CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES
https://cajmtcs.centralasianstudies.org

Volume: 04 Issue: 12 | Dec 2023 ISSN: 2660-5309

ECG HEARTBEAT CLASSIFICATION: A DEEP LEARNING USING CNN ALGORITHM

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Abstract

One of the more thorough tests for identifying diseases affecting the cardiovascular system is the electrocardiogram (ECG). Computer-based technologies are now employed in ECG analysis, building on the crude techniques that were previously used to analyze these tests. Over time, sophisticated technological methods have been developed that use ECG analysis to identify cardiovascular problems. We built and trained CNN model on MITBIH dataset for two classes (Normal, Abnormal) to classify ECG heartbeat. The training and testing results were (98.6)% and (99)% respectively, which are very good and promise.

ARTICLE INFO

Article history:
Received 14 Oct 2023
Revised form 15 Nov 2023
Accepted 16 Dec 2023

Key words:
ECG, CNN, Heartbeats, Artificial Intelligence.

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Introduction

The leading cause of the high death rate worldwide is heart disease. Heart disease represents 16% of wholly deaths from all causes, according to the world health organization. The number of heart disease fatalities has increased by more than (2) millions from year 2000, and in 2019 became (9) million [1]. The signal from ECG is a recording of the heart's bioelectrical activity [2]. By effective treatment, early diagnosis of cardiac illnesses (abnormalities) can lengthen life and improve life’s quality [3]. ECG is often utilized by cardiologists to evaluate heart health. The primary issue with manual ECG signal analysis is the difficulty in recognizing different waves and in the signal, which is a problem with many other time-series data. This task needs a lot of human effort and is susceptible to mistakes [4].

ECG is a quick test that uses electrodes placed on the skin to assess the electrical activity of the heart. It displays the intensity and timing of the electrical impulses traveling through your heart, as well as whether the rhythm of your heartbeats is normal or abnormal. Numerous cardiac disorders, such as disturbed heart rhythm, and electrolyte imbalances, can lead to changes in normal ECG patterns. Physicians can identify cardiovascular problems via computer-aided ECG analysis [5]. ECG signals are the most reliable indicators of heart activity status. a typical ECG signal is made up of T wave and QRS, which together represent the most significant champers of the signal and are used to analyze the heart's status as well as other aspects of the signal. P wave represents the activity of the upper champers of the heart. Hence, any cardiac condition may be seen in these parts of the waveform, notably the QRS complex, which is identified by a shortening, broadening, or lengthening of the QRS complex [6-9].

A recurrent pattern of P, QRS, T represents the rhythmic depolarization and repolarization of the myocardium associated with the contraction of the atria and ventricles throughout every cardiac cycle. See Fig. 1 [10].

The term artificial intelligence (AI) is notoriously difficult to define. It is quite likely the most amazing and complicated generation of humans to date. Science's definition AI is a series of computational technologies inspired by how humans use their neurological systems to perceive, observe, comprehend, and act [11,12,13]. One of the major issues in the fields of AI and machine learning is deep learning (DL) [14].

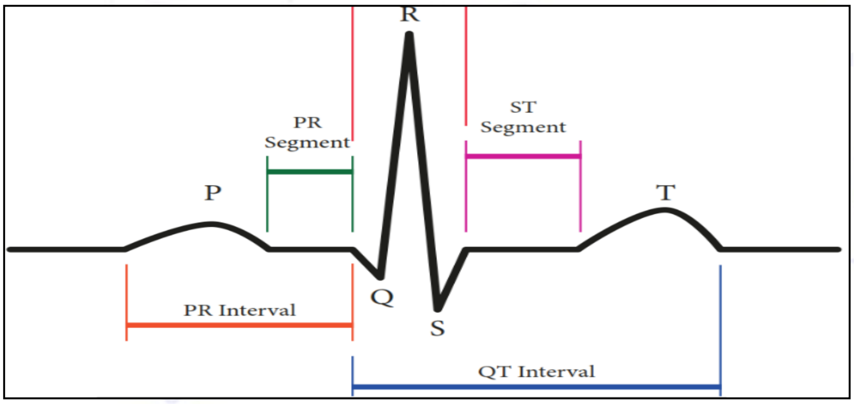


Fig. 1. ECG signal waves

As DL is a subset of ML and AI in terms of working domain, it is an AI function that simulates how the human brain deals with data [4,15].

