Compression, Denoising and Classification of ECG Signals using the Discrete Wavelet Transform and Deep Convolutional Neural Networks

M. Chowdhury[1], K. Poudel[2] and Y. Hu[1,3]

1. Computational Science Program, Middle Tennessee State University, Murfreesboro, Tennessee, USA
2. Department of Mathematics & Computer Science, East Central University, Ada, Oklahoma, USA
3. Department of Engineering Technology, Middle Tennessee State University, Murfreesboro, Tennessee, USA

{mc7d, knp4k}@mtmail.mtsu.edu, Yating.Hu@mtsu.edu

Electrocardiogram (ECG) is the widely known and most common diagnosis test to analyze the electrical signal in the heart and to detect cardiac anomalies. The functionality of the human heart can be properly monitored, and cardiovascular diseases can be detected through the ECG signal. Early detection of cardiac arrhythmia is also possible by analyzing ECG heartbeats continuously. Millions of people in the world are suffering from cardiac arrhythmia which refers to irregular heartbeats. Accurate detection of irregular heartbeats in the primary stage can be also detected through the ECG signal which is very important to reduce the death caused by heart diseases.

Remote monitoring of the ECG signal can help to rise the survival rate of patients suffering from cardiac diseases and decrease their hospitalized rate. Therefore, continuous ECG signal monitoring has a high potential to detect abnormal heartbeats in the primary stage. However, continuous ECG signal monitoring requires a large storage to save the signal and to transport from home to clinic. Moreover, different kinds of noises make it difficult to extract meaningful clinical diagnosis information from ECG signals. So, compression and denoising of ECG signals are necessary during such continuous monitoring technique [1]-[3]. In this paper we have proposed a method to compress and denoise ECG signals by employing the Discrete Wavelet Transform (DWT). This compressed and denoised ECG signals are then used to classify heartbeats into five different arrhythmias by using a convolutional Neural Network (CNN). Performances of the proposed compression and classification algorithms were compared with other algorithms and our proposed techniques outperformed those techniques by a very large margin.

The main objective of any compression or denoising method is to separate the original signal from all kinds of noises and redundant information without losing any clinical information. Though Fourier Transform (FT) is the most popular and widely used signal analysis technique, it shows poor performance while analyzing non-stationary signals like ECG. DWT gives better performance in analyzing non-stationary signals because of its multi-resolution analysis ability [1]-[4]. By using DWT, we divided each ECG signal into different frequency bands. Afterwards, the energy of each sub-band was calculated to select the required sub-band which contained all the important pathological information. The other sub-bands with noise and unnecessary information were discarded from the original signal. Beside compressing and denoising ECG signals, this method will also encrypt ECG signals while transferring from home to clinic [5]. Thus, it will maintain the privacy of patients. Only the doctor can reconstruct signals using the Inverse Discrete Wavelet Transform (IDWT). PhysioNet MIT-BIH database was used to validate our proposed methods [6].

Selection of the mother wavelet is very crucial to reconstruct ECG signals. A total of 55 orthogonal wavelets were compared and the Coif6 wavelet was chosen from the Coiflets family as it gave the best performance among all wavelets. An average compression of 74.57% was achieved using our proposed method. The average compression ratio (CR) and percent root mean square difference (PRD) were 3.95 and 0.17%, respectively. We compared the proposed compression technique with 20 others compression methods [7]. By comparing quality scores (QS) of different algorithms, we evaluated their performance. QS is the ratio of CR and PRD. The average QS of the proposed method was around 23.24, while the QS of the other algorithms ranged from 0.57 to 20.89, which proved that the proposed ECG compression algorithm outperformed all the other ECG compression algorithms.

Machine Learning (ML) and Deep Learning (DL) have played a vital role to detect abnormalities in the ECG signal. ML techniques are usually employed to classify ECG heartbeats. However, the main limitation of ML is the feature extraction. Extracting appropriate features from the raw signal is very challenging. DL can solve this problem by extracting high-quality optimal features through its own neural network and reduce the need for feature engineering. Thus, DL algorithms lead to better performance and high accuracy compared to ML algorithms.

