Deep Learning for ECG Signal Classification in Remote Healthcare Applications

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Abstract. Due to several current medical applications, the significance of Electrocardiogram (ECG) classification has increased significantly. To evaluate and classify ECG data, a variety of machine learning methods are now available. Utilizing deep learning architectures, where the top layers operate as feature extractors and the bottom layers are completely coupled, is one of the solutions that has been suggested. In addition to classification results, this work also proposes a learning architecture for ECG classification utilizing 1D convolutional layers and Fully Convolution Network (FCN) layers. We made several changes to get the best result, getting 98% accuracy and 0.2% loss. A comparison has been made and showed that our work is better than other related works. The problem that we found in the rest of the research is the use of less efficient algorithms, so this thing is the reason for the lack of accuracy of the results and an increase in the loss.

Keywords: ECG, CNN, classification, heart arrhythmias.

1. Introduction

The main cause of mortality worldwide is heart disease. According to estimates, in 2017, 17.8 million people died from heart disease globally, making up close to 31% of all fatalities. World Health Organization data on human mortality. For effective therapy to work and to lower mortality, early identification of heart disease is essential. Electrocardiography is a low-cost, quick method that helps us understand how the heart works and, in turn, aids in the diagnosis of cardiac disorders. The electrical activity of the heart is recorded by an electrocardiogram (ECG), which a cardiologist uses to detect a variety of illnesses by identifying aberrant cardiac function. However, it takes a lot of time and requires the focus and attention of a qualified specialist to analyze an ECG recording. Using electrodes positioned on the skin. It is important to note that he used his idea for the galvanometer, which measures the strength of electric current. At the time of his drawing, the device was large and difficult to manufacture, but with the passage of time and the introduction of constant improvements, it shrank and became precise in displaying the outcome. Keep a record of your heart's electrical activity. Many cardiac conditions, including arrhythmias, cause changes in the typical ECG pattern. It is also possible to monitor how these signals go from the heart to the skin's surface. During an ECG, the fluctuations in electrical signals (or actual voltage) in the different skin layers are measured and graphed. The ECG's resulting graph is known as an electrocardiogram. The ECG measures the depolarization of the heart's muscles, which are all negatively charged. To do this, a collection of positive ions, specifically sodium + and calcium ++, are drawn into the ventricles and cause them to swell. The graphic is either shown on the device screen or created on specialized thermal paper by attaching two electrodes to the sides of the heart. In order to create the layout, more than two electrodes may be used. For instance, one electrode may be placed on the left hand, a second on the right hand, a third on the left leg, and so on. The result is a typical ECG pattern, with the first peak (P wave) illustrating how the electrical impulse (excitation) from the heart travels through the atria. The atria instantly relax after contracting (compressing), pushing blood into the ventricles. The electrical impulses then enter the ventricles. This is demonstrated by the ECG's Q, R, and S waves, or the QRS complex. Ventricles constrict. The ventricles subsequently start to relax again once the electrical impulse ceases propagating, as shown by the T wave. [1]. Machine learning, of which deep learning is a subset, only employs neural networks of three layers or more. These neural networks try to function like the human brain, but they fall short, letting the brain "learn" from vast volumes of data. A neural network may be able to approximate predictions with just one layer, but accuracy may be improved by including additional hidden layers. By performing mental and physical activities without requiring human input, deep learning, a technique that serves as the foundation for many artificial intelligence (AI) products and services, encourages automation. Deep learning is used to power both new and old technology, like voice-activated TV remote controls, digital assistants, and credit card fraud detection. Deep learning differs from conventional machine learning in terms of the kind of data it uses and the learning strategies it employs. Machine learning methods employ structured, labeled data to produce predictions, which implies that the model's distinctive properties are established from the input data and organized in tables. This doesn't mean that it doesn't use unstructured data; rather, it only means that, if it does, it usually goes through some pre-processing to organize it. Recent developments have allowed deep learning-based ECG signal classification systems to reach cardiologist-level performance [2]. In terms of precision and memory, the model performed better than the typical cardiologist. Deep convolutional neural networks and sequence-to-sequence models were used by Mousavi et al. [3] to construct an automated heartbeat categorization technique. A lengthy short-term memory and CNN combination was suggested by Murugesan et al. [4]. (LSTM) without any preprocessing, a model-based feature extractor that can be instantly trained. By using an attention mechanism and a recurrent neural network (RNN), Schwab et al. [5] classified a single channel ECG data. For medical professionals to feel confident using computer-assisted electrocardiography, an interpretable model and consistent performance are essential. Although much effort has been done to increase the interpretability of deep learning models in computer vision applications, there Despite recent attention, there hasn't been much progress in the interpretation of ECG classification methods. This paper includes several paragraphs, the first paragraph is the literature review in which we talked about most of the previous research related to our research, then the comparison paragraph, which included a discussion of the research in which we compared our current research, later we talked about the method of work and the algorithms that were used, after that we talked about how to work and the results obtained, and the last paragraph was the conclusion of this work.

