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Electrocardiogram Waveforms Diagnosis based on Wavelet Representation and SqueezeNet Model

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ABSTRACT

Arrhythmia is an irregular in a person's beating heart that can happen occasionally. Heart rhythm problems can have disastrous results and seriously endanger health. Visually analyzing ECG data might be complex due to its large amount of information. Designing an automated method to assess the massive amount of ECG data is crucial. This research shows continuous wavelet transform (CWT) and deep learning strategies to automate detection and classification processes to examine three different ECG signals: congestive heart failure (CHF), normal sinus rhythm (NSR), and arrhythmia (ARR). CWT converts ECG signals into scalogram images for noise reduction and feature extraction. In deep learning, the modified SqueezeNet is employed to recognize the output of CWT, which is produced by the input of the ECG data. The proposed technique achieved 83.3%, 100%, and 94.7% accuracy in detecting CHF, NSR, and ARR. A modren approach for classifying arrhythmias has been devloped, in which scalogram pictures of ECG waves are trained using the SqueezeNet model. The obtained results are better than those of the various methods currently in use and will significantly lessen the level of medical intervention that physicians must perform. The suggested approach can be used on a few live ECG data for further research.

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1. INTRODUCTION

People are concerned about the health of the entire world as heart disease increases with time. ECG signals are the most accurate method for identifying abnormal heart functions. The irregular of the heart has been diagnosis for decades. Numerous cardiac and cancer-related problems are progressively getting worse due to our active and lethargic lifestyle [1]. Medical practitioners utilize the Electrocardiogram (ECG) as a crucial tool to assess and evaluate a patient's cardiac health. A healthy person's heart activity can be determined using a variety of factors, including the T-wave, QT interval, PR interval, QRS complex, and P-wave [2]. Heart issues can be found by examining these waves for sequences and abnormalities. A various heart diseases diagnosis by computer has become more common due to advancements in deep learning methods over the past ten years [3]. Heart disorders, known as arrhythmia (ARR), affect the rate of heartbeat, and the improper production of electrical impulses that control the heartbeat are some of the fundamental causes. Due to the disorders, These erroneous electrical impulses cause the heart to beat extremely slowly, very fast, or wildly all at once. Therefore, inadequate medical care may cause an abrupt cardiac arrest, heart failure, or heart attack [4]. A healthy heart's regular electrical activity is represented by the Normal Sinus Rhythm (NSR). It demonstrates how the sinus node generates and sends the electrical pulse accurately [5]. A person suffering from chronic congestive heart failure (CHF) has significantly reduced heartbeating ability. The primary causes of the heart's insufficient pumping capacity, which over time results in the heart being fragile, are cardiac artery constriction and high blood pressure [6]. Therefore, it is essential to identify and categorize any anomalies present in the ECG signal. Therefore, recognizing certain ECG irregularities will be helpful for physicians and other health professionals so they can take the appropriate medical action [7]. Deep learning employs several layers as a single processing unit to extract features. Each layer that extracts a particular feature uses the output of the layer that came before it as its input [8]. Deep learning employs several layers as a single processing unit to extract features. Each layer that extracts a particular feature uses the output of the layer that came before it as its input [9]. A novel wavelet-based layer in a deep bidirectional network was presented to categorize ECG waves. When a wavelet technique is used, the ECG waves were divided into frequency subbands at different scales [10]. These sub-bands provided an input sequence for the network. Using the MIT-BIH arrhythmia, three different heart types were identified. These sub-bands functioned as sequences for network input. Three distinct types were determined using the MIT-BIH arrhythmia [11].

Riyadi et al. [12] proposes a method for classifying multiclass EEG signals by combining the Adaptive Neuro-Fuzzy Inference System (ANFIS), Wavelet Packet Decomposition (WPD), and Subtractive Clustering. Enhancing the classification efficiency of EEG signals, which are frequently complicated and noisy is the aim. This technique provides a reliable and effective way to categorize EEG signals into multiple categories, with potential uses in cognitive status monitoring, healthcare diagnosis, and brain-computer interfaces.

Çınar et al. [13] presents Long Short Time Memory (LSTM) and hybrid convitional nueral network-Support Vector Machine (CNN-SVM) for accurate arrhythmia detection using ECG signals. With the best accuracy of 96.77%, the most efficient technique entails transforming ECG data into spectrograms and then using a Hybrid Alexnet-SVM algorithm on these images.

Madan et al. [14] suggested an automated method employing hybrid deep learning for identifying and categorizing the vast amount of ECG data. Noise reduction and feature extraction are automated by converting ECG data to scalogram images. Two networks are used, the Long Term Memory (LSTM) network and the 2D-CNN, combined to create the design model, known as the hybrid model. The acquired findings demonstrate that the suggested method offers accuracy of around 99%, 98.7%, and 99% for CHF, ARR, and NSR.