Our proposed method based on 4 hidden layers of a CNN can accurately detect cardiac arrhythmias. We used the labeled MIT- BIH Arrhythmia dataset to validate our proposed DL model [6]. There are total 48 ECG recordings collected from 47 different patients of Beth Israel Hospital (BIH) in this dataset which has been widely used to classify different cardiac arrhythmias. Each recording is a minimum of 30 minutes long and sampled at 360 Hz. Each heartbeat was confirmed by minimum two cardiovascular specialists. There are total 1,09,446 heartbeats which are divided into five different beat categories [9]. The ratio of normal beat to other beat categories is 1:4. 80% of the ECG heartbeats were used to train the proposed classification model, and 10% heartbeats were used to validate the model. Synthetic Minority Over-sampling Technique (SMOTE) was employed for making the training data balanced [8]. Over-sampling technique was not used in the testing dataset as we wanted to test the model on unseen data.

In our proposed method we used each ECG beat as input to our deep learning model. We did not need to extract any feature from each ECG beat manually, as our deep intelligent model used different layers of CNN and more computation to identify important features for generating the correct output. We used a 1D CNN model of 4 hidden layers in our research to classify each heartbeat in the database. Four hidden layers (1st layer with 32 filters, 2nd layer with 64 filters, 3rd layer with 128 filters, 4th layer with 256 filters) were used to build the model. The ReLU activation function was used in each hidden layer. Each layer had the same kernel size of 4. A max-pooling layer of kernel size 2 was also deployed in each layer to downsample the input and to reduce the number of dimensions. The last hidden layer of the convolutional neural network was connected with a final dense layer having 64 nodes. The SoftMax activation function was used in the output layer to predict output class probabilities. To overcome the overfitting problem, we used the dropout technique. The dropout technique usually deletes random samples of the activations during the training by making them zero and helps the network to learn robust features that are useful to increase classification accuracy. The value of the learning rate was 0.0001. Network weights had been updated iteratively in each epoch based on training data using the Adam optimization algorithm. Finally, the performance of the model was validated by using the unseen test data.

Our proposed CNN model was evaluated by using precision, recall, and accuracy metrices. Out of predictive positive, how many of them are actual positive is defined by the precision metric. The recall is also known as sensitivity which indicates the percentage of the accurately predicted true positives. The overall classification accuracy is the percentage of accurately identified normal and abnormal heartbeats out of all heartbeats. These important evaluation metrices were found by analyzing the confusion matrix.
An overall accuracy score of 99.34% was achieved by using our proposed model. Both precision and recall of the model were recorded as 88.00%. We compared our proposed classifier with other recent classifying models and got better accuracy compared to them [9] [10]. In the future, we can develop a wearable sensor based on the performance of our proposed compression and classification algorithms. This wearable sensor will be connected to the chest to collect the ECG signal continuously and will send the signal to a smartphone via Bluetooth. This recorded ECG signal can be displayed in the smartphone and will be sent to physicians through internet for proper clinical diagnosis. This tool can help cardiologists to detect any cardiac anomaly in the initial stage which can lower the mortality rate due to cardiac disorders.

REFERENCES

[1] M. T. H. Chowdhury, K. N. Poudel, and Y. Hu, “Phonocardiography Data Compression Using Discrete Wavelet Transform,” *2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, Philadelphia, PA, USA, pp. 01–03, Dec. 2018.

[2] M. T. H. Chowdhury, K. N. Poudel, and Y. Hu, “Automatic Phonocardiography Analysis using Discrete Wavelet Transform,” *3rd International Conference on Vision, Image, and Signal Processing*, Vancouver, BC, Canada, August 2019.

[3] M. T. H. Chowdhury, K. N. Poudel, and Y. Hu, “Time-Frequency Analysis, Denoising, Compression, Segmentation, and Classification of PCG Signals,” in *IEEE Access*, vol. 8, pp. 160882-160890, 2020.

[4] G. M. Stephane, “A Theory of Multiresolution Signal Decomposition: The Wavelet Representation,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 07, pp. 674–693, July. 1989.

[5] S. A. Chouakri, M. M. Benaiad, and A. T. Ahmed, “Run length encoding and wavelet transform based ECG compression algorithm for transmission via IEEE802.11b WLAN,” *ACM international Conference Proceeding Series*, pp. 37-40, 2011.

[6] G. B. Moody and R. G. Mark, “The impact of the MIT-BIH Arrhythmia Database,” *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.

[7] B. Singh, A. Kaur, and J. Singh, “A review of ECG data compression techniques,” *International Journal of Computer Application*, vol. 116, no. 11, pp. 1-6, 2015.