As the amount of data grows, DL is less effective than traditional ML. To develop computational models, DL represents data abstractions utilizing numerous layers. In difference to ML, DL runs fast in testing even if it tokens a long time for training since the many parameters. Fig.2 compares the situation of DL with that of ML and AI [16].

The purpose of this system is to balance the proposed system's accuracy of heartbeat classification with the size of the model by performing experiments using MIT-BIH dataset. The proposed system successfully classify heartbeat using Deep learning networks with an accuracy of (99%) after we carried out the process of training the neural network using the mentioned dataset.

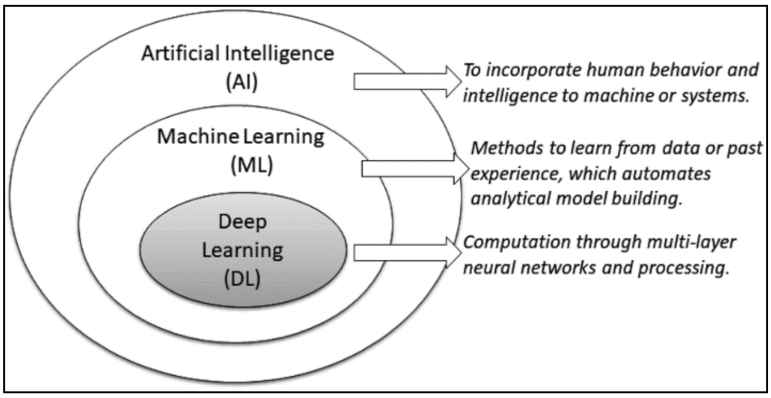


Fig. 2. DL relation to ML and AI

Several strategies used by researchers to categorize ECG heartbeats will be reviewed.

I. Fathail and D. Bhagilewe (2022) devised a method to digitize the ECG paper, recognizing R peaks, computing the average heart rate, and sending SMS in abnormality case. The system works by having users upload an ECG picture, then reduced in dimension, has its features extracted as digital signals, and is then saved in a CSV file utilizing MATLAB. The system then recovers the signals so that the raw signals may be processed further. The device uses the Python programming language to send SMS alerts to doctors if the heart rate is irregular using a technological platform called Twilio. They examined 10 ECG papers. The accuracy of the peak detection was approximately 90%, true positive was around 90%, false positive rate was up to 8% [1]. A. Farooq et al. (2021) developed a method that enables LabVIEW to classify the observed ECG waveform. The input ECG sensor signal is first gathered using the sensor system, then processed in LabVIEW to provide a classification. They presented a simulation built on LabVIEW that categorizes the ECG signal as healthy, unhealthy, or not specified. ML is used to train the categorization system (K-mean clustering). They treated three patients for a total of 14 days. An automated appointment can be made in 27.5 seconds through SMS in the event of a health issue [2].