In his paper, Jawad et al. [15] explained that the feature extraction process was done using the wavelet transform (WT). An optimized ANN is employed to recognize the eight types of ECG signals. Two ECG signals were used to collect this data (ST-T and MIT-BIH databases). The invasive weed optimization (IWO) algorithm improves the WT coefficients utilized for the ANN learning process. More than 70% sensitivity, more than 94% specificity, over 65% positive predictive value, over 93% negative predictive value, and more than 80% classification accuracy are shown by the recommended approach. Fu'adah et al. [16] deal with an ECG wave categorization method for both AF and CHF by a 1D-CNN to provide a dependable identification system effectiveness. The research utilized 5600 ECG data records of AF, CHF, and NSR provided by the Physionet website. The results showed that the 1-D CNN can categorize data with a 99.643% accuracy, recall, precision, and f1-score of 99.6 for NSR, AF, and CHF. Panjaitan et al. [17] deals with the dataset of comparison groups to five groups of ECG data. CNN is used for recognition and enhancement by setting the batch size, learning rate, and number of layers. Among other hyperparameters, CNN able to classify Heart Rate Variability (HRV), Sudden cardiac death(SCD), NSR, CHF, Coronary Artery Disease (CAD), and Ventricular Tachycardia (VT), signals analysis in a way that significantly affects prediction accuracy using CNN to optimize the number of layers, learning rate, and batch size. The results show accuracy around 99.30%, 97.87% precision, 99.60% specificity, and 97% sensitivity.

Baliarsingh et al. [18] focuses on a novel method of compressing electrocardiograms (ECGs) for effective data transfer and storage by combining Wavelet Transform with machine learning algorithms. Heart disease diagnosis requires the use of ECG signals. A potential approach for effective ECG signal storage and transmission is the hybrid technique, which combines machine learning models for compression with wavelet-based feature extraction.

Our work has contributed to the following:

1. Through transfer learning, we identified trained SqueezeNet and used them for ECG classification. This network is used for image classification, but with CWT, it can be used for ECG classification.

2. We have effectively employed CWT for feature extraction and ECG representation techniques to provide retrained SqueezeNet.

3. SqueezeNet is modfied by replace drop9 be new_dropout layer of probability 0.6, conv10 by new_conv layer to increase the learning rate factors of the fully connected layer, and classificationlayer_predication by new_classouput layer to the number of filters equal to the number of classes.

4. We assessed transfer learning on a subset of modified SqueezeNet based on the resources required for learning and the classification accuracy using publicly available ECG datasets.

5. We assessed the consistency of the classification outcomes across several training options avialable to looked into potential gains.

This study employed a large dataset of 162 individuals' 65,536 ECG records. The CNN model produces a collection of rhythm classifications from an ECG data set. In terms of accuracy, the proposed approach performed better than that of an exceptional cardiologist when the CNN model's performance with three various types was examined. Substantial data is required to extract intricate ECG patterns and learn from multiple available inputs. Achieving higher accuracy levels and output that are on par with human standards won't be possible until then. A modified version of SqueezeNet is used to categorize the ECG data in this investigation. ECG signal categorization was done, and the efficacy of CNN designs was assessed by modifying a few output layers and applying a transfer learning technique.

A 1D ECG output, which is noisy due to baseline wandering effects, power line interference, and electromyographic disturbances, has been used to train models in most previous work. Several preprocessing steps are needed for filtering and feature extraction, which may compromise the model's accuracy and the data's integrity. Therefore, automating the detection and categorization process is the primary goal of this work. The CWT with a 227 × 227 × 3 resolution converts ECG waves into scalogram images. Automatic feature extraction is done with CWT, while classification is done with modified SqueezeNet. The main contribution is the suggestion of using a modified version of SqueezeNet to classify ECG signals. Using CWT, we first transformed all of the ECG signals into pictures. Next, we used SqueezeNet to categorize arrhythmias. The deep learning toolbox on MATLAB constructed the method. By allocating 20% of the dataset for testing and validation and 80% for training, the MIT-BIH Arrhythmia database is used to verify the performance of the suggested method. This work is divided into multiple sections: Part 2 summarizes the literature, whereas Part 3 explains the study methodology. Part 4 presents the findings and debate. Ultimately, the conclusions are presented in Part 5.

2. METHOD

Electrocardiographs (ECGs) are diagnostic instruments practitioners use to identify cardiovascular illnesses known as arrhythmias. ECG waves are the electrical responses of the heart throughout diagnostics. When an ECG instrument is coupled to a person's body, ECG waves are displayed as waves; ten electrodes were needed to catch 12 leads to provide a precise heart performance measure. Twelve ECG leads—which are broken down into intelligent leads (I, II, III, aVL, aVR, and aVF) and precordial leads (V1, V2, V3, V4, V5, and V6)—are needed for a correct diagnosis. Figure 1, as a specific electrical event, indicates negative and positive deviations from the baseline, which depicts P, Q, R, S, T, and U depending on the heart's anatomy. Traditionally, research on arrhythmia identification has concentrated on manually extracting features, segmenting waveforms, and filtering noise from ECG signals. Scientists attempted various artificial intelligence and data mining techniques to categorize arrhythmias [19][20]. Several approaches for classifying arrhythmias using machine learning and deep learning are covered in this section.

