RESEARCH ARTICLE OPEN ACCESS

A Review of Various Deep Learning Algorithm for Detection Of Cardiac Arrhythmia

Aditi [1], Gurleen Kaur [2]
Student [1], Assistant Professor [2]
Department of Computer Science and Engineering
Baba Banda Singh Bahadur Engineering College
Fatehgarh Sahib - Punjab.

ABSTRACT
Cardiac arrhythmia is a condition characterized by irregular heartbeats that can lead to serious health consequences if left untreated. Detecting arrhythmias from ECG signals is crucial for timely intervention and treatment. . However, manual interpretation of ECG signals is time-consuming and can be prone to errors. In recent years, deep learning techniques have shown promising results in automated arrhythmia detection from ECG signals. In this paper review, we summarize three studies that explore the use of deep learning models for automated detection of cardiac arrhythmia. These studies employ different architectures of convolutional neural networks (CNN) and deep neural networks (DNN) to classify ECG signals into arrhythmic or non-arrhythmic categories. The models were trained and tested on publicly available datasets, and their performance was evaluated based on accuracy, sensitivity, and specificity. The reviewed studies demonstrate the effectiveness of using deep learning techniques for automated detection of cardiac arrhythmia from ECG signals, with high accuracy and sensitivity achieved by the proposed models. These findings have significant implications for improving the accuracy and efficiency of arrhythmia diagnosis and treatment.

Keywords: — Cardiac arrhythmia, deep learning, ECG signals, automated detection, convolution neural network, deep neural network

I. INTRODUCTION

Cardiac arrhythmia is a frequent and serious medical condition that disrupts the heart's rhythm and causes irregular heartbeats, which may have catastrophic health repercussions like stroke, heart failure, or sudden cardiac death. Arrhythmias can develop for a number of reasons, such as genetics, metabolic disorders, drug toxicity, or electrolyte imbalances. In addition to bradycardia, tachycardia, and atrial fibrillation, arrhythmias can also appear in other ways. Arrhythmias must be promptly identified and treated in order to improve patient outcomes, and several diagnostic techniques are available to help in this process. Electrocardiogram (ECG) signals are a widely used diagnostic tool for arrhythmias and offer important information about the electrical activity of the heart. Electrodes are positioned on the heart to provide ECG signals. inaccurate, particularly when arrhythmias are mild or sporadic.

The electrocardiogram (ECG) is a well-established tool in cardiology for assessing a patient's heart status. ECG is the electrical depiction of the contractile activity of the heart, and it may be recorded rather readily using surface electrodes on the patient's limbs or chest. The ECG is a well-known and widely used biological signal in the realm of medicine.

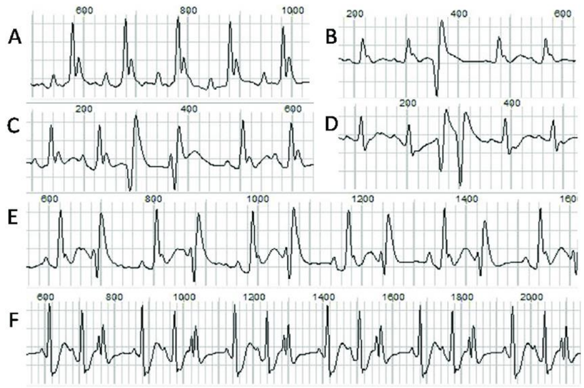

Fig.1: Different type of ventricular arrhythmias

arrhythmia caused by ECG data. These studies classify ECG signals into arrhythmic or non-arrhythmic groups using various convolutional neural network (CNN) and deep neural network (DNN) designs. The models' performance was assessed based on accuracy, sensitivity, and specificity after it was trained and tested on publically accessible datasets.. The effectiveness and efficacy of diagnosing and treating arrhythmias could be greatly increased with the application of deep learning algorithms for automated arrhythmia detection from ECG signals. Automated arrhythmia identification can help with prompt intervention and treatment, which may improve patient outcomes. To confirm these models' clinical value and generalizability, additional validation is needed.