[8] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “Smote: synthetic minority over-sampling technique,” *Journal of artificial intelligence research*, vol. 16, pp. 321–357, 2002.

[9] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, “ECG Heartbeat Classification: A Deep Transferable Representation,” *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, New York, NY, pp. 443-444, 2018.

[10] R. J. Martis, U. R. Acharya, K. M. Mandana, A. K. Ray, C. Chakraborty, “Cardiac decision making using higher order spectra,” *Biomedical Signal Processing and Control,* vol. 08, pp. 193-203, Mar. 2013.

Compression, Denoising and Classification of ECG Signals using the Discrete Wavelet Transform and Deep Convolutional Neural Networks

M. Chowdhury[1], K. Poudel[2] and Y. Hu[1,3]

1. Computational Science Program, Middle Tennessee State University, Murfreesboro, Tennessee, USA
2. Department of Mathematics & Computer Science, East Central University, Ada, Oklahoma, USA
3. Department of Engineering Technology, Middle Tennessee State university, Murfreesboro, Tennessee, USA

Abstract

Electrocardiogram (ECG or EKG) is the most widely used and powerful diagnostic tool to analyze the electrical activity of the heart and to detect cardiac abnormalities. The functionality of the human heart can be properly monitored, and cardiovascular diseases can be detected through the ECG signal. Early detection of cardiac arrhythmia is also possible by analyzing ECG heartbeats continuously. We have proposed an ECG compression, denoising and classification method in this paper.

We compressed, denoised and classified ECG signals using the following techniques:

- Discrete Wavelet Transform was used to denoise and compress ECG signals.
- 55 different mother wavelets were compared to choose the best mother wavelet.
- The compression and encryption algorithm is validated by testing on the large sets of normal and abnormal ECG signals available in the MIT-BIH Arrhythmia database.
- Evaluated the performance of the algorithm by using compression ratio (CR), percentage of compression (PC), and percent root mean square difference (PRD).
- All the ECG signals in the database were compressed at about 74.57% with an average CR of 3.95 and an average PRD of around 0.17%.
- The performance of this method was compared with 20 ECG compression techniques and it showed better performance compare to other techniques.
- The QS of those compression methods ranged from 0.57 to 20.89, while average QS of the proposed method was around 23.24.
- 1,09,446 heartbeats were divided into five different beat categories. The 80% data was used for the training purpose and the 20% data was used for the testing purpose.
- We used a 1D CNN model of 4 hidden layers with 32, 64, 128, and 256 filters, which were implemented with the ReLU activation function to classify each ECG heartbeat in the database.
- This proposed model can detect normal and abnormal ECG heartbeats with a very good testing accuracy of 99.34%. The achieved precision and the recall of the model were 98.00% and 98.00%, respectively.
- The performance of the proposed ECG heartbeat detection classifier was compared with other existing state-of-the-art classifying model and our model outperformed those models significantly in terms of overall accuracy.

Materials and Methods

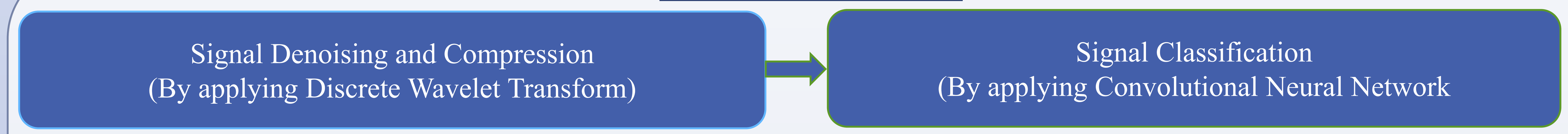

Figure.1: Block diagram of the ECG signal denoising, compression and classification.

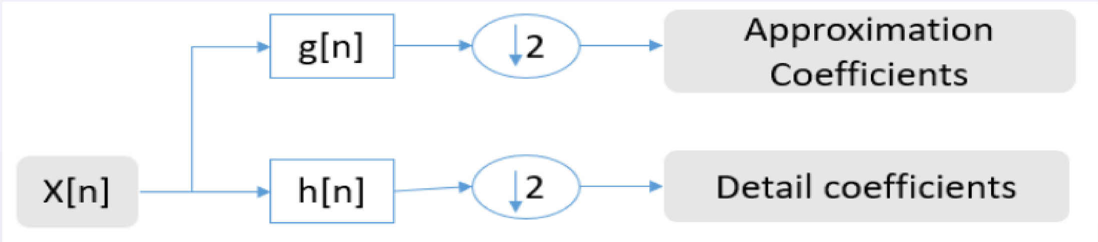

Figure 2: A Discrete wavelet transform model of 1 level decomposition.