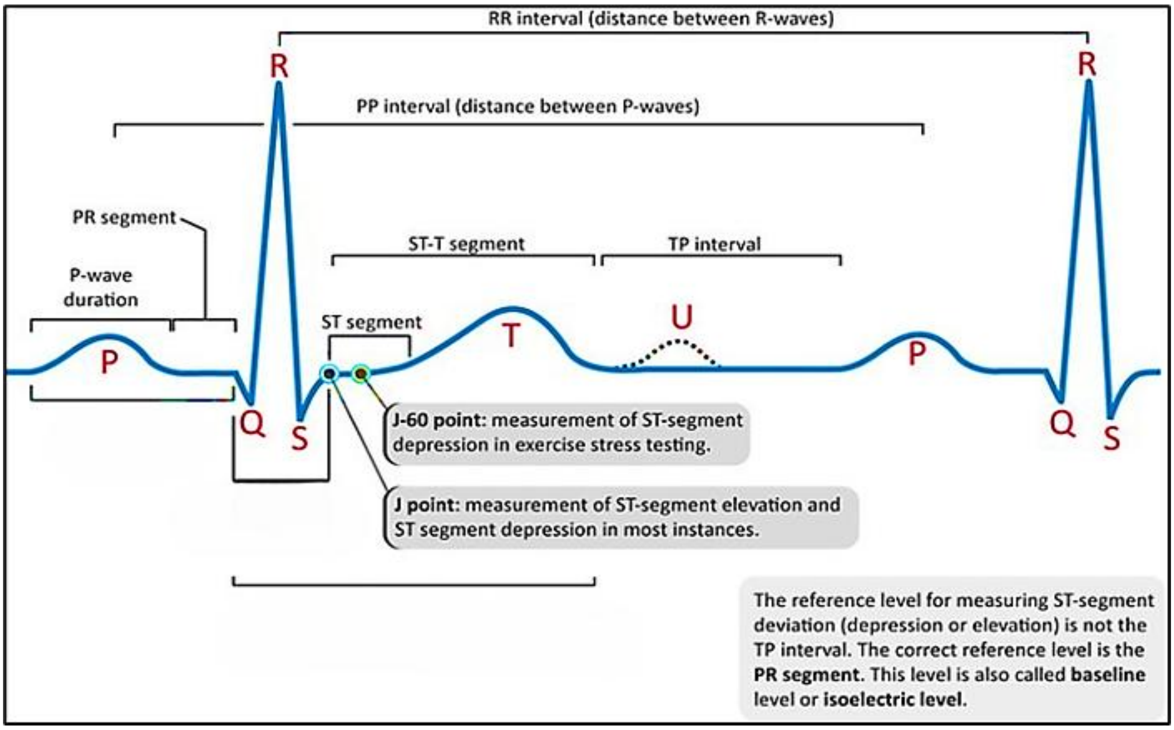


Figure 1. An illustration of the heart's whole electrical function [19].

2.1 Dataset

With the help of ECG records from three different Physionet datasets, we assessed the accuracy of our SqueezeNet model. These can be described as follows. The two types of sections that make up the structure of a database are labels and data. Each recording has 65,536 samples in total. Consequently, data is re-sampled at the usual rate of 128 Hz and processed as a 162 × 65,536 matrix, meaning it consists of an overall 162 ECG readings with a maximum number of samples of 65,536. On the other hand, labels provide information about ECG signals. Specifically, ARR signals are found in an array from rows 1 through 96, whereas CHF signals are seen in a variety from rows 97 through 126. On the other hand, NSR signals are represented by the rows 127–162 [19].

2.2. Data Preprocessing and Segmentation

This step aims to prepare the data for testing and training. The resize data helper function and a converted data store segment the data. Also, 1-D ECG data were converted into scalogram photos by CWT. CNN and other dynamic DL techniques are utilized for feature extraction, and a large amount of ECG waves is needed to train the network. The projected performance may deteriorate when very long input signals are transmitted over the SqueezeNet. The ECG waves and associated label titles must be divided using customized databases with the resizing data to avoid these adverse effects. ECG data obtained from the Physionet datasets, comprising ECG data from 162 patients—each of which contained 65,536 waveform segments—was utilized in our research. Here, 65,536 sequence segments have been split into ten sections, each containing 500 samples, and the other portions of the segment have been discarded. Thirty-two from CHF, thirty from ARR, and thirty from NSR were used in our analysis. We selected 30 recordings from each NSR, CHF, and ARR database to ensure they were proportionately distributed. Consequently, 900 recordings exist, each split into 10 segments of 500 samples, providing an abundance of data to train SqueezeNet for categorization.

2.3. Modify SqueezeNet neural network

The proposed approach is independent of the ECG domain and several ECG classification approaches, and it takes advantage of transfer learning from different categories. Specifically, instead of training the deep neural networks on initial ECG data, pre-trained designs related to image recognition and recognizing objects are employed. In these areas, large datasets are easily accessible, facilitating efficient feature map extraction and training and acknowledging tiny features and patterns in the pictures [21]. Transferring such acquired and readable feature maps for ECG categorization is impossible after 1-dimensional ECG waveform data can be converted using CWT to a 2-dimensional Scalogram representation of ECG waveform. [19]. For this investigation, the SqueezeNet topology was utilized due to its ability to extract features from a limited sample of ECG effectively.

