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A NOVEL APPROACH FOR ECG CLASSIFICATION USING PROBABILITY CONTINUOUS WAVELET TRANSFORM AND ALEX NET-DEEP NEURAL NETWORK

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Abstract

Biomedical signal processing and pattern recognition relies on the use of electrocardiograms (ECGs) to detect arrhythmia. ECG arrhythmias may be classified using features extracted from the Extreme Value Distributor of the Probability Density Function (PDF) and a neural network training model created using the Alex net architecture (CNN). Wavelet transforms helped translate feature space into two-dimensional images (CWT). A side-by-side comparison of the two approaches was also carried out. In the first instance, we employed CWT to reduce the three-dimensionality of ECG pictures. CWT was used to extract features from PDF files and transform them into picture data in the second scenario. With a learning rate of 0.001 and a batch size of 250, the accuracy of tests was 98.67%. Based on the findings, it seems that the suggested technique is more effective at extracting characteristics than the more conventional approach.

Keywords: Cardiovascular diseases (CVDs), Diagnosis, ECG arrhythmias classification, Alex net CNN.

1. Introduction

Electrocardiography (ECG) is a technique that permits the monitoring and recording of electrical activity during cardiac operations by use of leads placed around the heart. Patients who suffer from cardiac arrhythmias may be identified by their doctors using ECG recordings. Doctors benefit greatly from the ability to identify cardiac activity based on a characteristic in a signal [1]. Biomedical signal processing implementations and applications for deep neural networks have recently received a lot of attention. To make computers smart enough to take action, deep learning combines principles from neurology and psychology, statistical arithmetic, and physics (s). ECG data may be applied directly to a convolutional neural network (CNN) without any preprocessing or feature selection. In this situation, our suggested work created data as 2D to each high accuracy using CNN input intended to analyses picture data. A DNN model was used to compare two datasets (set1=7 classes, set2=11) and the accuracy belongs to the first set (7 classes) is 92.24 percent and the accuracy belongs to the second set (11 classes) is 96.13 percent, compared to our work, where the method proposed in our work during a feature normalization is based on probability density function (PDF) for and then apply continuous wavelet transform (CWT) to convert feature from 1D to image.. When it comes to classifying ECG pulse patterns, method block-based neural networks have been shown to perform better than our proposed work in [3] using various configurations of batch size and learning rate. [4] used a 1-D CNN approach for classifying ECGs, but in our study, a 1-D feature was transformed to a 2-dimensional picture spectrogram using CWT. There is an additional SoftMax layer on top of the hidden layer in [5], which is a deep neural network method, where the labelling for classes of ECG in the test record is done during iteration and applied to modifying the DNN weights, and the other 9-layers of CNN have been justified to classify 1-D ECG arrhythmias in [6]. By setting the number of layers within CNN, a training processing takes more time and this compared to our work by setting the size An arrhythmic heart illness was the subject of this study, which examined a variety of complicated and variable cardiac symptoms. Using a dataset of 12100 recorded beats and an RBF in NN parameters optimized using the cuckoo search algorithm after converting a 1D ECG signal to a 2D spectrogram based on CWT, the implemented algorithms were successful in distinguishing between two classes of normal and abnormal beats, with an accuracy of 98.32 compared to our work's (3) and 98.67. When a wavelet algorithm and CWT were used to remove noise in [9], the accuracy for both 1D and 2D was 99.02 percent and 97.38%, respectively. Whereas in [9] many stages of processing consumed resources such as processors and memory, in our work, PDF function has basic math operations and consumes a high amount of processing and memory space. There were two methods employed in this research [10]. To train the CNN, the first way uses ECG data in time-series form and the spectrogram (2D) picture, which requires the use of processing and memory resources. Epileptic seizures may now be detected using an ECG signal, according to a novel method described in [11].