A unique classifier two dimensional (CNN) was used by P. Seitanidis et al. (2022), and it was optimized for storage and computational complexity, making it appropriate for implementation on edge devices. According to the tests conducted on the MITBIH arrhythmia database, the suggested two dimensional CNN achieves accuracy of 95.3% [17]. A unique technique for detecting vital signs based on fall posture and chest discomfort was developed by H. Mohan et al. (2021) using an intelligence surveillance camera with Using single shot detectors Inception V2, MobileNet V2, and NVIDIA's Jetson Nano. 3000 indoor color photo files were processed using the proprietary RMS dataset and the Red, Blue, Green, and Depth dataset from Nanyang Technological University. After examining the measures, they came to an average accuracy and recall of 76.4% and 80%, respectively [18]. M. Sotorra (2019) created and built a data visualizer for the MITBIH dataset. He also used a deep autoencoder to compress the beats and a principal component analysis to minimize the data's dimensionality. The initial work is a convolutional autoencoder with ten neurons. The calculated loss is 22.8 percent. The correlation coefficient between the input vector and the autoencoder result is, correspondingly, 0.99, 0.89, 0.96, 0.93, and 0.92 for beats N, L, R, V, and A. Moreover, a 5-neuron autoencoder has been trained for even more compression. The loss outcomes are equal to 22.8%, and the correlation coefficients are, correspondingly, 0.95, 0.86, 0.83, 0.89, and 0.71 [19].

Z. Zhang and W. Yan preprocessed ECG database data using combination of median filter and bandstop filter to account for individual variations in ECG waveforms. A model is built by using deep neural network techniques to solve the issue of feature important variability in MIT-BIH dataset. The suggested multiorder classification method's average recognition rates with the enhanced wavelet features and improved RBP algorithm are 78.8% and 64.5%, respectively [20]. Learning the optimal ECG features from every heartbeat window using an auto-encoder convolution network, M. Ojha et al. (2021) built a one-dimensional CNN model. The Support Vector Machine classifier then used to recognize the four various forms of arrhythmic beats, including regular beats, using auto-encode characteristics. Tenfold cross-validation techniques are used to analyze the model's statistical performance, and the results show that the model has 98.84%accuracy, 99.53%average accuracy, 98.24% sensitivity, and 97.58% precision, respectively [21]. W. Ullah et al. (2021) used two different types of datasets. The MIT-BIH database, with 109446 ECG beats with a sampling frequency of 125 Hz, is one dataset. The classes N, S, V, F, and Q are included in the first dataset. The second dataset is the PTB ECG dataset. It has double classes. CNN, CNN+LSTM, and CNN+LSTM is used on the above datasets. Eighty percent of dataset for training, 20% for testing. Combining the techniques led to accuracy results of 99.12 percent for CNN, 99.3 percent for CNN + LSTM, and 99.29 percent for CNN+LSTM [10]. S. Irfan et al. (2022) proposed DL framework that combines several techniques by stacking related layers in every technique for creating a single, reliable model. Five classes of arrhythmias have been identified using the proposed methodology on two datasets. The suggested technique accuracy was 99.35% [22]. F. Ibrahem and M. Younes (2019) assessed the effectiveness of their method using a dataset containing 205,146 records. Classification techniques, Decision Trees, Random Forests and Gradient-Boosted Trees (GDB), constructed used on the MIT-BIH and Baseline MIT-BIH databases, the suggested approach is assessed and verified. their findings indicate that overall accuracy for binary classification measured by the GDB Tree algorithm and the random forest technique was 96.75%. With Random Forest, it was possible to attain a 98.03% accuracy rate for multi-class classification [23].

PROPOSED METHOD

Deep CNN architecture is built and trained on MITBIH dataset with many parameters as well explained be later, then, the system tested for many ECG heartbeats. Fig. 3 shows a flowchart for the proposed system.