2. Related work

In this part, we have tried to collect the closest works that have a correlation to our proposed work. When Sharda Singh and colleagues applied the method, a sizable amount of standard data, such as ECG time-series data, was used as input to the long-term memory network. Subsets of the data set were created for training and testing. Their method was shown to be effective, accurate, and capable of detecting arrhythmia. Quantitative comparisons with several RNN team models showed an accuracy of 88.1% when they assumed 5 iterations and 3 hidden layers, with 64,256 and 100 neurons for each hidden layer, respectively. This shows that LSTM is superior to RNN and GRU in identifying arrhythmia, whose accuracy is lower than LSTM at 85.4% and 82.5%, respectively. Database with no prior processing carried out. As a result, their model's complexity is substantially lower than that of conventional machine learning techniques. The results of this paper's bilateral categorization of arrhythmias can be enhanced by expanding it to include many categories. The suggested approach produces the same results and leaves room for future research in this area of binary classification (arrhythmia detection), where little significant work has been done. The number of eras can be increased while maintaining classification accuracy. The research illustrates that convolutional neural networks may be used to further classify arrhythmias in the MIT BIH classification dataset, with long-term memory producing the greatest results in binary classification of arrhythmias [12]. The classification of 27 cardiac anomalies using a data collection of 43,101 ECG recordings was the goal of the study that Christian Tronstad and others suggested. a hybrid method that integrates many rule-based deep learning architectures. In this study, the researchers examined two alternative convolutional neural network designs: a completely CNN and an En-coder network, a hybrid of the two that added a second neural network that took into account factors like age and gender. Using derived ECG characteristics, two of these groups were ultimately integrated using a rule-based model. During model development, each of the models was assessed using the validation data [13]. The models are then evaluated on a Challenge validation suite, trained on the supplied development data, and deployed on a Docker image. The best performing models on the challenge validation set were then published and tested on the full challenge test set. A specific challenge score was used to evaluate performance. The best form for their squad, Team UIO, had a complete test score of 0.206 and a challenge validation score of 0.377. We were ranked Based on the outcomes for the whole test group, 20th out of 41 teams made up the official rankings [14]. Minh Huang Nguyen and others an efficient approach for classifying ECGs using 2D convolutional neural networks and ECG images is presented in this study. An ECG recording is transformed into 128 x 128 grayscale pictures for the MIT-BIH database. Eight different heartbeat types, including a regular pulse and seven abnormal heartbeats, are used to create more than 100,000 ECG pictures. The optimized CNN model was created with key ideas including data augmentation, structure, and K-fold validation in mind. With 0.89 AUC, average accuracy of 96.05%, specificity of 62.57%, sensitivity of 93.85%, and average positive predictive value of 98.55%, this proposed strategy performed well. According to the results of grading arrhythmias on the electrocardiogram, identifying arrhythmias with the use of ECG pictures and a CNN model can be a useful strategy for helping professionals in the diagnosis of cardiovascular illness that can be observed from ECG signals. A medical robot or scanner that can monitor ECG signals and assist medical professionals in more precisely and quickly identifying arrhythmias can also be used to implement the suggested arrhythmia categorization approach. In order to detect the arrhythmia and alert the doctor[15]. In this work, Enbiao Jing suggested a more effective ResNet-18 model for categorizing ECGs. The data was categorized using slicing technology, which aided its pre-processing. The outcomes of the experiment demonstrated that types of arrhythmias may be successfully identified using the enhanced ResNet-18 model. The suggested model also outperformed the most current models that were taken into consideration in terms of classification accuracy, attaining the maximum 96.50%, according to the data. As a result, there are many potential therapeutic applications for the model, which justifies more research and analysis. By changing the loss function and utilizing the weighted loss that arises from batch processing, one way to mitigate the effects of heartbeat class imbalance on model performance is to overweight a small class of losses. Data optimization is a different technique that doubles the data by chopping and dicing the ECG data to enhance training outcomes. Last but not least, to improve the neural network's ability to distinguish small classes of distortions, smaller classes might be given certain features [16]. An effective hybridization method for categorizing electrocardiogram (ECG) samples into key arrhythmia classes to identify irregular heartbeats is presented in Pooja Sharma and colleagues' proposed study. The most frequently used and recognized automated detection technology for keeping track of heart health is the physiological detection utilizing electrocardiogram (ECG) data. Additionally, electrocardiogram (ECG) study focused on elucidating cardiac health state while examining heart rhythm plays a significant role in arrhythmia beat categorization. The authors use discrete wavelet modification to remove the inherent noise of ECG signals during the pre-processing step in order to properly categorize ECG samples into main arrhythmia classifications (DWT). The identification of an ECG signal depends heavily About the QRS complex. Therefore, the position and magnitude of the R peak are calculated to identify the QRS complex. In order to select the collection of the most relevant features, the feature vector is further enhanced using a Cuckoo Search (CS) optimization approach in addition to denoising the signal using DWT. The support vectors trained on the support vector machine (SVM) include the DWT and CS versions by training a feedforward backpropagation neural network (FFBPNN), and the SVM-FFBPNN to classify the signal into five classes. Contains the best training data used for. Various forms of heartbeat are examined using the MIT-BIH arrhythmia database. Heart rate can be calculated with 98.319% accuracy using variant-based classification analysis with feature vectors enhanced using the cuckoo-hunting method and SVM-FFBPNN. In contrast, the FFBPNN variant achieves 97.95 curacy without optimization. Thanks to the improved performance of the new classifier mix, the overall classification accuracy was 98.53%, with precision and recall reaching 98.247% and 95.68%, respectively. The 3600 samples and 1160 heartbeats in the simulation analysis performed better than the existing neural network-based arrhythmia diagnosis. This exemplifies how well the suggested ECG classification model categorizes ECG data in order to categorize arrhythmias [17].

