Detection of Arrythmia using 1D - Convolutional Neural Network

Abstract -

Heart arrhythmias are a common cardiac disorder that can lead to serious health problems if not detected and treated in a timely manner. In recent years, deep learning techniques have shown great promise in the field of medical diagnosis, including the detection of heart arrhythmias. This paper proposes a system architecture for detecting heart arrhythmias using deep learning techniques in Keras with CNN model. The proposed system involves data collection, preprocessing, model development, and evaluation. The collected ECG data is preprocessed by normalizing, filtering, and segmenting it into smaller ECG signals, which are then augmented to improve the model's performance. CNN models are developed using the Sequential API in Keras, and their hyperparameters are fine-tuned to achieve the desired accuracy. The models are evaluated using metrics such as accuracy, precision, recall, and F1-score. This paper also provides a comprehensive review of related work on heart arrhythmia detection using deep learning techniques. The proposed system has the potential to automate the detection of heart arrhythmias and improve the accuracy and efficiency of the diagnosis and treatment of heart disease.

Introduction -

Cardiovascular issues are currently the primary cause of human morbidity, causing more than 17 million deaths each year. The World Heart Federation report witness about three fourth of the total cardiovascular disease (CVD) patients reside inside low-income regions across the globe. Electrocardiogram (ECG) records the electrical activity generated by heart muscle depolarizations, which propagate in pulsating electrical waves towards the skin. Although the electricity amount is, in fact, very small, it can be picked up reliably with ECG electrodes attached to the skin (in microvolts, or uV). ECG signals contain no less than two critical pieces of statistics, including correlated to biomedicine's healthiness and associated with personal credentials or biometrics. As a result of its easiness, several ECG categorizations processes have been established, counting manuals methods and machine learning approaches. The manual process is complicated. It is used for transient signals like ECG, often necessary for machine learning procedures with excessive computer assets. For better classification accuracy, machine learning methods are preferred compared to manual processes, though, a useful algorithm needed to diminish it.

One of the most common cardiovascular conditions is arrhythmias, where the heartbeats pattern deviates from its routine. These irregular patterns require classification into their subclasses; this information can be used to precisely suggest cure the patients. The ECG is widely used to diagnose and predict the irregular pattern of the human heart to diagnose cardiological diseases. The analysis of arrhythmia is primarily liable on the ECG. It is a significant current medical instrument that can record cardiac excitability, the process of transmission, and recovery.

ECG is an essential and reliable diagnostic tool in modern medicine—the reliable automation of the interpretation of ECG signals is extremely beneficial for clinical routine and patient safety. Arrhythmia is an issue that deals with the irregular activity and pattern of the human heart.

CNN is used in many studies to isolate the best characteristics from the ECG wave and analyze the extracted features for various determinations, i.e., detection of QRS wave, ST segment, as shown in **Figure 1** or classification of a heartbeat. 1D CNN is trained to extract the best features from the ECG signal then classified these characteristics into various types of arrhythmias. To remove noise from the wave, it uses the wavelet method. The output layer is the last layer of the CNN model