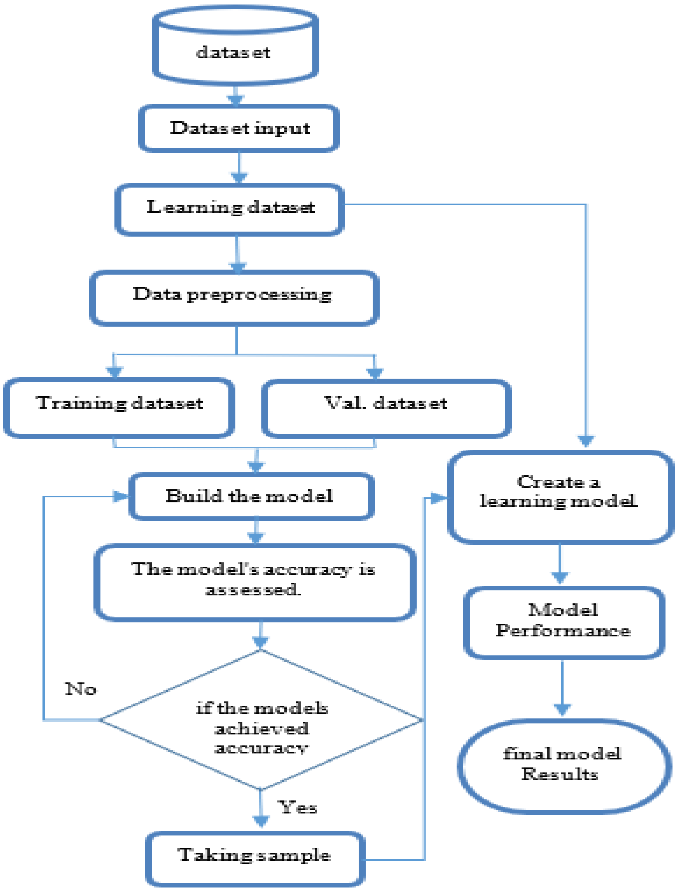
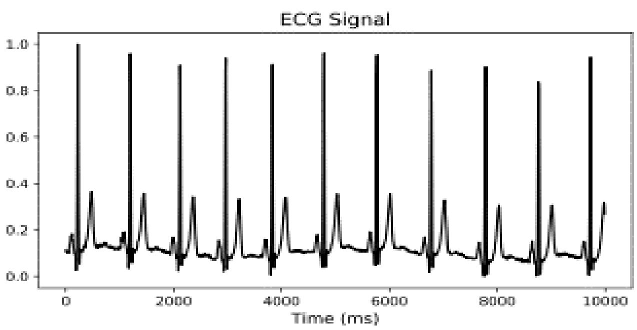


Fig. 3. The proposed system flowchart

Easy approach for preprocessing ECG data and extracting beats proposed where ECG beats are inputs of it. These are the procedures for separating beats from an ECG signal (see Fig. 4). The recommended beat extraction approach is clear and useful for obtaining R-R intervals from signals. Any processing -such as filtering- or made any presumptions about the signal's morphology or spectrum are made, each extracted beat has the same duration, which is important for usage as inputs in the next processing steps.



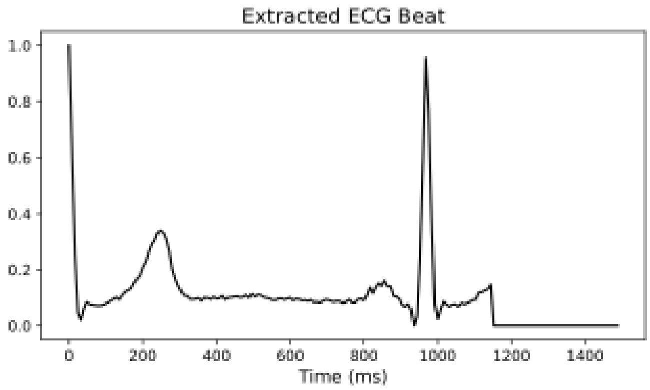


Fig. 4. An ECG heartbeat and the extracted beat from it.

Dataset

MIT-BIH Dataset used as data source for labeled ECG records. The dataset employed in the research is comprises of ECG recordings made at a 360Hz sample rate on 47 distinct people with 30-min raw ECG recordings, 25 of whom are female and 22 of whom are male. At least two cardiologists mark each beat as they hear it. The (109,446) rows and (188) columns of the MIT-BIH dataset from Kaggle were split into two excel files (MIT-BIH train.csv) and (MIT-BIH test.csv) were utilized to train our built CNN. (87554) rows and (21892) rows, or 80% and 20%, respectively, for the training set and validation set [22,24].