Analysis of the ECG signal is done using absolute deviation of fast Fourier transform coefficients and spectral entropy as spectral analysis methods to extract the characteristics. A 94.2 percent accuracy rate was achieved in this study, which focused on an epileptic case and compared to our work; three ECGs were recorded and the result was 98.67 percent for [12] noise reduction in ECG signal utilizing independent component analysis (ICA) with various capacity comparisons. While our work focused on classifying ECG instances, this study simply compares approaches for removing noise from ECG signals using the signal-to-noise ratio (SNR). The goal of the proposed research is to improve performance while classifying ECG signals. The MIT-BIH arrhythmia database used PDF as a new characteristic of ECG data and created reliable predictions of ECG signal (variable and continuous data) for this function of statistics operation, and this approach is applied to all records in the dataset. When preparing data for CNN, a 2D vector may be used as a feature vector. Here, the CWT is used to convert 1-D data to 2-D data and then shown as a spectrogram picture. During the post-processing phase, a deep learning approach known as CNN with a pre-trained architecture termed Alex net is employed to apply the training and validation processes. An additional tool used to compare traditional and suggested methodologies is a confusion matrix.

2. ECG dataset

ECG signals from Physio Net have been analyzed in different ways via the MIT-BIH ECG database [13]. The database's structure consists of two files: one containing ECG data, and one containing a list of labels. There are 192 samples in all, with 96 samples in ARR, 30 samples in CHF, and 35 samples in NSR in each of the three classes. The data length of each signal sample is 65536 bytes. A total of 65536 records, 30 from each class, are used in this project. While ARR is characterized by an irregular series of heartbeats that may be rapid or slow (or both), CHF occurs when the heart muscle does not pump blood correctly. NSR is a healthy human heartbeat's rhythm.

3. Feature extraction based on PDF

The preprocessing of the ECG signal is done using the PDF approach in this study. As a statistical approach, the PDF estimates the probability that a particular value will be assigned to a vector. The integral of the variable's density across the area is used to get the PDF, which is usually connected with a continuous invariant vector [14].

4. Extreme value distribution function

The distribution probability of an extreme value is represented by the extreme value function, which includes parameters, a model description, and sample data. In order to model the lowest or greatest value among an excessive number of randomly generated values, the function of the extreme value distribution is utilized. If the tails of an exponentially decaying distribution are to be modelled, the extreme value distribution provides the best fit. Although the greatest distribution value is a positive number, this function takes into account negative values of the initial values [15]. Given a distribution with size and location parameters, this equation depicts a probability density function for the extreme value distribution.

$$f(x|\mu,\sigma) = \sigma^{-1} \exp\left(\frac{x-\mu}{\sigma}\right) \exp\left(-\exp\left(\frac{x-\mu}{\sigma}\right)\right) \quad (1)$$

Where x is data, $\boldsymbol{\mu}$ is the mean of x, and $\boldsymbol{\sigma}$ is the standard deviation of x.

5. 1-D vector to 2-D using

This technique is called CWT, which stands for continuous wavelet transform. [21] CWT performs arithmetic operations on all scales. There is a substantial link between low-frequency sounds and high-domain data. When the scale of high frequency sounds is applied to the low domain of data, a substantial connection is seen. A powerful analysis of analogue signals may be done using complex-valued time/frequency contained filters with threshold support on negative values [16].

$$W_{\Psi}(t,s) = \int_{-\infty}^{\infty} \frac{1}{s^n} \Psi^* \left(\frac{\tau - t}{s}\right) x(\tau) d\tau \qquad (2)$$

With normalization set to 1, or a set of projections that are indexed by the scale set, the CWT set of bandpass operations may be normalized to n=1. They're called Morse Wavelets, and they combine all wavelet types and the analytic filter into one wavelet that depicts the hard exponentials. The frequency domain definition of these Morse wavelets is as follows:

$$W_{\beta,\gamma}(\omega) = \int_{-\infty}^{\infty} \Psi_{\beta,\gamma}(t) e^{-i\omega t}\, dt = U(\omega)\alpha_{\beta,\gamma}\omega^{\beta} e^{-\omega\gamma} \qquad (3)$$

There is a normalization value, U () is the step value function, and the two parameters used to govern the waveform in the wavelet. Network of neurons that has undergone convolution (CNN) Research and development for bettering performance has made extensive use of ECG data analysis. An example of one of these approaches is deep learning using convolutional neural networks (CNNs). Deep learning algorithms like convolutional neural networks are included here (CNNs). In signal processing, notably in electrocardiography, signal analysis has become more popular. Data in two dimensions may be immediately fed into the network, which is a benefit of CNN's multidimensional input. ECG classification algorithms should be studied further after the CNN offered a more complete picture of multiple CNN applications and recommended more study [17, 18]. A typical CNN architecture is shown in Figure 1.