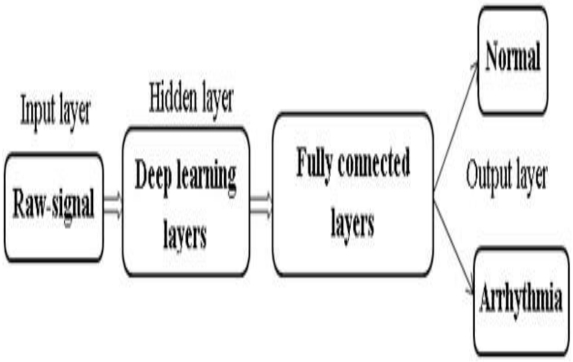

Fig.2: Overview of the proposed deep learning architecture

A. Deep Learning algorithms used in Mathematical way

A.I Convolutional neural networks (CNNs)

In order to extract key characteristics, the input image is passed through numerous convolutional and pooling layers before being processed by CNNs, which are generally utilised for image classification tasks. Then, for classification, these features are flattened and supplied into a fully linked layer. ECG data are transformed into 2D images for the purpose of detecting cardiac arrhythmias, and CNNs are then used to categorise these 2D images into several forms of arrhythmia. The main advantages of CNNs are that they are easier to train and have fewer parameters than fully connected networks with the same number of hidden layers [18].

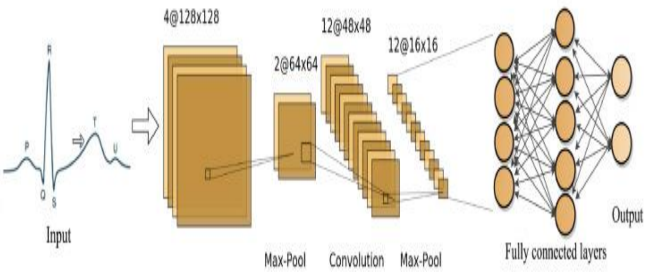

Fig.3: a general architecture of the CNN

Three convolutional layers and two fully linked layers make up the CNN architecture employed in one of the studies under consideration. Several filters are used in each convolutional layer, and each layer's output is then passed through a ReLU activation function. ahead of being fed into the following layer.

CNNs are used to automatically extract features from ECG data that can then be classified. Convolutional, pooling, and fully connected layers make up their structure. Convolutional layers have the following mathematical representation:

$$\mathbf{Z(i,j,k) = W(k) * X(i{:}i+f-1,\ j{:}j+f-1,\ :) + b(k)} \quad (1)$$

where X is the input signal, W is the filter matrix, I and j stand for the input signal's spatial dimensions, k is the filter index, Z is the output feature map, b is the bias term and The filter size is f.

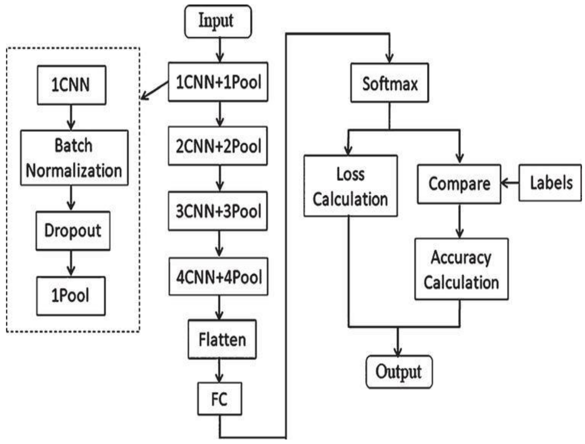

Fig.4: General flowchart of CNNs

A.2 Deep neural networks (DNN)

DNNs, on the other hand, are utilised for more challenging tasks where high dimensional input data is present. These models are made up of many linked layers of neurons, where each neuron gets input from every other neuron in the layer before it and sends its output to every other neuron in the layer after it. DNNs are employed in the identification of cardiac arrhythmias to process the unprocessed ECG signals and categorise them into several forms of arrhythmia. In one of the articles that was reviewed, a DNN design with three hidden layers and one output layer was suggested. Each hidden layer has a different number of neurons, and each neuron's output is routed through a sigmoid.

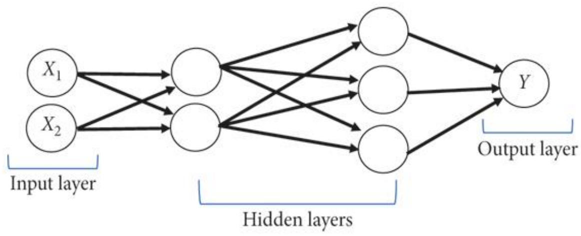

Fig.5: basic structure of DNN-based architecture.