Algorithm

An algorithm must be evaluated in order to comprehend its comparative properties. Empirical techniques may be used to characterize the main approaches of evaluation. Algorithms for learning tasks are used in the experimental assessment to examine how well they work in real-world situations. When analyzed, some models could produce good outcomes, while others might produce poor results. As a result, it is a great way to assess DL algorithms. Because the algorithm is the most common ones that yield high accuracy in classify heartbeats, we utilized them to evaluate the model's performance [8]. This work aims to make a system that performs a portion of the functions that monitors heartbeats. After performing CNN training process, the proposed system classifies heartbeats to (Normal/ Abnormal) using deep learning CNN, where the CNN is trained on MIT-BIH dataset. Figure 5 shows our model layers.

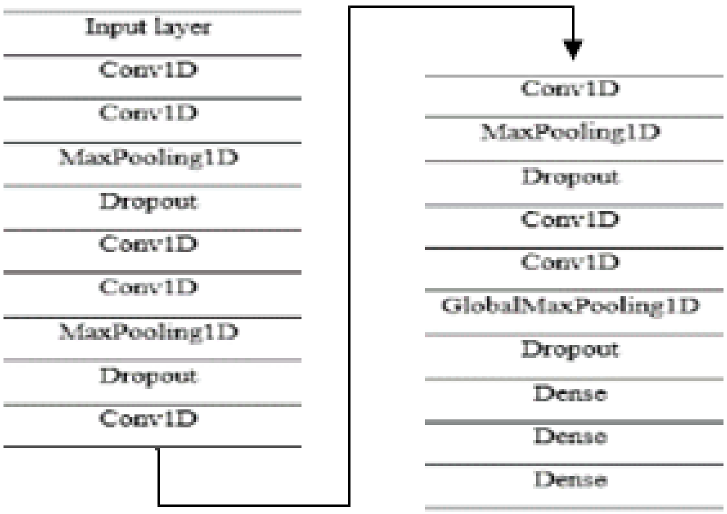


FIG. 5. Algorithm architecture

EXPERIMENTAL SETUP

The following system components were installed on a laptop: An Intel Core I7 CPU from the 6th generation, 8 GB of RAM, and an internal display with Intel HD graphics 4600 resolution (2 GB).

Python Language and Parameters

Python (3.9.7) programming language used with libraries (Pandas, Numpy, Keras, Torch, Matplotlib, Seaborn and Sklearn) for ECG classification for two classes (Normal, abnormal) with several hyper parameters are applied to the model. These are used to train the model, and the best results are retained for comparison and performance analysis of the model in the future.

Precision

It is defined as the proportion of truthfully predicted positive classes all items with a positive prediction, the precision show in equation (1) [17,[21].

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

Recall

It is the ratio of TP and total of ground truth positives, usually referred to as the sensitivity. The Recall show in equation (2) [17,25].

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

F1-Score

The conflict between accuracy and recall; these two parameters are the two essential components in calculating the F1-score [26,27], which stated mathematically as follows:

$$F1= \frac{Two \times TP}{2TP + FP + FN} \qquad (3)$$

Model Training

Used the feature extractions to train the pre-trained Convolutional Neural Network (CNN) models[4,28], which leverages the MIT-BIH Dataset to import the weights of the trained model. To retrain the model for new classification tasks, the final completely connected layer with 1000 neurons was deleted and replaced with a fully connected layer with two neurons to categorize the necessary classes. The parameters of the frozen layers do not update during training, resulting in a fast rise in the model's training speed. In this case, Softmax was employed as an activation function. Moreover, insert innovative layers afterward. This is accomplished by setting the upper layers to False. The model's last three layers are changed to adapt to the unique categorization task: Average Pooling, Dense FC with ReLU activation function (AF), Dense FC with Softmax function, and classification output layers. A pooling layer is added to increase feature extraction (FE) [26] performance. Additional FC layers are introduced to achieve classification using features learned from a new input set. In CNN, the AF ReLU is often used. The input size is (188x 1), and each model has a summary to evaluate layers and feature maps for correctness. Utilized a learning rate of (1e-4) and patch size classifiers (32) for a total of (50) epochs. The feature map is utilized as an input to a complete communication layer to get classification results. the original convolutional neural network model does not minimize overfitting. As a result, these models need image data optimization and parameter fine-tuning.