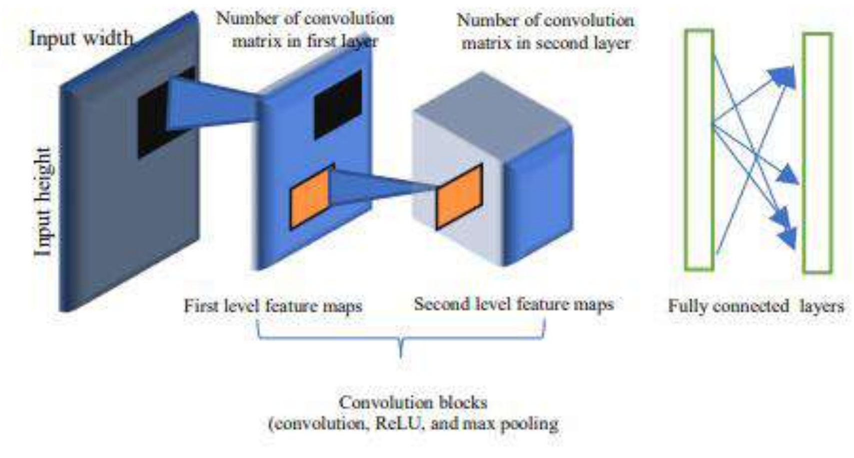

Figure. 1 A typical CNN architecture consisting of an input layer, convolution layer, a max-pooling layer, and a fully connected layer [17]

a. Input layer

The two-dimensional vectors from the pictures dataset are sent into the input layer. As previously stated, CNN is made up of many levels. A multidimensional matrix of picture data should be included in the CNN's input layer. Layer of convolution. It is one of the layers that distinguishes the convolutional layer from the known neural network (NN). Convolution kernels are used to concatenate the output of the previous convolutional layer, which is then fed into the next convolutional layer. The convolution result develops a feature of the input picture by repeatedly using convolution kernels in each sensory field of the full data set. Using multiplication and summing between the filter and the input, convolution filters are applied over the width and length of a picture. It is the weight matrix w and the bias matrix b that make up the convolution kernels, which are the components of the convolution layer. The following is the mathematical formula for the layer:

$$Xjl = f\left(\sum_{i \in M_j^{l-1}} x_i^{l-1} k_{ij}^l + b_j^l\right) \qquad (4)$$

The convolution kernel, bias, and layer information are all represented by the letters in l, k, b, x, and l, respectively.

b. Pooling layer

The pooling layer is another important aspect of CNN. Images have the characteristic of "stationarity," which indicates that features that are valuable in one area are likely to be useful in other areas. This is the theoretical foundation for the pooling layer. To create a single output, the pooling algorithm subsamples rectangular blocks obtained from the convolutional layer. The pooling increases the intensity of visual changes such as distortion, noise, and rotation. This method also results in a smaller file size while retaining all of the useful information. Both the average pooling and the maximum pooling are examples of pooling. This is the highest possible pool formula: [19]

$$y_{j(m,n)}^{l+1} = \max_{0 \le r,k} \{x_{(m.s+r,n.s+k)}^l\} \qquad (5)$$

in which m ≥ 0, n ≥ 0, s ≥ 0, and yl+1 the neuron unit (m) in the ith output feature map (yl+1) of neuron (m.s+r, n.s+k) in the ith input (x) map (l+1) has a value of xl, yl+1 is derived by calculating the greatest value across (m.s+rn.s+k)(mn) a ss non-overlapping local area in the input (x) map (l+1).

c. ReLU layer (rectified linear unit)