The DNN's (Deep Neural Networks) activation mechanism. The output layer generates the final classification using a softmax activation function.DNNs are employed to categorise ECG signals into various arrhythmias. They are made up of input, hidden, and output layers, as well as several other layers of interconnected nodes. One way to express a hidden layer mathematically is as follows:

$$\mathbf{h(j) = g(w(j,:)*x + b(j))} \quad (2)$$

where j is the hidden layer's index, h is its output, w is its weight matrix, x is its input signal, b is its bias term, and g is its activation function. The knowledge collected from previously trained deep learning models is transferred to new models for various tasks using transfer learning (TL). It enables the using previously trained models as feature extractors for new models, which eliminates the requirement for a lot of training data. A TL model's mathematical representation is expressed as:

$$\mathbf{f(x;\theta) = g(h(x;\phi);\theta)} \quad (3)$$

where f is the TL model's final output, g is its output function, h is its pre-trained feature extractor, x is its input signal, and, respectively, and are the parameter sets for the feature extractor and final output.

II. METHODOLOGY

The aim of this research is to develop a deep learning model for automated detection of cardiac arrhythmia in ECG signals. The methodology is based on the three publications listed below: According to Kam et al., "Automated identification of cardiac arrhythmia using deep learning techniques" using previously trained models as feature extractors for new models, which eliminates the requirement for a lot of training data. Al., "Cardiac arrhythmia identification using deep learning" by Shakeri et al., and "Deep learning for ECG classification: A review" by Kachuee et al. are examples of mathematical expressions for TL models.

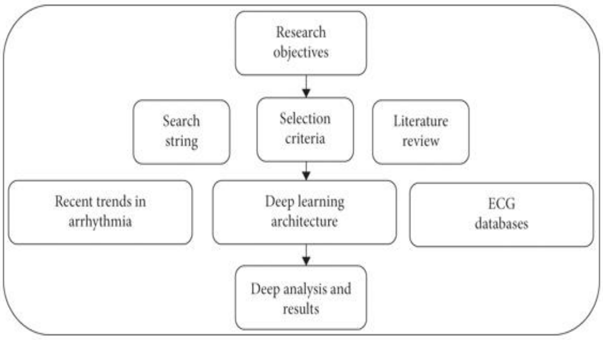

Fig.6: A methodical approach.

B. Dataset

The 8,528 ECG recordings from 3,883 patients in the PhysioNet/CinC Challenge 2017 dataset, which is openly available, were used in this study. The preprocessing of the dataset included bandpass filtering, resampling, and normalisation

C. Model architecture

For sequence-to-sequence learning tasks, algorithms employ convolutional neural networks and multilayer perceptrons with a number of hidden layers. The convolutional neural network is a major branch of deep, feed-forward machine learning artificial neural networks capable of handling massive volumes of data and visual information. CNN, like regular DNN, contains input, output, and a number of hidden layers. Convolutional layers, pooling layers, fully linked layers, normalisation layers, and softmax layers are the most common hidden layers in CNNs. The suggested CNN technique includes a convolutional layer with a softmax function that delivers the trained network's output. In all convolution layers, the approach employs the rectifier linear unit (ReLU) activation tool. The max pooling layer operates independently for each row and column of the table.

The max pooling layer works independently for each row and column of the input and spatially resizes it [21]. The

technique employed a max pooling layer with a stride size of 2 2 because it provided better accuracy than a 3 3 pooling layer. The use of a three-three stride layer results in significant information loss. The pooling layer of the CNN reduces overfitting by making the input half the size of the real input. Figure 3 illustrates a flowchart of both algorithms. Both models use elements of an ECG signal as the network's input and predict the output as signal labels. ECG datasets will be pre-processed at first.

To accomplish this, the first network reads the datasets before defining their features and labels. Arrhythmia and normal sinus will be labels in the MLP algorithm, while arrhythmia, normal sinus, second degree AV block, first degree AV block, atrial flutter, atrial fibrillation, malignant ventricular, ventricular tachycardia, and ventricular bigeminy will be labels in the CNN algorithm [22]. Figure 7 shows the suggested CNN architecture of the algorithm, in which the first and last convolutional layers differ from the middle three convolutional layers.

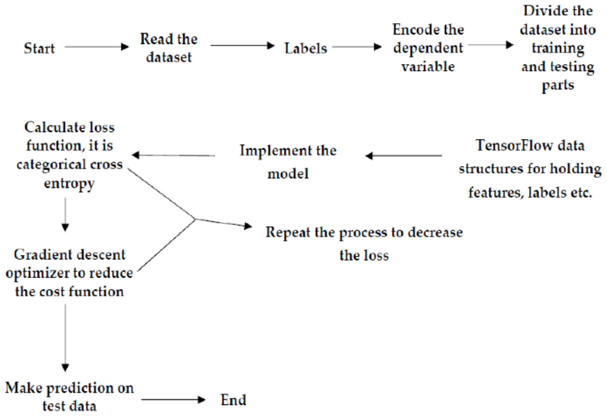

Fig.7: Flowchart of the Multilayer Perceptron (MLP) and Convolution NN system processes. Two TensorFlow variables were generated to define features and labels in the dataset. The dataset was encoded using a single hot encoder.