The CNN designed include convolution layers, pooling layers, and fully connected layers. Forward propagation is the method to convert input data into output. The convolution layer performs feature extraction including the convolution operation and the activation function. A pooling layer employs the conventional downsampling procedure to reduce the in-plane dimensionality of the feature maps in order to add translation invariance to small shifts and distortions and to restrict the number of consequent learnable parameters. a max pooling with a (2x1) filter and two strides used. The output feature maps from the final convolution or pooling layer are typically flattened, or transformed into 1D array, and linked fully connected layers, where every input and every output are connected by a trainable weight. The characteristics produced by the convolution layers and the downsampling layers then mapped to the network's final outputs, like every class probability in classification, by a collection of fully connected layers, each of them is followed by activation function [25,28,29, 30].

The Training parameters used in CNN training are (Dropout=0.4, learning rate=1x10-3, optimizer=Adam, Batch size= 1024, steps/epoch= 10). The hardware used in the training is a computer with specifications shown in Table 1.

TABLE 1. Hardware Requirements

Microprocessor	intel Core-i7, 7th generation
Microprocessor speed	2.7
RAM	8 G
The Operating system	Windows 64 bits
Graphical processing unit	Intel HD Graphics 620 internal
Hard disk drive	SSD

Results and discussion

The first ECG signal in the dataset and its accompanying label was displayed as shown in Fig.6 at the beginning of training.

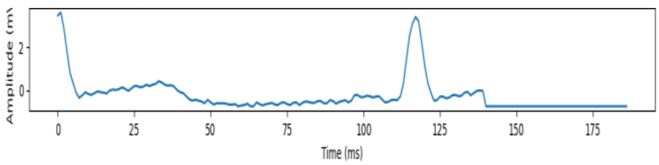


Fig. 6. The first 5 ECG signals in the dataset and their labels

After that, the dataset's data will be normalized, as shown in Fig. 7. The normalized data will then be saved to a csv file to be used later.

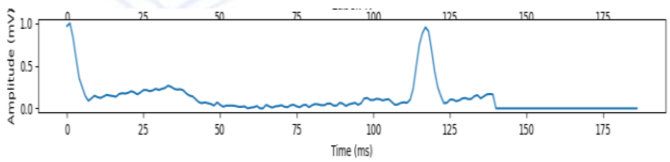


Fig. 7. Normalized data

Figure 8 displays the smooth-lined training and validation losses. The two losses is closed to zero, these are perfect results for training and validation losses.

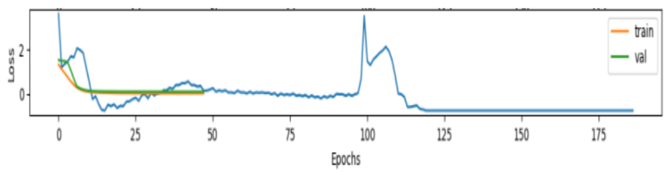
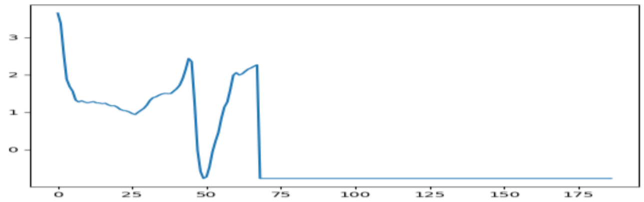
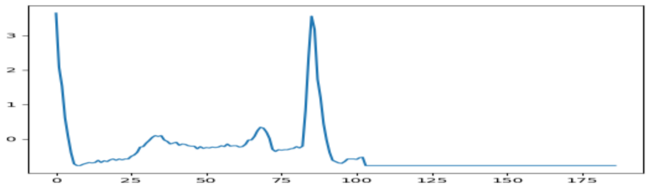


Fig. 8. The training and validation losses

Figure 9 shows two samples for ECG signals for the two classes normal and abnormal heartbeats. The proposed system will classify the entered ECG signal to one of the classes.