'ReLU' is a non-linear operation, and it involves units that employ the rectifier. An element-wise operation is implemented per pixel, and zero reconstitutes all negative values in the feature map. If positive, it maintains its value without any change. It is presumed that there is a neuron input given as x in an attempt to comprehend how the ReLU functions, and from that, the rectifier is represented as

$$\mathrm{f(x) = max(0,x)} \qquad (6)$$

d. Fully connected layer

To say that a filter is completely connected to all the filters in the next layer, we use a word like (FCL). Using convolution, ReLU, and max-pooling, we can extract the image's most prominent details. The FCL's objective is to utilize these characteristics to categories the input picture based on the training dataset. The activation function of softmax is used by FCL as the last pooling layer before the features are sent to a classifier.

e. Softmax layer

The non-linear classification power of softmax is being used since the ECG classifications and features are significantly more complicated and there is no unifying template. Just before the output layer, Softmax is implemented using a neural layer. The number of neurons in each layer of softmax must be the same as the number of neurons in the output layer. This concept is being expanded by Softmax. $\boldsymbol{\sigma}$: ℝk → ℝk is defined by the formula

$$\sigma\,(z)i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \text{ for i = 1 ... K and z = } (z1 \ldots zk) \in \mathbb{R}k \qquad (7)$$

f. Classification layer

The classifier layer is the neural network's output layer. The solution is in the last convolutional neural network layer (s).

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6. Performance evaluation of classifiers

The accuracy, precision, and recall of a classification test are all statistical metrics of that test's performance. A confusion matrix is a visual representation of all the potential results of such a test. The following equations describe precision, sensitivity (recall), and accuracy in terms of TP (true positive), TN (true negative), FP (false positive), and FN (false negative).

$$\text{Sensitivity}=\frac{TP}{TP+FN} \qquad (8)$$

$$\text{Specificity}=\frac{TN}{TN+FP} \qquad (9)$$

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+TN+TF} \qquad (10)$$

False positives (TP) are the number of beats categorized incorrectly for the given class, whereas true negatives (TN) are the total number of incorrectly classified beats. Similarly, the number of beats that are wrongly identified as belonging to a certain class (FP) or as not belonging to a specific class (FN) is called a false positive (FP) or a false negative (FN).

7. Results and discussion

Robust ECG categorization using alternative viewing and signal amplitude and time-based time scales are shown in this study. The following experimental findings are discussed in order to arrive at a representation of the proposed work's performance.

1. ECG data was subjected to a preprocessing approach known as the Extreme Value of PDF distribution for normalization.

ECG data is shown in Figs. 2-7 as a 1D dataset with (3-class) probability density extreme value distribution function applied, and the number of records in this dataset is (162). (65536). this dataset's classes are all labelled as (ARR, CHF, and NSR).

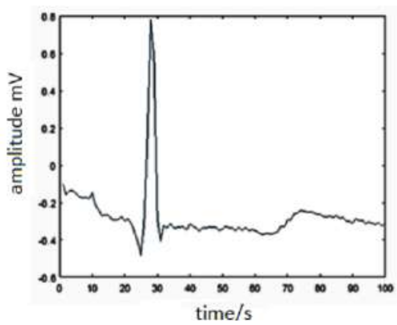

Figure. 2 Original sample of ARR

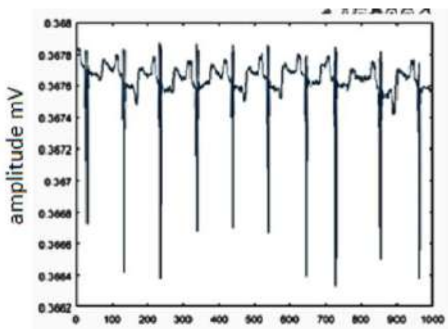

Figure. 3 Extreme value PDF of ARR sample

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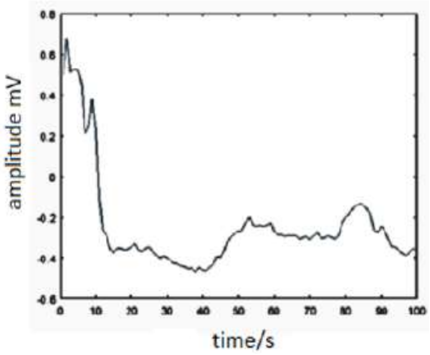