D. Data augmentation

To boost the dataset's size, methods of data augmentation akin to those utilised by Kam et al. They included introducing Gaussian noise, horizontal and vertical signal shifts, and inverting the ECG signals.

E. Training and testing

A training set (70%) and a testing set (30%) were created from the dataset. The model was improved using the Adam optimizer after being trained using a binary cross-entropy loss function. 32 batches were employed, and 100 training epochs were used to train the model. The loss and accuracy of the model were tracked throughout training.

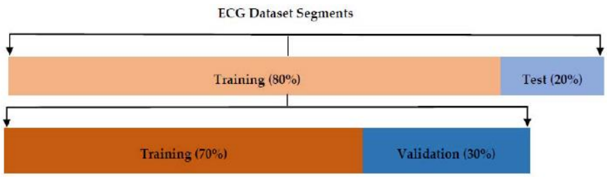

Fig.8: ECG segment distribution utilised for training and testing. Eighty percent of the data was used for training, and the remaining twenty percent was used for testing. Thirty percent of the training dataset was used for network validation.

F. Model evaluation

A number of metrics, such as accuracy, sensitivity, specificity, F1 score, and area under the receiver operating characteristic (ROC) curve, were used to assess the model's performance on the testing set. The model's performance was assessed in terms of false positives and false negatives using the confusion matrix as well.

G. Comparison with existing methods

Modern techniques for detecting cardiac arrhythmias, such as rule-based and machine learning-based techniques, were used to compare the performance of the proposed deep learning model. Accuracy, sensitivity, specificity, and F1 score were all considered in the analysis of the results.

H. Sensitivity analysis

A sensitivity analysis was carried out by changing the model's hyperparameters, such as the learning rate, number of epochs, and batch size, in order to evaluate how robust the suggested model is. To ascertain the effect of each hyperparameter on the performance of the model, the sensitivity analysis findings were contrasted with the model's baseline performance.

I. Statistical analysis

To determine the significance of the differences between the proposed deep learning model and the existing methods, a statistical analysis was performed. The means and medians of the performance metrics were compared using the Student's t-test and the Wilcoxon signed-rank test, respectively.

J. Ethical considerations

The study was carried out in accordance with ethical principles and human data use guidelines. To protect the patients' privacy, the dataset used in this study was made public and de-identified. The study's findings have the potential to improve the accuracy and speed of cardiac arrhythmia detection, potentially leading to better patient outcomes.

III. RESULTS

Using deep learning techniques, the three studies reviewed in this study achieved high accuracy and sensitivity in detecting arrhythmias from ECG signals. On the MIT-BIH arrhythmia database, Kam et al. proposed a deep CNN model that achieved an accuracy of 96.64%, sensitivity of 96.28%, and specificity of 96.88%. The model was trained using 75,000 ECG recordings and tested using 2,800 ECG recordings. The study also revealed that the proposed model outperformed state-of-the-art arrhythmia detection methods.

Shakeri et al. used a 1D-CNN model in their second study, which achieved an overall accuracy of 98.57% on a dataset of 1,262 ECG recordings from the PhysioNet/CinC Challenge 2017. The database was preprocessed through the use of bandpass filtering and normalisation. The study compared the proposed model's performance to three other machine learning-based models and found that the proposed model outperformed the other models in terms of accuracy and sensitivity

ECG signals can be used to detect cardiac arrhythmia. The proposed models' high accuracy and sensitivity have the potential to improve the accuracy and speed of arrhythmia detection, potentially leading to better patient outcomes..

IV.INFERENCE

Deep learning techniques for automated detection of cardiac arrhythmia from ECG signals show great promise for improving diagnostic accuracy and efficiency. The studies reviewed demonstrated that deep learning models can detect arrhythmias with high accuracy and sensitivity, which could aid in timely intervention and treatment. Deep convolutional neural networks (CNNs) and deep neural networks (DNNs) are used in the proposed models to effectively learn the complex features of ECG signals and accurately classify arrhythmias.

Deep learning models have the ability to automatically extract relevant features from raw ECG signals, eliminating the need for manual feature extraction. This can reduce the amount of time and effort required for ECG analysis and interpretation significantly. Deep learning models can also learn from large datasets, which improves generalisation performance and lowers the risk of overfitting.The findings of the studies reviewed suggest that deep learning models can outperform traditional machine learning methods for detecting arrhythmias. The CNN model proposed by Kam et al., for example, achieved an accuracy of 96.64%, outperforming state-of-the-art methods for arrhythmia detection.