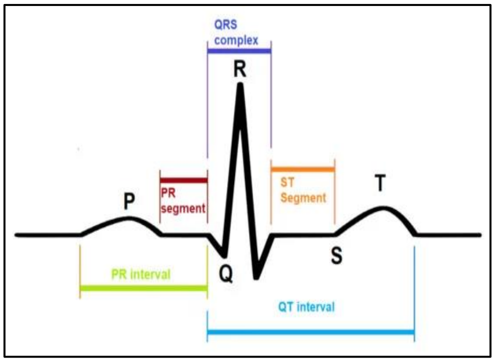


Figure 1, Basic ECG signal parts

Related Work -

Traditional machine learning methods use various hand-engineered features to obtain representations of input data. Since the ECG waveform and its morphological characteristics, such as the shapes of QRS complex and P waves, significantly vary under different circumstances and for different patients, the fixed features employed in such algorithms are not sufficient for accurately distinguishing among different types of arrhythmias for all patients [4]. As the feature extraction process is automated with convolutional neural networks (CNNs), the use of CNN has become widespread in this field. These networks are used to classify patient-specific beats [5] and long duration ECG signals containing multiple rhythm classes [6], to detect different interval ECG segments [7], different types of ECG beats [8], and atrial fibrillation [9]. Most related works have aimed at enhancing the accuracy of heart-beats classification [5,8,10], and focused less on the issues of energy consumption. Artificial intelligence to detect arrhythmia using a dataset of electrocardiogram (ECG) signals [11]. An ECG classification system using wavelet transform, support vector machines, and random forests was proposed [12]. A review was conducted on the use of deep learning for ECG classification, including arrhythmia detection [13]. A convolutional neural network optimized by genetic algorithm for detecting cardiac arrhythmias was developed [14]. These studies demonstrate the potential of machine learning in accurately detecting arrhythmias in ECG signals.

Proposed Methodology -

The proposed 1D – CNN model is suggested for classifying cardiac arrythmia into 4 phases

1) Data acquisition – In this process we, collect the data testing the designed model. I collected the data from MITBIH ECG data source.
2) Data preprocessing – In this part of method, the data is checked and analyzed about the distribution over different scenario which we be helpful for us or not. We refine the data as per our need.
3) Training of 1D-CNN for classification – Here comes our developed model to be tested with the pre-processed data. I run the training and testing set separately. Then checked the performance values.
4) Performance Evaluation- After testing and training, here we perform different graphical representation, curves to the difference between different scenarios.

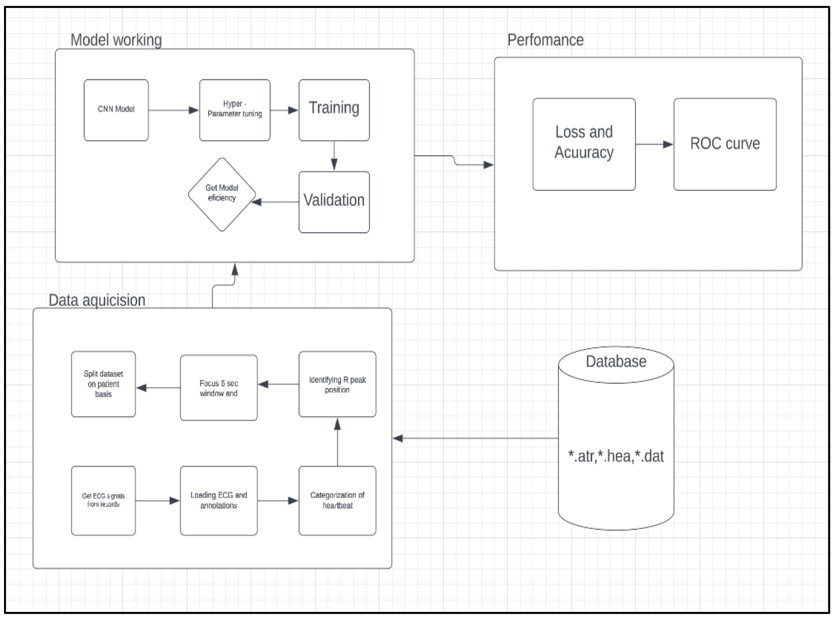


Figure 2, Proposed Methodology work flow

Convolutional neural network (CNN) is a type of deep learning network that is capable of extracting high-level features from input data. A CNN generally consists of three main layers: the convolutional layer, the pooling layer, and the fully connected layer.

1D-CNN is a modified version of CNN specifically designed to process 1D signals, particularly those with sparse data that are not suitable for traditional CNN. They are particularly useful for signal data that has a temporal component, such as time series data, because they can extract local features from the signal that are resistant to small temporal shifts. Here are a few reasons why 1D CNNs are particularly well suited for signal data:

- Time-invariant feature learning: 1D CNNs can learn time-invariant features from a signal, which allows them to extract features that are robust to small temporal variations, noise, and changes in measurement scales. This can result in improved performance for signal data.

- Local feature extraction: The convolutional layers in 1D CNNs can extract local features from the signal. As signals are often composed of local patterns, such as variations in frequency, amplitude, or shape, the CNN can learn and extract these patterns.
- Translation invariance: 1D CNNs are translation invariant, meaning they can detect the same pattern regardless of its location in the signal. This feature is particularly useful for signals where the pattern's location is unknown.