3. Problem definition

Overserving ECG using a visual method is difficult, time-consuming, costly, and subjective. Due to the complexity of the data amount and clinical content, automatic identification of the arrhythmia in the ECG signal is often a challenging task. Additionally, noise (such as patient movement and disruptions brought on by electrical equipment or infrastructure) often interferes with ECG readings, lowering the quality of the data gathered. The capacity of machine learning (ML) to perform better than conventional classifiers has increased attention in health care systems. In this study, we look into the newest automatic algorithms for identifying aberrant electrocardiograms (ECGs) in a range of cardiac arrhythmias. Choosing which class, the patient's ECG should be allocated is the current ECG classification task. There are four different classes: arrhythmic, highly loud, various types of rhythm, and regular rhythm [18]. The presented data is unbalanced, with 60% of the data falling under the usual sinus rhythm. A quick summary of the data is shown in Tabel 1. Different processes, such as multiplying an existing ECG for a certain class by moving time values, were utilized to create a balanced dataset. Additionally, there was an attempt to uniformly measure the duration of the ECG using duplicate time-series readings. The input and output layers in Figure 1a show how the three key features of CNN—locally responsive field, shared weights, and pooling—are mirrored throughout: The convolutional layer continually learns the entire information from samples while traversing to get many feature maps through weight sharing. It makes use of movable windows that represent sample information pieces (locally acceptable domain). To make its output more straightforward, the pooling layer conducts data compression on the convolutional layer's feature map. The frequently used max-pool method converts the data, removes any values that are not the maximum value in the sample region, and then enhances the method to increase algorithmic robustness. The output of the network is shown in the top complete layer.[20]

Table 1. The classification of the data that related to the last works.

part	info	mean	Sd	Maximum	Midd	last
Normal	5154	31.9	10.0	61.0	30	9.0
AF	771	31.6	12.5	60	30	10.0
Other rhythm	2557	34.1	11.8	60.9	30	9.1
Noisy	46	27.1	9.0	60	30	10.2
Total	8528	32.5	10.9	61.0	30	9.0