Figure. 4 Original sample of CHF

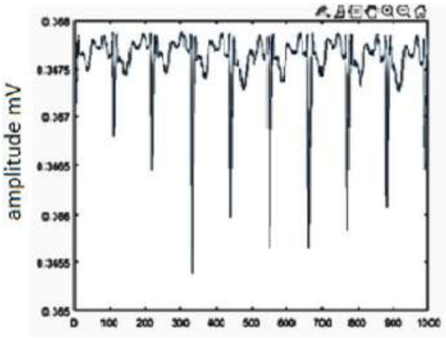

Figure. 5 Extreme value PDF of CHF sample

2. Two-dimensional vectors may be used as the first layer's input data. The processed ECG data is now a 1-D vector, and the CWT filter bank is the suggested mechanism for converting this vector to a 2-D vector. A new resolution of (227, 227), which is more in line with Alex Net's recommended size, has been applied to the spectrogram picture (CNN). Figures 8-13 in the CWT domain show the same samples as were displayed in preprocessing.

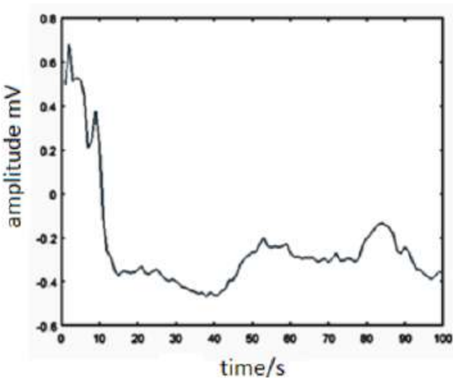

Figure. 6 Original sample of NSR

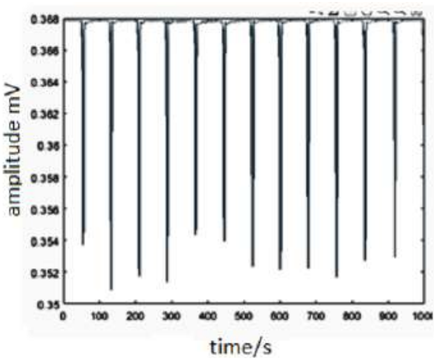

Figure. 7 Extreme value PDF of NSR sample

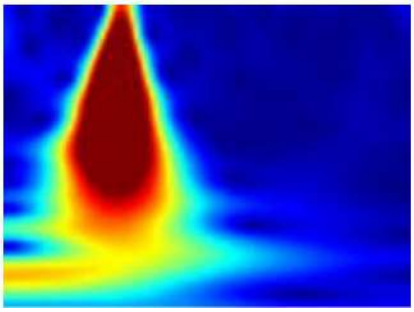

Figure. 8 CWT (ECG signal) sample ARR

3. As shown in Fig. 14, Alex Net architecture type of CNN was used for both training and classification in both situations (conventional and suggested approaches).

4. 4. In this research, a test data assessment over the training model, (750) samples of three classes were assessed. The confusion matrix influences which performance measurement is used in the assessment phase (accuracy). Table 1 demonstrates that our suggested technique has the greatest accuracy when compared to three current methods. According to [4], for example, the accuracy of the suggested DWT approach for ECG feature extraction is 96.95 percent; this is based on averaging out the ECG signals' average, mean, standard deviation, energy, and entropy values. 1D ECG data was normalized between 0 and 1 in [7], and CWT technique was utilized to convert 1D to 2D spectrogram picture and employed in CNN and achieved an accuracy of 97.10 in [10].