Algorithm -

	1D-CNN pseudocode
	1D-CNN model architecture
	Input: input_data, test_data, filters, kernel_size, input_shape
	Output: Predictions
	Start Algorithm (1D-CNN)
1	| model = Sequential ()
2	| model. Add (Conv1D (filters, (kernel_size,), activation = ’relu’,input_shape)
3	| model. Add (Dropout (0.25))
4	| model. Add (Flatten ())
5	| model. Add (Dense (1), activation = ‘sigmoid’)
	Phase 1, Compile the model
6	| model. Compile (loss = ‘binary_crossentropy’, optimizer = ‘adam’, metrics = [‘accuracy’])
	Phase 2, Fit the model
7	| model. Fit (input_data, batch_size = 32, epochs = 2, Verbose = 1)
	Phase 3, Predict arrhythmias
	| Predictions = model.predict(test_data,verbose =1)
	| **Return** Predictions
8	**End;//Algorithm**

One 1D-CNN layer contains 128 filters with a kernel-window size of 5 for each filter. A layer of a 1D-CNN 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. The setting of the network hyperparameters was determined through an empirical approach, involving experimentation with different values to find the optimal configuration.

Code - [Arrythmia-Detection-using-1D-CNN/mitbih.ipynb at main · avnis838/Arrythmia-Detection-using-1D-CNN (github.com)]

Simulation parameter -

To reduce the overfitting, a dropout layer of 0.25. 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. The dropped neuron weights are ignored, significantly improving the model's generalization capacity. The test size used for splitting the data is 0.2. Sampling frequency is 360 and I am focusing on 6 sec window of abnormal

Parameter	Values
Filter	128
Kernel size	5
Dropout	0.25
Epoch	2
batch size	32
input shape	(2160,1)

Table 1, Simulation parameter used in Evaluation

Performance Evaluation –

The initial phase of the experiments involved dividing the dataset into 80% for training and validation and 25% for testing. The model was trained for 10 epochs with a batch size of 32 per epoch. The loss function in 1D-CNN quantifies the discrepancy between the expected outcome and the outcome produced by the 1D-CNN algorithm. It is used to measure how far an estimated value is from its true value. In this experiment, the sparse categorical cross entropy loss function is used for our multiclass classification task.

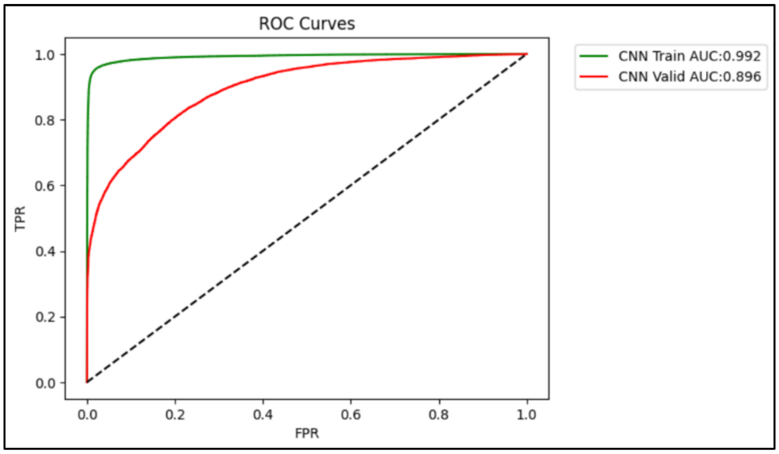


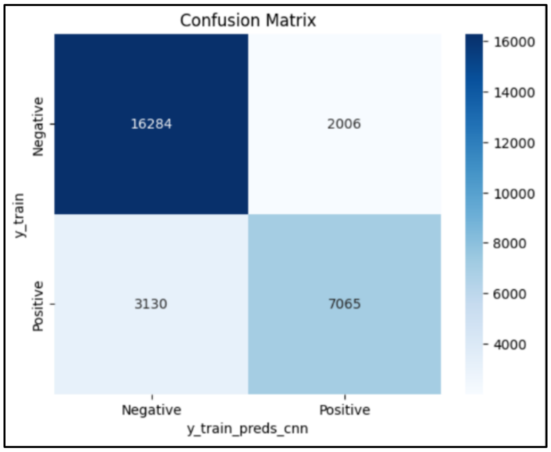
Figure 3, ROC curve of the 1D- CNN model for Arrythmia detection

The proposed model achieved remarkable precision, recall, f1-score, AUC, average accuracy, and loss in the training and testing datasets. Table 3 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 decimals numbers.