It is essential to examine patient-provided ECG data before choosing the preprocessing and machine learning technique to be applied, often lasting 30 or 60 seconds and sampling every 0.003 seconds. There are several ML that handle time series data and make suitable feature choices. Convolutional neural networks (CNNs) are specific instances of feature extractors, as mentioned in the work's introduction. The developers should no longer be dependent on specialized expertise or custom features thanks to this feature extraction. Rather than eliminating specialist knowledge entirely from the development process, this will speed up the release of the first prototype of ECG classification. [22]

Table 2. literature survey on the ECG classification.

Author	Method	Type of Classification
Sharda Singh et al.	RNN	1 D
Christian Tronstad	CNN	1 D
Huang Minh Nguy	SVM	1 D
Jiaoyang Li1	RNN	1 D
Enbiao Jing	Optimized CNN	1 D

Ten lead wires in a typical ECG provide twelve images of the heart. Your heart rate, rhythm, electrical signal strength, and timing may all be determined via an ECG. Numerous heart-related diseases can be assessed with the test. Because there is no electrical activity and an unequal distribution of ions across the cell membranes while the cardiac muscle cells are at rest, they are said to be depolarized. Ions like sodium (Na+), potassium (K+), and calcium (Ca2+) are at resting potential and have varying concentrations both within and outside the cell. These ions cross the cell membrane in response to an electrical impulse, resulting in a depolarization or action potential. The heart contracts as a result of depolarization. Regular heartbeats and blood flow throughout the body are maintained by the depolarization and repolarization of the heart. The heart has two atria and two ventricles, making up its four chambers. The atria and ventricles' depolarization and repolarization in succession are represented as waves in the ECG. P Wave: Atrial Depolarization Associated Small Deflection Wave The PR interval. The T-wave represents the ventricular repolarization waveform. By blocking atrial repolarization, the QRS complex. The QRS-to-T wave interval (QT interval) is the period of time between these two waves. The cycle from ventricular depolarization to ventricular repolarization is represented by it.[21]

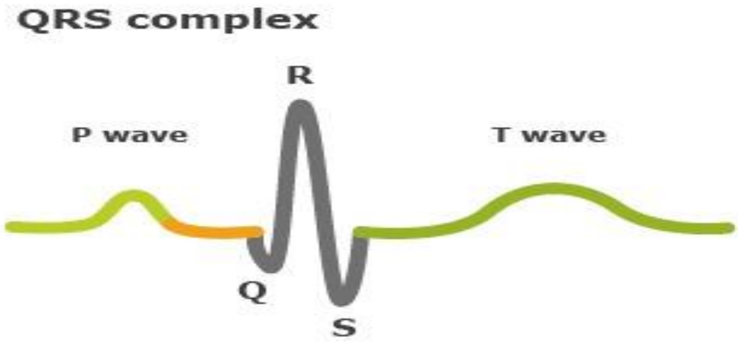

Figure. 2. The typical ECG pattern.

4. The proposed solution

This specific situation of ECG is different from the standard picture recognition task for which CNN is used. Contrary to time series, which normally use 1D data, data is always shown in the latter case as 2D data with a few color channels. Whatever the situation, a CNN with the right architecture, which is dependent on the dimensionality and structure of the data, may successfully complete a classification assignment. In this case, CNN 1D is utilized in conjunction with the following buildings: GlovalAverage-Pooling.

5. The method of CNN

The neural network in general is designed just like the neurons of the human brain, each in the form of a programmer. Where it contains several cells and nodes, each of which has its function to obtain results that match our brains, more accurate results. These layers are called neural layers. When we talk about deep learning, we are talking about neural networks. We start by talking about the inputs or how the neural network works in general and how to enter data into the network. The inputs are entered on the layers in the neural network and have a certain weight. Each node can be affected by multiple weights because the weights are assigned to the links between these nodes. The neural network takes all the training data in the input layer and then passes this data to the hidden layers, after which it is transformed These values are based on the weights of each node and finally give us the result in the output layer. Choosing the neural network is very important to determine which features are the most important to use for the model. Also, the process of training data within the neural network can take a long time in order to get better, reliable and coordinated results.