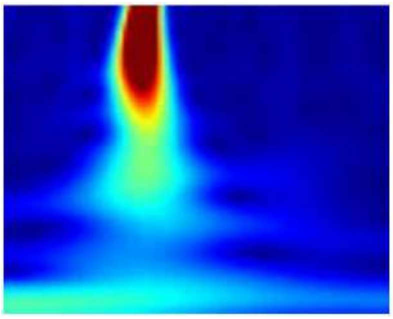

Figure. 9 CWT–PDF of ARR sample

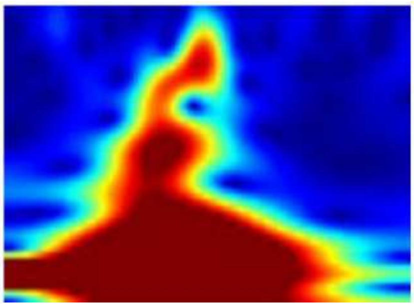

Figure. 10 CWT (ECG signal) sample CHF

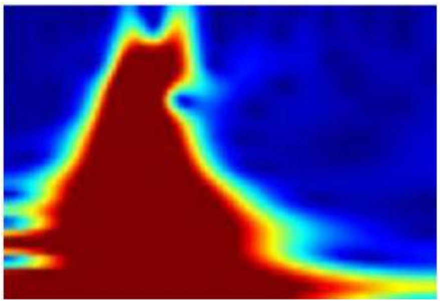

Figure. 11 CWT–PDF of CHF sample

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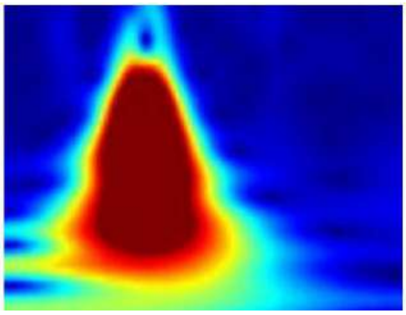