Table 1: Different levels and their coefficients and frequency spectrum

Levels	Frequency range (Hz)	Coefficients	Sub-bands
2	0 to 45	2526	App. Band (A_2)
2	45 to 90	2526	Detail Band (D_2)
1	90 to 180	5017	Detail Band (D_1)

Table.2: Energy Packing Efficiency of each sub-band.

Sub-bands	Energy	Value of EPE (%)	Coefficients
App. Band (A_2)	7066.6520	99.9996	2526
Detail Band (D_2)	0.01339	1.89×10^{-06}	2526
Detail Band (D_1)	0.0088	1.24×10^{-06}	5017

Table 3: Performance analysis of 14 different mother wavelets.

Wavelets	PRD (%)	CR (%)	Wavelets	PRD (%)	CR (%)
db1	0.91	3.98	bior2.2	0.34	3.98
db3	0.35	3.97	bior1.5	0.96	3.95
db11	0.20	3.91	bior1.3	0.94	3.97
db18	0.19	3.87	coif3	0.23	3.93
db20	0.19	3.85	coif10	0.18	3.78
coif1	0.50	3.97	bio4.4	0.24	3.95
coif6	**0.17**	**3.95**	bio6.8	0.21	3.93

Results

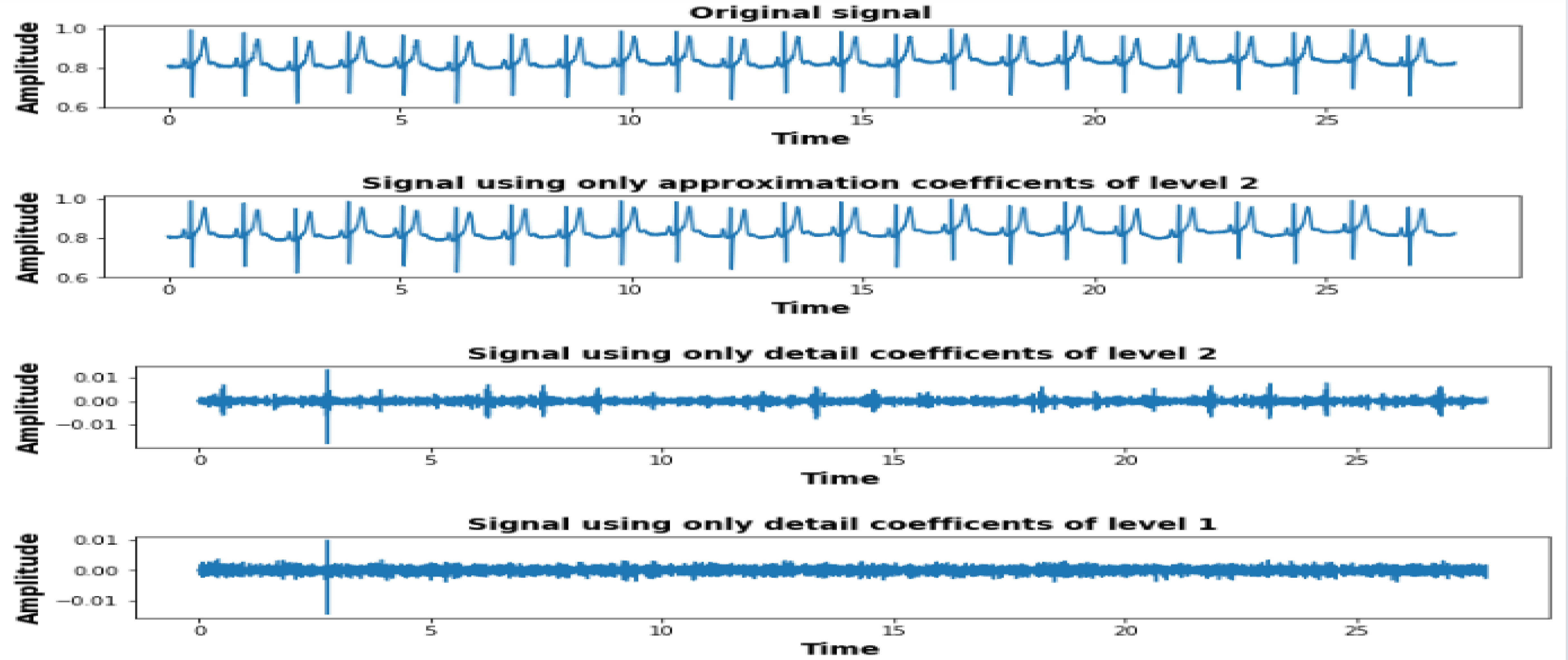

Figure.3: Signals in different sub-bands.

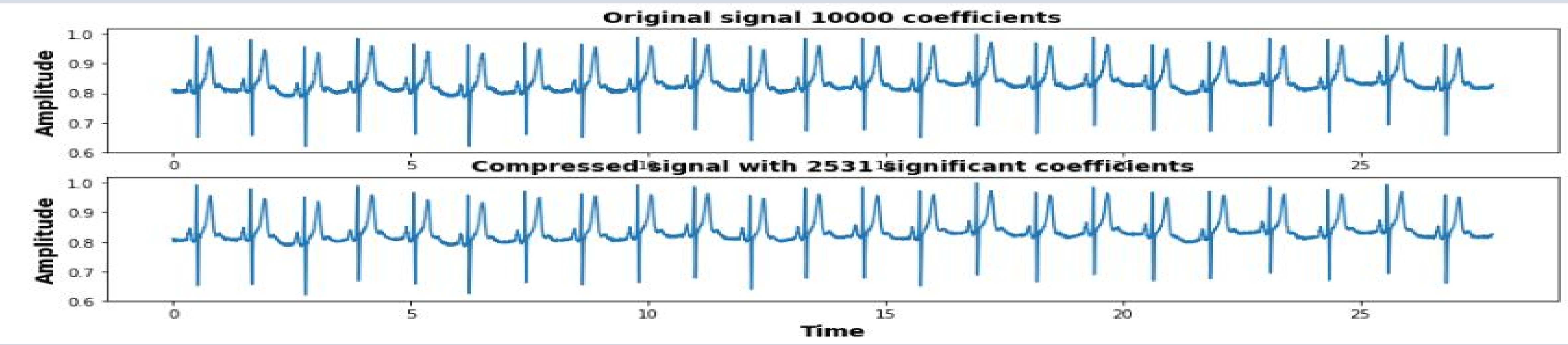

Figure 4: a) Original ECG signal (Record-117) b) Compressed and denoised ECG Signal.

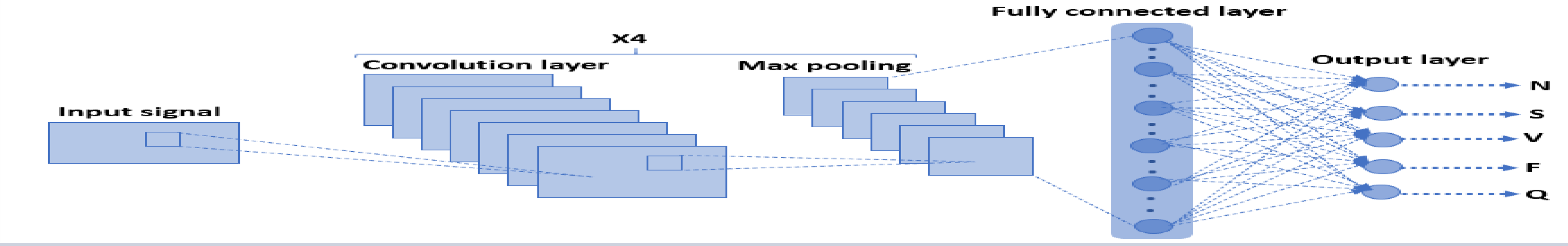

Figure 5: Our proposed convolutional neural network model to classify ECG heartbeats.