A convolutional neural network is an artificial intelligence algorithm, a specific type of neural network that uses a CNN for classification, such as image classification. It has multiple layers. Through these layers, a more accurate and clear result is obtained. Where the CNN is that it helps you get images without pre-processing them. Since the convolutional neural network works accurately and intelligently, thanks to its neural layers, it does not need many parameters to give us the result we are looking for. It also does not need much time to do so. As a result, the CNN knows the most important properties of the filters and considers the optimal handling of the filter. The CNN algorithm is very great for dealing with a somewhat huge dataset and working with high-resolution images that contain thousands of pixels because it simply transforms this data into models that are easy to process without losing important features to know what this data represents. One might ask what the difference between a normal neural network and a convolutional neural network is, or what is the importance of having convolutions in a CNN. Scientifically and practically, convolutions deal with the math in network programming, but behind the scenes, where convolutions take two functions instead of matrix multiplication in at least one layer of the network. Whereas convolutions return the function instead. What makes CNN so special is that it knows very well how to handle filters and how to set them. Speaking of filters, we will explain what they are in general terms. Filters help us get a better result for our work, as filters are associated with the input. This helps us improve accuracy and reduce loss. This is when convolutions handle these filters well, as they have a different effect on the result, such as opacity, or removing noise from an image. One of the things that can improve the work of the CNN is the use of data, as the more training data and the better, the better the network will be. Choosing the data to be classified and well formatted, this will help the network to train better and faster and give us an accurate result.

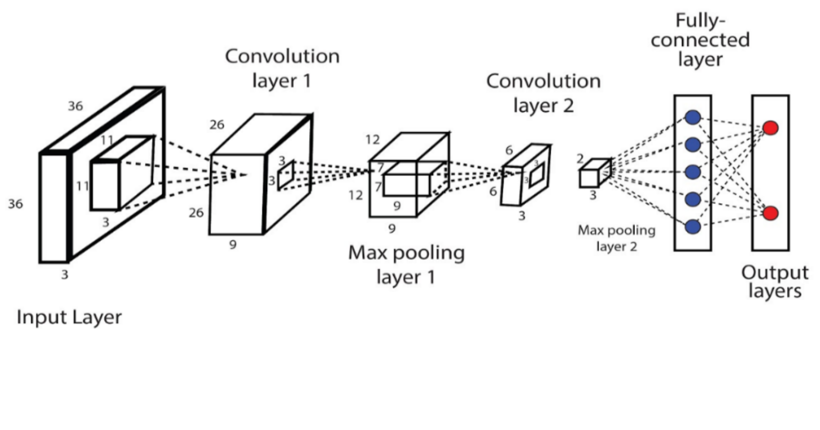

Figure. 3. How maxpooling is work.

5.1 A convolutional neural network works

As mentioned, a convolutional neural network works like a human brain and consists of nodes. It is these nodes that represent the neurons in the network that are like the cells of the human brain. Nodes are specific functions in the network that calculate the weight of the interstitial bits of the network and return the activation map. When the input is an image defined here, these nodes take the pixels from that image and select some visual feature for it, such as colors, and will give you the activation result as a result of this function. Usually the first thing CNN takes from this image is the edges as the definition of the input image, and this definition is passed to the next layer, and the next layer begins to detect other, more subtle parts of the image. , such as angles and color combinations, and it is passed to the next layer, and so on until it reaches the last layer, which is the final layer, and this process is called classification. The last layer of CNN that determines the result for us is the classification. The meaning of classification in general is the real knowledge of what is inside this image. It is possible for a person, when he looks with his eyes at a certain image, to classify his mind what is the thing he is looking at through the brain cells that he has. He can know if the thing he is looking at is a human, cat, dog, etc. CNN also works in the same way. For example, self-driving vehicles work when they recognize the object, is it a human or another car. For convolutional neural network layers, the first layer is the convolutional layer, which was mentioned in detail, followed by the max pooling layer. CNN has a MaxPooling setting that can be used to improve the performance of networks with high latency. the pooling layer is designed to aggregate features (local image patterns) into a fixed size feature map at each location in the feature space of the input images. These output features are stored in an array that has the same shape as the input images. The goal of the pooling layer is to reduce the spatial dimensionality of the network by extracting the most meaningful information from each part of the input image. As a rule of thumb, the more layers you have, the more computationally expensive your algorithm will be. So, reducing the number of parameters in the network can make it more efficient for large-scale applications. Typically, this is done by selecting fewer weights for each neuron, but this comes at the cost of accuracy. Max Pooling: selecting only the largest activation value at each node in each channel reduces the number of parameters in the network without affecting the accuracy. This reduces the number of parameters in the network without changing the overall structure of the network.