<u>Performance report for proposed 1D CNN – Model</u> -

Matrix	Training Dataset	Testing Dataset
Specificity	0.980	0.890
Prevalence	0.299	0.358
Precision	0.953	0.779
AUC	0.992	0.896
Accuracy	0.972	0.820
Recall	0.954	0.693

Table 2, Evaluation values of training and testing data distribution



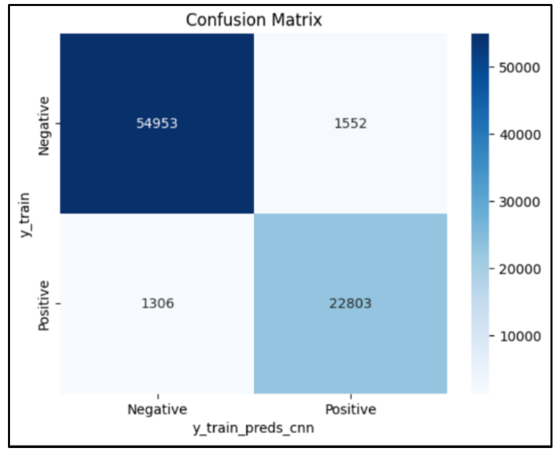


Figure 4

Figure 5

Figure 4 - Testing based Confusion Matrix, Figure 5 – Training based Confusion Matrix

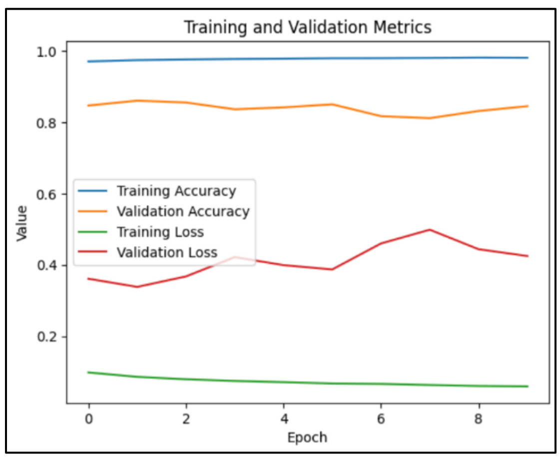


Figure 6, Accuracy and Loss Curve

Result and Conclusion -

A classification model comprising of 1D CNN has been proposed to accurately classify cardiac arrhythmias from ECG lead II signals. This model has shown excellent performance in predicting four arrhythmia classes, making it a useful tool for physicians to diagnose cardiovascular diseases while reducing their workload. Despite the impressive performance, it is important to consider some limitations when interpreting the results. One such limitation is the unbalanced distribution of categories in the MIT-BIH dataset used for training and testing. Although we have addressed this issue using the class weight approach, the data imbalance may still impact the model's generalization. Additionally, cardiac arrhythmias can manifest differently in different patients, highlighting the need for a larger dataset to train deep learning models that can handle this variability and generalize well to new cases. In future work, we aim to address this limitation by using a larger and more diverse dataset to improve the model's generalization capabilities. A pre-processing detection procedure was completed based on the linear interpolation for allocating the date to one of only five categories. Encouraging results are obtained improving the arrhythmia diagnosis. Compared to previous studies, the proposed scheme proves high-accuracy more 97.2%. We notice that the proposed method is supplementary effectual than other considered methods even deep learning classifiers. The proposed linear interpolation framework can guarantee improved classification results. To increase the efficiency we can add more tuning parameters and increase the layers by adding different function with proper parameter values.

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