0.996 | 0.993 | 0.994 | 0.990 |
| PVC | 0.976 | 0.969 | 0.972 | 0.993 |
| PAB | 0.995 | 0.999 | 0.996 | 0.999 |
| RBB | 0.986 | 0.996 | 0.990 | 0.996 |
| LBB | 0.985 | 0.996 | 0.990 | 0.996 |
| APC | 0.996 | 0.946 | 0.970 | 0.995 |
| VEB | 0.934 | 0.971 | 0.952 | 0.999 |

The above table 3 shows the results of Precision, Recall, F1 Score, Accuracy with respect of different Arrhythmia classes.

The value of Precision is highest for NOR & APC i.e 0.996, the value of Recall is highest for PAB i.e 0.999, the value of F1 Score is highest for PAB i.e 0.996, the value of Accuracy is highest for PAB & VEB i.e 0.999.

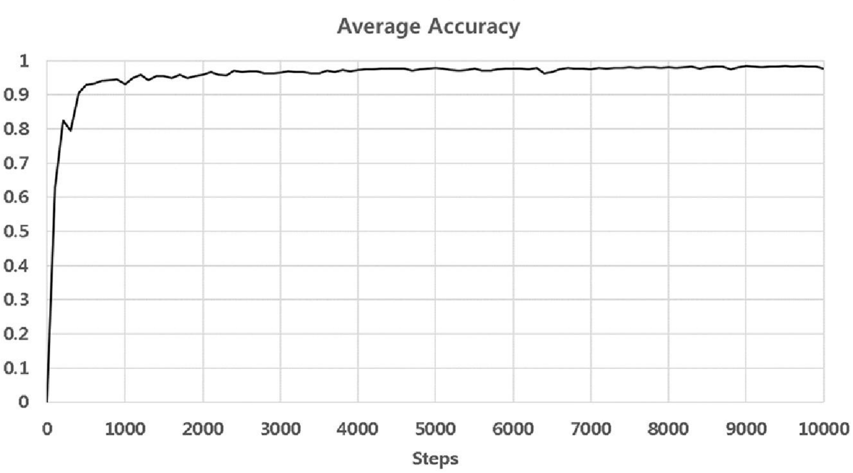


Fig. 3 - Average Accuracy graph

The above figure 3 shows the evaluation graph for the Average Accuracy. It shows the amount of accuracy for every 1000 steps for each Arrhythmia until 10000 steps.

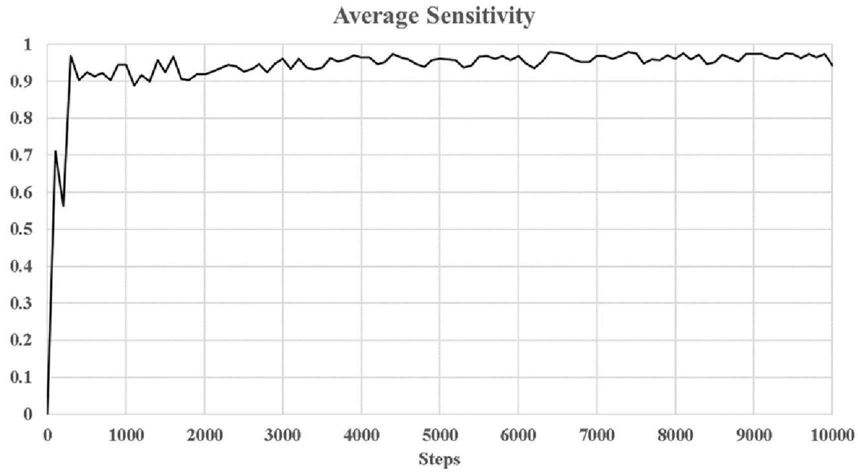


Fig. 4 - Average Sensitivity graph

The figure 4 shows the evaluation graph for the Average Sensitivity. It shows the amount of sensitivity ranging on the scale between 0-1 for every 1000 steps of Arrhythmia until it reaches 10000 steps. The CNN model halts training and proceeds to evaluate its performance on the test set when there's been a consistent increase in the lowest sensitivity over the last 500 global steps.

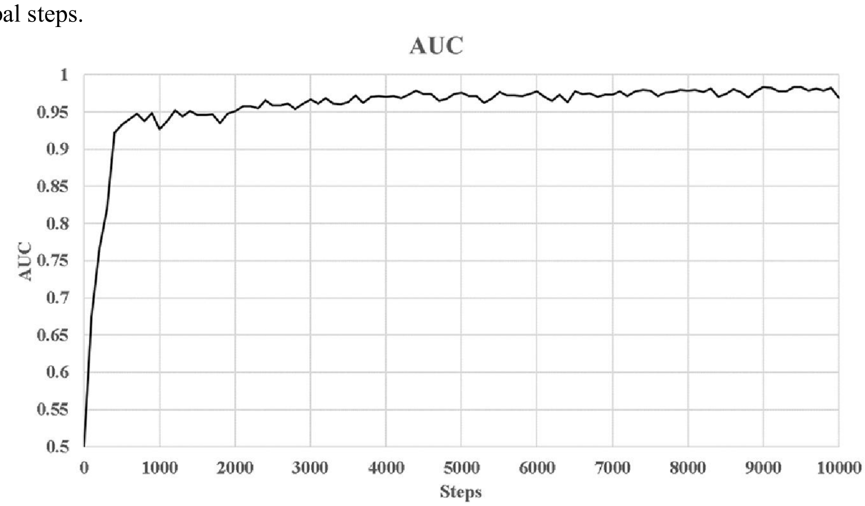


Fig. 5 - AUC graph

The figure no. 5 shows the evaluation graph for the Area under the Curve (AUC). Similar to the previous graphs, AUC graph also ranges between 0-1 for every 1000 steps of Arrhythmia until it reaches 10000 steps.

From these graphs, loss value starts to converge near 1,000 steps while other evaluation metrics do not. Thus, we can notice that early stopping with loss value may results in low accuracy and sensitivity when there is unbalanced distribution between positive and negative classes.

## VI. CONCLUSION

The integration of deep learning, particularly Convolutional Neural Networks (CNNs), into the classification of arrhythmias marks a remarkable advancement in cardiac healthcare. By leveraging CNNs, which eliminate the need for manual feature extraction and introduce more scalable and accurate solutions, the detection of irregular heart rhythms from Electrocardiogram (ECG) signals becomes significantly enhanced. This innovation addresses the inherent limitations of traditional manual interpretation methods, such as subjectivity and potential delays in diagnosis.

Moreover, CNNs optimize the diagnostic process by ensuring that crucial information is retained during preprocessing, thereby facilitating early identification and intervention in cases of arrhythmias.

Furthermore, the impact of deep learning integration extends beyond the diagnostic realm, significantly influencing patient outcomes. Timely detection of arrhythmias through CNN-based classification not only improves the efficiency of treatment and management but also opens new horizons for proactive healthcare interventions. By enabling early identification, CNNs enhance the potential for implementing targeted therapies and preventive measures, ultimately enhancing the overall well-being of individuals affected by cardiovascular diseases. Thus, the integration of deep learning into ECG arrhythmia classification signifies not only a technical advancement but also a profound stride forward in optimizing cardiac healthcare and enhancing patient outcomes on a global scale. As a result, our system achieved 99.05% average accuracy with 97.85% average sensitivity.

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