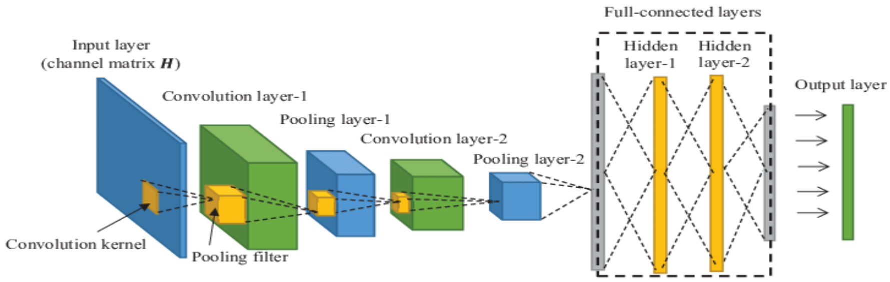

Figure. 4. Convolutional neural network.

The fully connected layer is one of the CNN layers comes after the pooling layer. The task of this layer is to connect all the inputs in the input vector with the outputs in the output vector, because not all nodes are connected to each other in the convolutional layer. This means that all the input nodes will connect to the output nodes in the FC layer. This layer consists of weights and biases with neurons and is used to connect neurons with two different networks. The term "fully connected" means that each neuron of the previous layer is connected to the current layer. The number of neurons in a fully connected layer cannot in any way be related to the number of units in the previous layer. You can even place a single fully connected neuron after a layer of 10,000 neurons. The major advantage of fully connected networks is that they are “structure agnostic” i.e., there are no special assumptions needed to be made about the input. While being structure agnostic makes fully connected networks very broadly applicable, such networks do tend to have weaker performance than special-purpose networks tuned to the structure of a problem space [10].

5.2 The analysis of the result and discussion

We utilize a CPU i7 and GPU NVIDIA GeForce GTX for all computational research. Tables 3, 4, and 5 offer a comparison of the results in terms of accuracy scores for the various models. In all of the trials, our model produces the best outcomes. Table 3 demonstrates that, when compared to the other models, our model performed the best, particularly when the parameter no was changed.

Table 3. Dropout effectiveness during the experiments.

Drop out l	Loss	Accuracy	Validation loss	Validation accuracy
0.8	1.05	0.80	1.14	0.77
0.75	1.00	0.81	1.08	0.79
0.7	0.99	0.83	1.12	0.77
0.63	0.93	0.84	1.17	0.76
0.19	0.5	0.89	0.90	0.77

A number of samples of cardiac patients were tested in order to improve the accuracy of the ECG by using the MIT-BIH database by entering it into the layers of the convolutional neural network, where in turn, through neurons, it improves accuracy and reduces loss, and this, in turn, helps cardiologists and recognize As soon as possible on the disease. table 2 shows the effect of dropout on the results. Dropout is an amazingly popular way to overcome overfitting in a neural network.

Table 4. Maxpoling effectiveness during the experiments.

Maxpooling 1d	Loss	Accuracy	Validation loss	Validation accuracy
16,8	0.55	0.87	0.93	0.74
14,6	0.5	0.88	0.89	0.77
13,5	0.5	0.88	0.99	0.76
13,8	0.5	0.89	0.78	0.89

One of the most important design aspects of convolutional neural networks is maxpooling (CNN). The main purpose of the pooling layer, a layer of CNN, is to gradually reduce the spatial size of the representation to minimize the number of parameters and computations in the network. Table 3 shows how the pooling layer affected the results. We can see that the smaller value of the pooling layer resulted in higher accuracy and better results.

Table 5. Regpart effectiveness during the experiments.