The present deep learning technique can produce accurate results by including more layers in the network to enhance its performance. The main problem with this method is that the computational cost grows significantly with the number of layers. To optimize the outputs of every single layer, each inner layer was modified to produce lots of correlation distributions by obtaining several distributions of probabilities with a high correlation to the input data. SqueezeNet is a convolutional neural network that can be used for image data classification [22]. It has an accuracy similar to AlexNet's with a reduced parameter. It provided various advantages, such as its smaller size, reduced links with less training time, and increased possibility of connection with other networks for deployment. While the convolutional layers can distinguish spatial details from the data provided as the input, maximum pooling provides various features by decreasing the size and channel of the input data. [23]. In MATLAB, SqueezeNet is accessible through the Deep Learning Toolbox.

SqueezeNet is a deep neural network for computer vision. University of California, Berkeley, Stanford University, and DeepScale researchers worked together to create SqueezeNet, which was developed in 2016. SqueezeNet networks and the CWT can classify ECG signals by converting time series data into pictures [24]. SqueezeNet requires 227 by 227 by 3 RGB pictures, regarded as a network's first layer's attributes. The network architecture's layers function as filters. The first layers may identify several common visual features, such as edges, points, and colors. The subsequent layers focus on more precise markers for categorical differentiation. The SqueezeNet network was designed to classify photos into several item categories [25]. This network can be retrained to address ECG categorization difficulties. Overfitting is avoided by using a dropout layer. This layer uses a predetermined probability to arbitrarily set all input segments to zero. The probability of the last dropout layer is set to 0.6. The input picture is then classified using the last learnable and categorization layers [26]. SqueezeNet is retrained to identify RGB photos by replacing the output layer with one suited to the data. The learning rate setting ensures that knowledge is absorbed by new layers faster than by previous layers. The analysis of the modified SqueezeNet is depicted in Figure 2. The last learnable layer of SqueezeNet is an incompletely coupled 1-by-1 convolutional layer. A new convolutional layer with a similar set of filters as classes takes the place of this particular layer. SqueezeNet uses one feature per channel to learn how to recognize meaningful features. The first convolutional layer has 64 channels. The layer receives a photo input with a specific input size [27]. Before traveling over the network, the input image can be resized. However, the network can transmit larger images, and network activations grow. It was trained on images of a particular size, so it cannot be trained to recognize characteristics larger than the size provided.

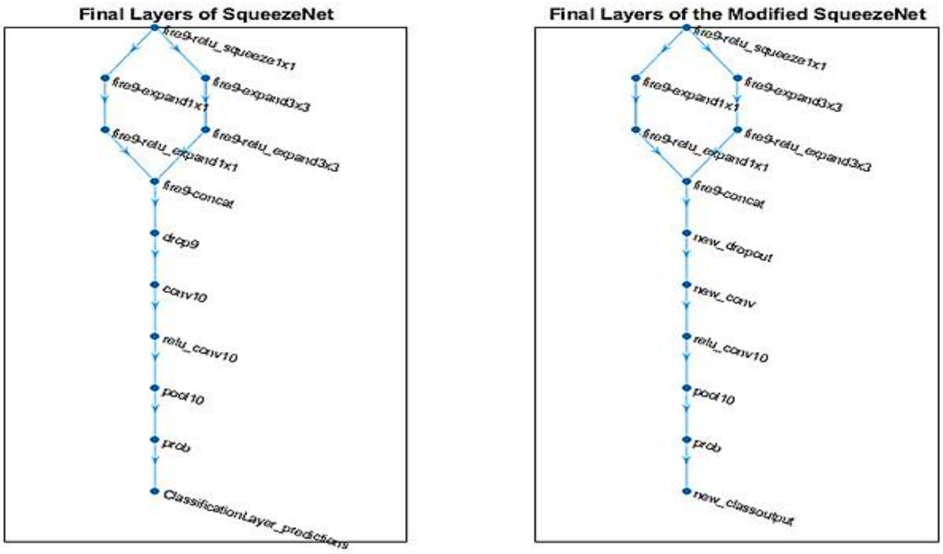


Figure 2. Squeeze network architecture

2.4 Hyperparameter Optimization

Selecting a set of ideal parameters for the neural network is called hyperparameter optimization. Hyperparameters are parameters that could impact a network's learning process. Similar deep-learning strategies could utilize varying learning rates, weights, and limitations to generalizing data patterns. Hyperparameters need to be adjusted to handle the problem as best as possible. A portion of the procedure for optimization is locating a tuple that lowers the loss function and provides a perfect model. There are several methods for performing hyperparameter adjusting. For our study, we employed the grid search technique, which evaluates performance and thoroughly explores a subset of the technique's hyperparameter set. Data is searched during the grid searching process to identify the ideal model settings for parameter change according to the kind of network. Grid searching can be used to choose the best parameters for any given model using deep learning, regardless of the kind of model. Grid searching generates several iterations by building a model using all possible parameter combinations. Grid searching is calculated as costly because these model options have been recorded within each parameter. Two standard methods for adjusting hyperparameters are grid search and random searches. A grid search tests every conceivable set of hyperparameter values from an identified list. The cross-validation score is used to determine which set of values is optimal. A set of parameters can be controlled by selecting arbitrary sets for training the model via an arbitrary search. It can analyze a wide range of values efficiently and reach an appealing set fast, but it has a fundamental problem: it can't guarantee the best possible set of parameters. In contrast, grid search yields the most meaningful results but is slower. We used grid search techniques to acquire the best three mean outcomes of tests (93.75, 84, and 77.4) that helped achieve the highest accuracy in real-time qualitative evaluation. We used grid search techniques, as Table 1 illustrates. With the maximum test score of 97.35, we could obtain the ideal hyperparameters to train designs, including an optimizer such as SGDM with a learning rate of 0.0001 and maximum epochs of 30, with a batch size of 20.