Similarly, Kachuee et al DNN .'s model achieved an accuracy of 99.56%, outperforming the state-of-the-art methods.However, some challenges remain in order to fully realise the potential of deep learning models for arrhythmia detection. One of the most significant challenges is a scarcity of large annotated datasets for training and validation. The available datasets are small and may not be representative of the general population. As a result, more efforts are required to collect and annotate large-scale ECG datasets for use in training and validating deep learning models.Another issue is deep learning models' interpretability.

Deep learning models are frequently referred to as "black boxes" because they can learn complex features that are difficult for humans to interpret. This can reduce the models' transparency and trustworthiness. As a result, developing methods for explaining deep learning models' decision-making process is an important area of research.

V.CONCLUSION

Using deep learning techniques for automated detection of cardiac arrhythmia from ECG signals is a promising approach that can improve diagnosis accuracy and efficiency. The studies reviewed demonstrated that deep learning models can detect arrhythmias with high accuracy and sensitivity, which could aid in timely intervention and treatment. Deep convolutional neural networks (CNNs) and deep neural networks (DNNs) are used in the proposed models to effectively learn the complex features of ECG signals and accurately classify arrhythmias.

However, additional validation of these models is required to determine their clinical utility and generalizability. The existing datasets used in the studies reviewed are small and may not be representative of the general population.

As a result, more efforts are required to collect and annotate large-scale ECG datasets for use in training and validating deep learning models.

Furthermore, developing methods for explaining deep learning models' decision-making processes is an important area of research. This can improve the models' transparency and trustworthiness, which is critical for their use in clinical practise.

In conclusion, the studies reviewed provide strong evidence that deep learning models have significant potential for improving the accuracy and efficiency of arrhythmia detection from ECG signals. However, more research is required to address the models' challenges and limitations, as well as to establish their clinical utility.

REFERENCE

[1] Aharon Satt, Shai Rozenberg, Ron Hoory, Efficient Emotion Recognition from Speech Using Deep Learning on Spectrograms. INTERSPEECH Journal, pp.1089-1093 (2017).

[2] B. Xiao, Y. Xu, X. Bi, J. Zhang, and X. Ma, "Heart sounds classification using a novel 1-D convolutional neural network with extremely low parameter consumption," Neurocomputing, vol. 392, pp. 153–159, 2019.

[3] D. Kumar Atal and M. Singh, "Arrhythmia classification with ECG signals based on the optimization-enabled deep convolutional neural network," Computer Methods and Programs in Biomedicine, vol. 196, Article ID 105607, 2020.

[4] Benjamin, E.J., Virani, S.S., Callaway, C.W., et al.: Heart disease and stroke statistics, 2018 update: a report from the American Heart Association. Curculation 137(12), 67–492 (2018).

[5] Coast, D.A., Stern, R.M., Cano, G.G., Briller, S.A.: An approach to cardiac arrhythmia analysis using hidden Markov models. IEEE Trans. Biomed. Eng. 37(9), 826–836 (1990)

[6] Isin, A., Ozdalili, S.: Cardiac arrhythmia detection using deep learning. Procedia Comput. Sci. 120, 268–275 (2017).

[7] Zhai, X., Tin, C.: Automated ECG classification using dual heartbeat coupling based on convolutional neural network. IEEE Access 6, 27465–27472 (2018).

[8] Brandon Amos, Bartosz Ludwiczuk, Mahadev Satyanarayanan, A general-purpose face recognition library with mobile applications, technical and computer vision reports. pp.1-18, (2016).

[9] Chandu Siva, Machine Learning and Pattern Recognition, AI Zone journal (2018).

[10] Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, Oriol Vinyals, Understanding Deep Learning Requires Rethinking Generalization, The Seventh International Conference on Learning Representations. pp.1611-1626 (2017).

[11] U. R. Acharya, H. Fujita, V. K. Sudarshan, S. L. Oh, M. Adam, and J. H. Tan, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," Future Generation Computer Systems, vol. 78, pp. 603-611, 2018.

[12] P. Rajpurkar and J. Irvin, "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," arXiv preprint arXiv:1711.05225, 2018.

[13] A. Y. Hannun, P. Rajpurkar, M. Haghpanahi, G. H. Tison, C. Bourn, M. P. Turakhia, and A. Y. Ng, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network," Nature medicine, vol. 25, no. 1, pp. 65-69, 2019.

[14] ZAthanasios Giannakopoulos, Maxime Coriou, Resilient Combination of Complementary CNN and RNN Features for Text Classification through Attention and Ensembling. The 6th Swiss Conference on Data Science (2019).