Regpar 1	Regpar2	Max pooling 1	Max pooling2	Max pooling3	loss	accuracy	Val_loss	Val_acc
0.002	002	31	13	8	0.5	0.88	0.78	0.77
0.0001	.0001	31	13	8	0.5	0.93	0.76	0.76
0.00001	.00001	31	13	8	0.3	0.94	0.73	0.71
0.00001	.00001	32	14	9	0.4	0.92	0.73	0.66
0.00001	.00001	10	10	7	0.2	0.98	1.44	0.72

Table 4 shows our latest results. As shown in the table, we made many changes in the maxpooling layer and the regpar. We reached the best result of accuracy, which is 98%, and the loss is 0.2%. Regpar is an acronym for "Receptive Field Paring" which is what is found in a convolutional neural network. Regpar is the technique you sometimes use when training a CNN on images that have a lot of noise. The idea behind regpar is that you want to filter out all the noise in the input image so that you are left with only the relevant parts of the image.

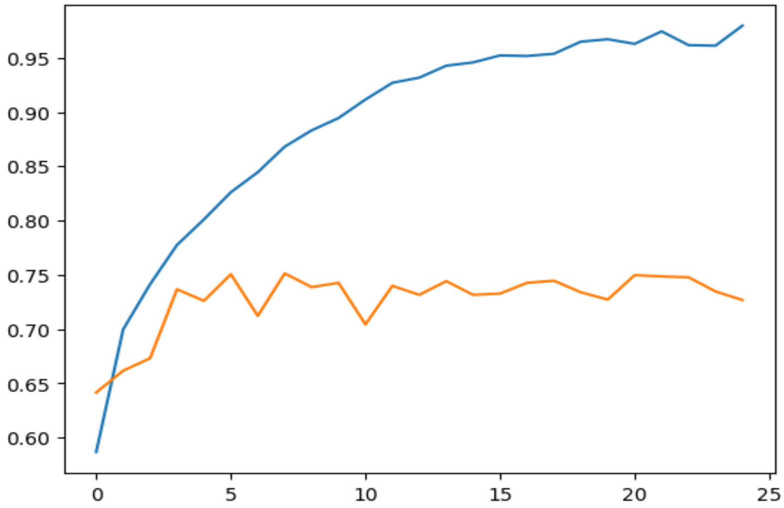

Figure. 5. Shows training and validation accuracy.

If the training data is unstructured, unbalanced, and can be represented as a 1D time series with typical time lengths for ambulatory monopolar ECG devices, the proposed deep learning solution is It can be used for the task of classifying ECGs according to their results. The classification obtained. The ability of the algorithm to extract features is also very useful when, for various reasons, there are no medical or related experts available for feature engineering. The shortcomings of this study can be characterized as a poor comparison with other DL solutions in terms of processing costs, recommended designs, and optimization methods.

Table 5. A Comparison of different classification Tanique.

Method Signal	Classification Accuracy	Method Signal
ANN & PCA [6] &NCA [28]	ECG	88.5
KNN classifier [29]	HRV	90.4
SVM Classifier	HRV	96
Fuzzy KNN [30]	RNN	92.5
Our proposed method	ECG	98

The proposed deep learning solution can be used to classify electrocardiogram (ECG) data when the training data is unstructured and unbalanced and is comparable to standard single-channel portable ECG devices. It can be represented as a 1D time series with time length. The classification obtained. The feature extraction algorithm's ability is also particularly useful when feature engineering is not available to medical or related professionals for a variety of reasons. A drawback of this study is that it does not compare well with other DL solutions in terms of processing costs, design recommendations, and optimization methods.

6. Conclusion and Future work

The suggested technique is concluded using the preprocessing, feature extraction and classification outcomes. The advantages of the learning algorithm include its infinite ability to make continuous, real-time diagnosis of heart arrhythmias, which helps patients who live in rural areas or in underdeveloped countries and cannot access heart disease care. The person using the circadian rhythm monitor will react immediately and alert emergency personnel to assist the person(s) in diagnosing an occupational arrhythmia when a potentially fatal heart rhythm manifests itself in high-risk groups. Through convolutional neural network layers, ECG devices have been developed, helping doctors in early detection of disease. We used samples from patients with heart disorders in the MIT-BIH database and inserted them into CNN layers. So, we made several changes to get the best result, getting 98% accuracy and 0.2% loss. Our method showed the best performance and great result compared to other related works. Our future work will examine the proposed method using the 2D dataset.

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31.

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