Table 1 The optimized hyperparameters using Grid Search Optimization with various test scores.

Learn-Rate	Batch-Size	Epochs	Mean-Test-Score
0.0001	20	30	93.75
0.0004	32	50	84
0.0005	64	25	77.5

Cost Function: This measure evaluates the neural network's capacity and explains the discrepancy between the actual trial sample's result and the predicted one. The optimizing function is used to lower the cost function. Generally, a cross-entropy function that has multiple shapes and sizes is used in deep learning. The cost function C has the following mathematical definition:

$$C = \frac{1}{n}\sum(y\log(x) + (1-y)\log(1-x)) \tag{1}$$

Where: n = batch-size; x= expected value; y = resultant value.

Through experimentation, we discovered that using SGDM quickly reaches the optimum point. As a result, we employed the SGDM optimizer method, which has a loss approach to zero for 100 steps and a learning rate 0.0001.

3. RESULTS AND PERFORMANCE EVALUATION

The current investigation used globally recognized ECG databases, including MIT-BIH normal sinus rhythm (NSR), BIDMC congestive heart failure (CHF), and cardiac arrhythmia (ARR), which include thorough expert labeling often used in modern ECG studies., as shown in Figure 3. The computer was used for experimental testing using an Intel Core-i7 processor and 8GB of RAM with training settings, as in Table 1. Model training took 12 minutes and 56 seconds overall. The first parameters set were MiniBatchSize to 20, MaxEpochs to 30, and Learn Rate drop period to 3. With an overall mean test score of 93.75%, a grid search hyperparameter optimization technique is applied to these parameters. In this case, 2D scalogram pictures of 227 × 227 × 3 were created from segmentation 1D ECG data and trained with the SqueezeNet model. Matlab 2023a was used for the studies.

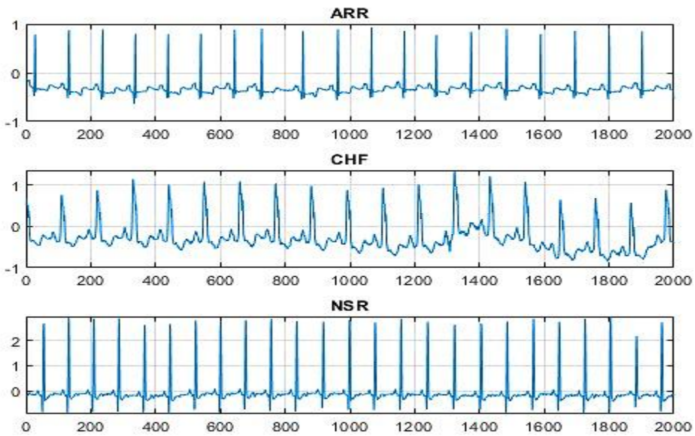


Figure 3. The ECG data representation for each type

3.1. Feature Extraction

Most earlier research trained the network by a 1D ECG input with much noise, objects, and baseline wandering effect. Filtering and extracting features require a lot of preprocessing procedures, which can jeopardize the data's correctness and the model's integrity. Consequently, in this research, ECG readings are converted into scalogram photos with a dimension of 227 × 227 × 3 using CWT, employed as the input parameters as illustrated by Figure 4, which uses CWT to transform a typical sinus rhythm waveform into a scalogram representation. Two applications of CWT are denoising and converting 1D waveforms into 2D scalogram representations.

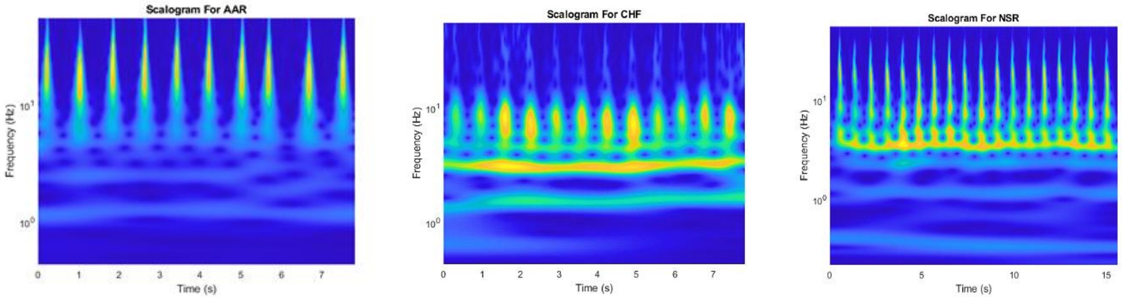


Figure 4. The scalograms representation for the ECG data type

3.4. SqueezeNet training

A crucial stage in the training of SqueezeNet is the iterative reduction of a loss function. It must utilize a gradient descent approach to reduce the loss function. The loss function gradient is evaluated in each iteration, and the weights are changed. In the SqueezeNet model, each epoch is finished in about 30 seconds and only includes 68 layers. SqueezeNet's training period, therefore, takes 13 minutes to complete. The learning rate is 0.0001, and the training choices are set to a maximum of 30 epochs with 6 iterations per epoch. Figure 5 shows the training process; the network converges to 93.7% accuracy in roughly 30 epochs.