Figure. 12 CWT (ECG signal) sample NSR

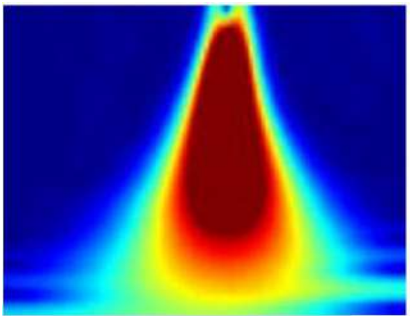

Figure. 13 CWT–PDF of NSR sample

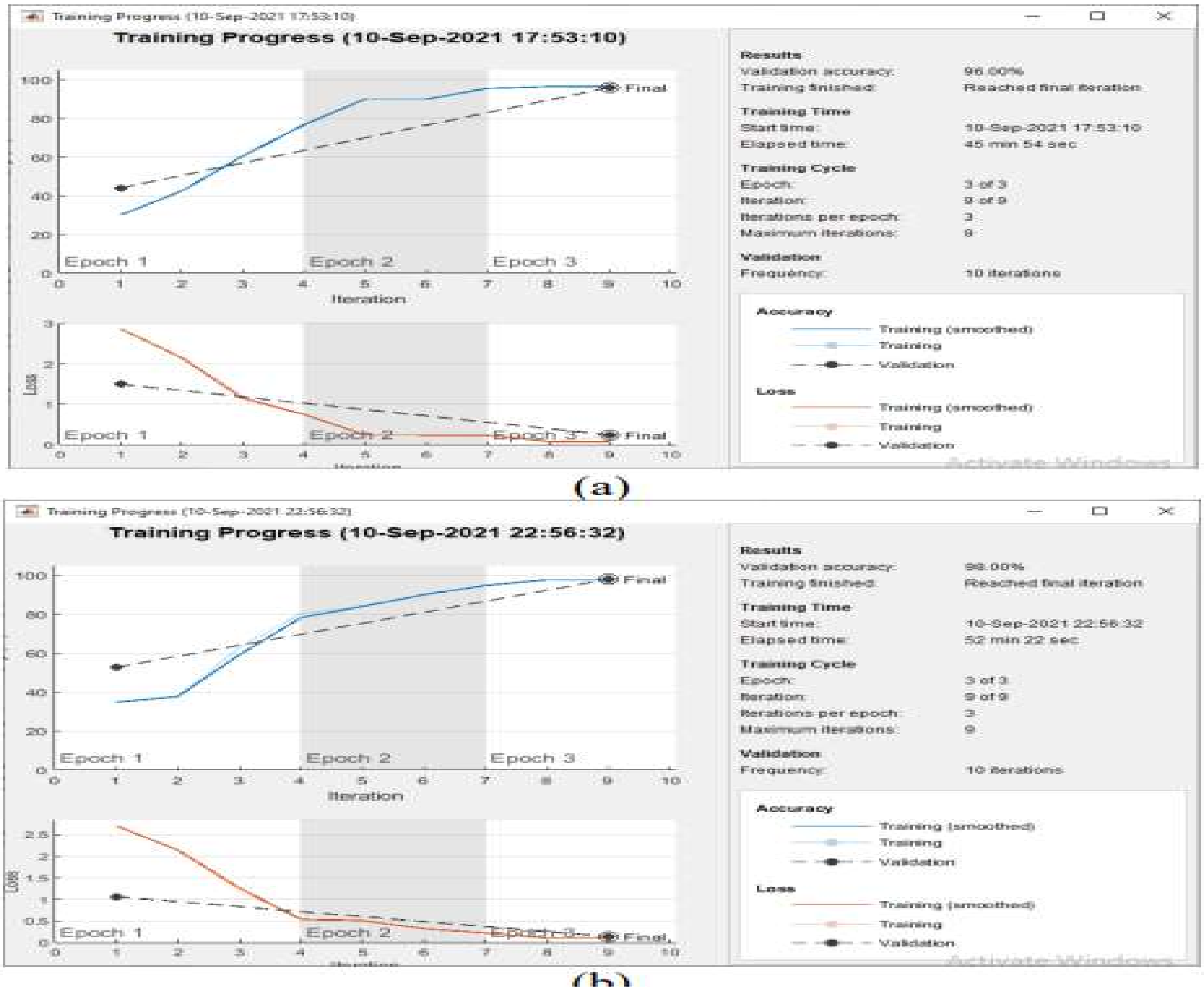

Figure. 14: (a) Result of CNN training conventional and (b) Result of CNN training proposed method

Table 1. Comparison of three approaches with proposed work

Work	Accuracy %
[4]	96.95
[7]	95.90
[10]time-series	97.10
Proposed work	**98.00**

Table 2. Evaluation compared with fixed batch size and different learning rate

Batch size	Learning rate	Accuracy	Precision	Recall
250	**0.001**	**98.67**	**98.67**	**98.67**
250	0.0025	98.67	98.67	98.67
250	0.005	98.00	98.00	98.00

Table 3. Evaluation compared with fixed learning rate and different batch size

Batch size	Learning rate	Accuracy	Precision	Recall
250	**0.001**	**98.67**	**98.67**	**98.6**
200	0.001	98.00	98.00	98.00
150	0.001	98.67	98.67	98.67

The creation of the 2D-CNN model represents yet another appraisal of the planned effort. Two of the individuals evaluated in the second round of testing had engaged in experimental behavior. Using a predetermined batch size and a range of learning rates (shown in table 2), the first experiment was conducted. Table 3 shows the results of the second experiment, which used a predetermined learning rate and a range of batch sizes. We may infer that for a batch size of 250 and a learning rate of 0.001, the 2D-CNN model chosen attained great accuracy during the assessment phase.

8. Conclusion

Deep learning algorithms are used in this work to classify ECG data. The MIT-BIH arrhythmia database categorized them into three categories: ARR, CHF, and NSR. Spliced together ECG signals, each record has a predetermined duration (65536). An alternative approach for transforming the time-domain ECG signals into two-dimensional, time-frequency spectrograms using CWT filter bank and the wavelet type "AMOR" was employed in this study as a normalization and imbalance data minimization method called PDF (Extreme Value). An example of a color picture input size of 227-by-227 is the "Alex net" deep CNN architecture. During the course of the experiments, an assessment of the performances was carried out. On the basis of an accuracy matrix comparison, our suggested method obtained accuracy as high as any of the other three techniques evaluated in this study (98.67 percent). Others assess the effects of varying learning rates and batch sizes on various 2D-CNN parameters. Experiments have shown that (learning rate=0.001 and batch size=250) are the optimum CNN settings.

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