(a)



(b)

Fig. 9. (a) Sample of Abnormal ECG signal and (b) Sample of normal ECG signal

The final results of training in final epoch (50) (Fig. 10) shows that training losses were (0.0070), validation losses were (0.0896), validation accuracy (0.9861) and the best accuracy is (0.9866). This is very good accuracy and promise in ECG heartbeat classification.

```
Adjusting learning rate of group 0 to 8.1000e-06.
Train Loss: 0.0070   Val Loss: 0.0893    Val Accuracy: 0.9859
Epoch 49/50
----------
Adjusting learning rate of group 0 to 8.1000e-06.
Train Loss: 0.0072   Val Loss: 0.0898    Val Accuracy: 0.9861
Epoch 50/50
----------
Adjusting learning rate of group 0 to 2.4300e-06.
Train Loss: 0.0070   Val Loss: 0.0896    Val Accuracy: 0.9861
Finished Training and the best accuracy is: 0.9866
```

Fig. 10. Training results of CNN algorithm

After training the proposed algorithm, weight file will be produced. The total parameters (254901) with fifty epochs takes about an hour for training, a part of the training process in Fig. 11.

```
Epoch 29: val_acc improved from 0.98755 to 0.98767, saving model to
baseline_cnn_mitbih.h5
2463/2463 - 96s - loss: 0.0278 - acc: 0.9911 - val_loss: 0.0474 - val_acc:
0.9877 - lr: 1.0000e-05 - 96s/epoch - 39ms/step
Epoch 30/50

Epoch 30: val_acc did not improve from 0.98767
2463/2463 - 97s - loss: 0.0281 - acc: 0.9910 - val_loss: 0.0475 - val_acc:
0.9876 - lr: 1.0000e-05 - 97s/epoch - 39ms/step
Epoch 31/50

Epoch 31: val_acc did not improve from 0.98767
2463/2463 - 98s - loss: 0.0278 - acc: 0.9911 - val_loss: 0.0476 - val_acc:
0.9877 - lr: 1.0000e-05 - 98s/epoch - 40ms/step
```

Fig. 11. Part of training process

After training, the proposed system has been tested for accuracy and performance. The system was tested on (100) heartbeats to see if their heartbeats were normal or not, taken one heartbeat for every test. The results were (99%) on the (100) heartbeats. These are very good results and promised in artificial intelligence. The system can be used in the medical fields after making improvements and testing it on thousands of cases to ensure excellent results.

Conclusions

Person's life is greatly threatened by cardiovascular disorders, and treating them rely heavily on proper ECG analysis. It takes a time and money for a medical professional for manually analyze ECG readings. Thus, it is crucial to create an automated technique for recognizing arrhythmias. The MIT-BIH Dataset serves as the primary source of data for this study.

In this paper, deep CNN for heartbeats classification is trained using CNN with (.csv) file as input, and with procedures optimized for speed and accuracy. Our system performs training losses (0.0070), validation losses (0.0896), validation accuracy (0.9861) and the best accuracy is (0.9866). The test accuracy for the (100) heartbeats were (99%). According to these results, the proposed method is efficient and capable of making predictions in both categories (normal, abnormal) with good and promising accuracy and performance. In addition, the proposed system architecture is simpler and less complex than the architectures mentioned in related works.

We'll leverage mobile and cloud technologies in the future. Also, it is essential to create wearable technology that uses less energy. The procedures that have been put into place may be rebuilt to operate with a variety of classes, work can be designed for use in the present, and precision can be improved and increased continuously. Furthermore, the same categorization procedure may be utilized to several kinds of datasets, including stress and clinical datasets.

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