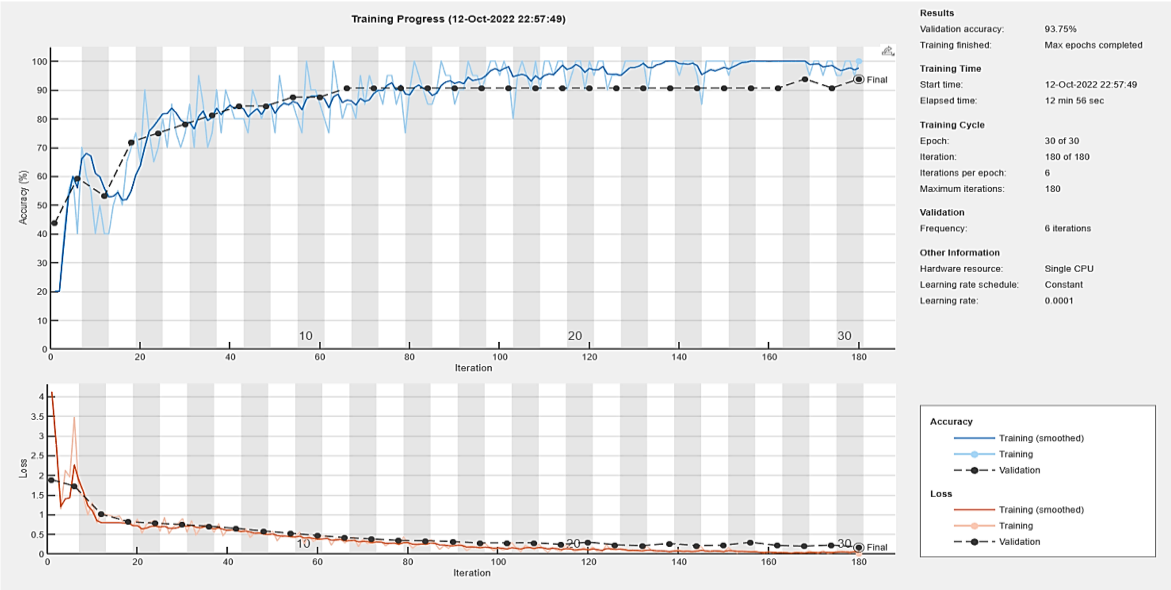


Figure 5. SqueezeNet training progress

3.2. SqueezeNet activations

A SqueezeNet generates each layer by activation according to an image being input. There may be a few levels that offer visual data. The oldest layers preserve fundamental aspects of vision. According to the sequence, every activation is adjusted to have a value between 0 and 1. A photo in the activation represents each of the 64 channels in the layer. An 8 × 8 pattern that depicts the activation is shown in Figure 6. By contrasting them with the corresponding regions in the initial photos, convolutional layer activation can be utilized to examine attributes in photographs.

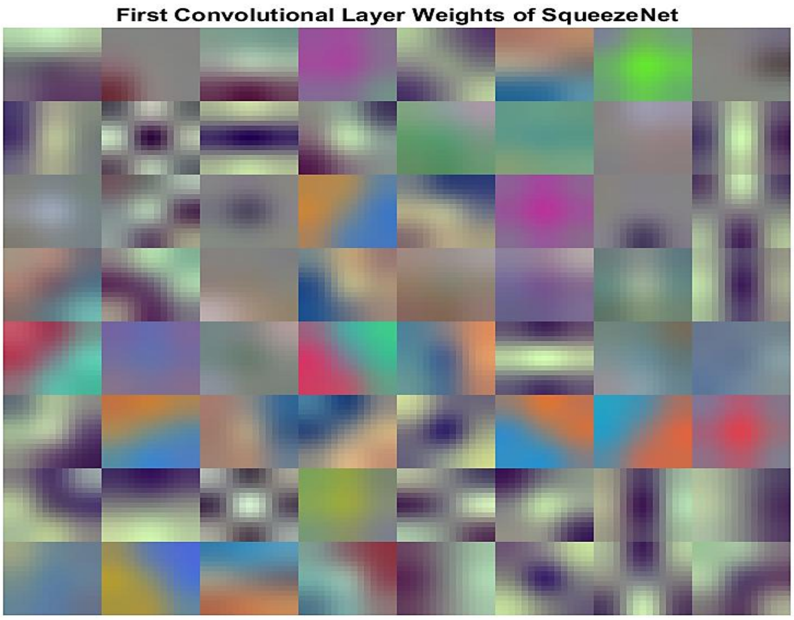
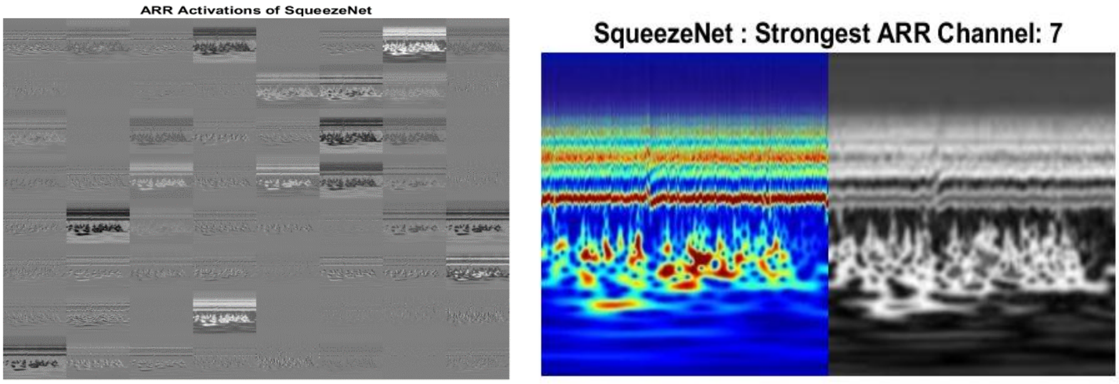


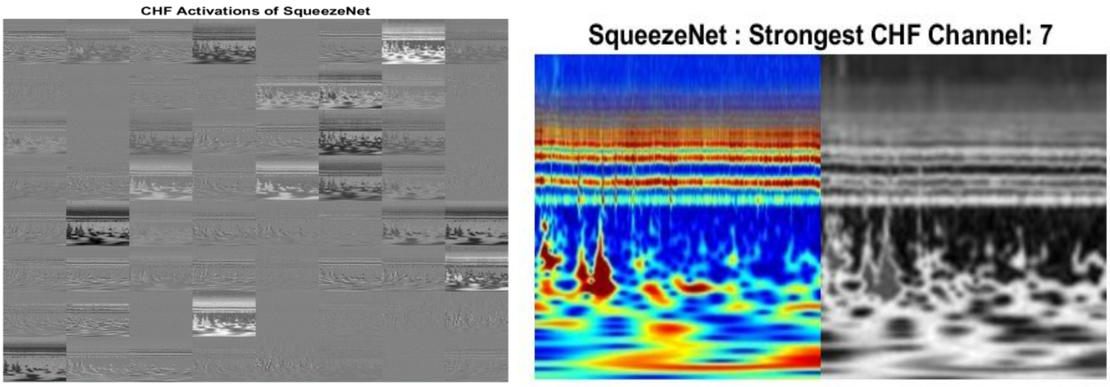
Figure 6. An 8 × 8 pattern that depicts the activation of the first convolutional layer

The components and a contrast between the primary photo and the activation regions SqueezeNet can be utilized to analyze and determine the ECG's condition. Active convolutional layer regions on pictures that include NSR, ARR, and CHF categories are shown in Figures 7, 8, and 9. It is possible to compare the areas with how the original image depicts them. Convolutional layers are made up of several 2-D arrays called channels. The first convolutional layer allows for examining the output activations as the image passes through the network. The activations grid's tiles correspond to the channel outputs of the convolutional layer. Significant positive activations are indicated by white pixels, and significant negative activations are indicated by black pixels. A mostly grayscale channel reacts to the incoming image with reduced intensity. The pixel's position in the original picture is the same as upon channel activation. When a white pixel occurs on a channel, it signifies that the channel is very busy. When presenting activations, the channel activations are scaled to match the dimensions of the original photo.



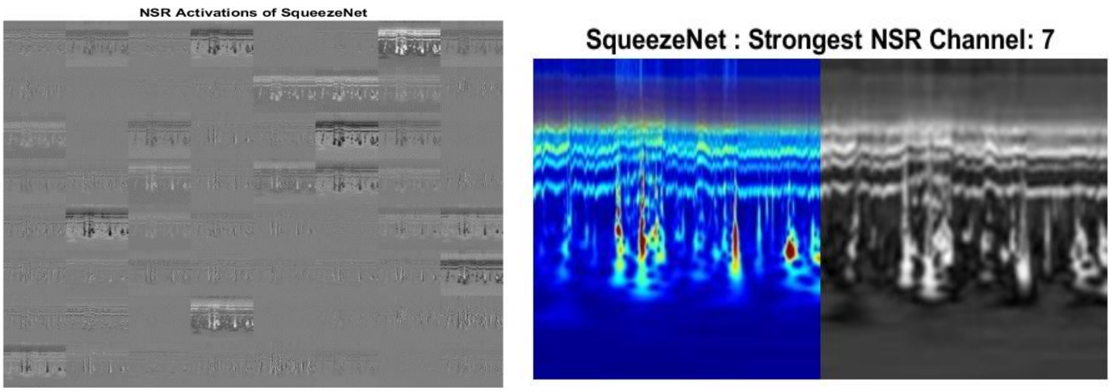
(a) (b)

Figure 7. (a) SqueezeNet ARR activation of the first layer and (b) Classification result for ARR



(a) (b)

Figure 8. (a) SqueezeNet CHF activation of the first layer and (b) Classification result for CHF



(a) (b)

Figure 9. (a) SqueezeNet NSR activation of the first layer and (b) Classification result for NSR

3.3. SqueezeNet confusion matrix

The dataset was initially split into 80% for the training data and 20% for the testing data. Then, using the hyperparameters as Table 1 and the optimizer as SDGM, InitialLearnRate as 0.0001, Batch-Size as 20, epochs as 30, and SqueezeNet, three different types of arrhythmias were classified with an accuracy of 94.7% for the ARR class, 83.3% for the CHF class, and 100% for the NSR class, as illustrated in Figure 10. Table 2 compares the proposed scheme to a few different current models with regards to of approach, accuracy, feature extraction (FE) techniques, and different analytical classifications.

Table 2. Comparison of the proposed scheme toward several other methods

Studies	Method	Application	Findings	Limitations
Our Work	CWT and SequeezeNet	ARR, CHF, and NSR	Average accuracy of 93.7 %	Pretrained Network Sample Network
Munawar A. Riyadi et al [12]	Adaptive Neuro-Fuzzy Inference System (ANFIS)	EEG Multiclass Signal Classification	accuracy of 68% and F1 Score of 38%	Small dataset Less accurate
Ahmet Çınar et al. [13]	LSTM and Hybrid CNN-SVM	ARR, CHF, and NSR	Average accuracy of 96.77%	More complex Not Pretrained Network
Parul Madan et al. [14]	Long Term Memory (LSTM) network and the 2D-CNN	ARR, CHF, and NSR	Average accuracy of 99%	More complex
Ali Talib Jawad et al. [15]	The invasive weed optimization (IWO) algorithm improves the WT coefficients utilized for the ANN learning process	ARR, CHF, and NSR	Average accuracy of 80%	No data Not Pretrained Network
Yunendah Nur Fu'adah et al. [16]	1D-CNN	AF, CHF, and NSR	Average accuracy of 99.643%	Small dataset Not Pretrained Network
Febriyanti Panjaitan et al. [17]	CNN	NSR, CAD, CHF, VT, SCD	Average accuracy of 99.3%	Small dataset Not Pretrained Network
Sudeshna Baliarsingh et al. [18]	Wavelet Transform with machine learning algorithms	Cardiovascular diseases	Average accuracy of 97%	Small dataset Not Pretrained Network

As shown in Table 2, we contrasted our results with the existing and standard approaches with respect to of feature extraction techniques, the approach, accuracy, and other analytical categories in order to validate our suggested technique. It is important to note that, in comparison to other models, the suggested work's accuracy and computing cost depart from the state-of-the-art provided in a pretty encouraging way. It would be intriguing to apply our suggested methodology to diagnose many essential ailments, such as gastrointestinal disorders, and differentiate between neoplastic and non-neoplastic tissues, given its potential and possibilities.

4. CONCLUSION

The categorization of arrhythmias is the most crucial topic in medicine. An irregular heartbeat, or arrhythmia, is what it is called. This work suggested a method for automatically employing the SqueezeNet model to investigate cardiac arrhythmias. Using the pre-trained SqueezeNet network, this study shows how to apply CWT with transfer learning to classify three distinct forms of ECG data. ECG signals are converted into scalograms using wavelet models. Scalograms are thus generated for each RGB photo. These photo scalograms are used to fine-tune the deep SqueezeNet. Moreover, many network layer activations were visible. The CWT parameters, samples per signal, and the duration of the ECG waves all significantly influence the outcomes. This paper shows how to use a modified SqueezeNet network structure to achieve better ECG signal categorization. A pre-trained network for some sections of the photo database is called SqueezeNet. Data reduction was also applied to the scalograms to fit the SqueezeNet network design. The trained network was highly accurate compared to human accuracy. SqueezeNet performed better than the optimized neural network in the multi-class ECG waveform classification challenge, with 93.7% accuracy compared to previous studies.

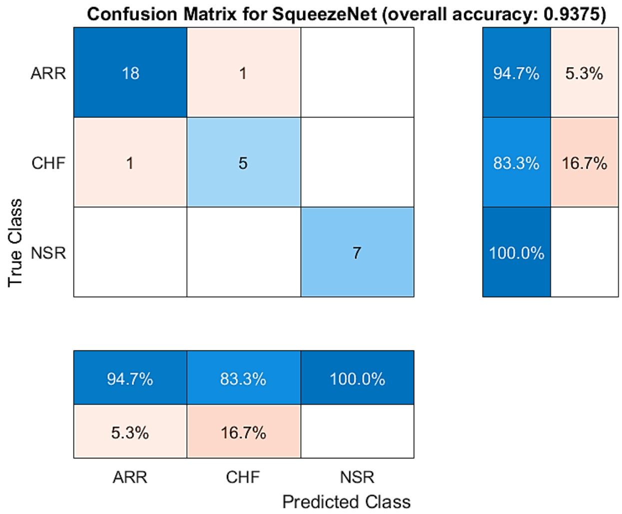


Figure 10. SqueezeNet confusion matrix.

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