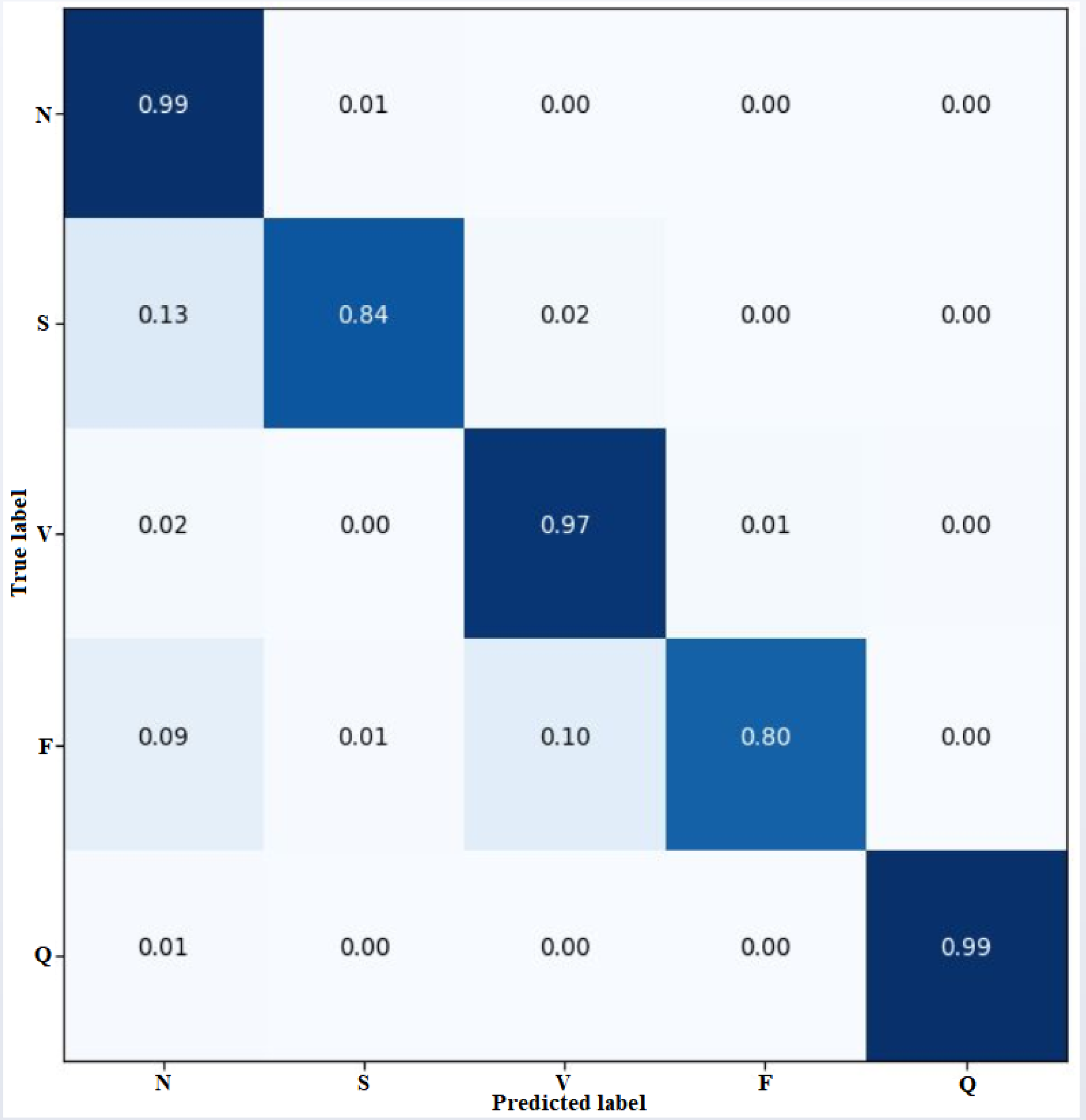

Figure 6: The confusion matrix

```
              precision    recall  f1-score

           0       0.99      0.99      0.99
           1       0.79      0.84      0.82
           2       0.94      0.97      0.95
           3       0.71      0.80      0.76
           4       0.99      0.99      0.99

    accuracy                           0.98
   macro avg       0.88      0.92      0.90
weighted avg       0.98      0.98      0.98
```

Figure 7: The classification report

Table 4: Comparison with other classification models

Author	Precision (%)	Recall (%)	Accuracy (%)
Kachuee et al., (2018)	–	–	93.40
Acharya et al., (2017)	–	96.01	93.47
Martis et al., (2013)	–	–	93.80
Li et al., (2016)	–	–	94.61
Elhaj et al., (2016)	–	–	98.90
Karanyaz et al., (2016)	–	93.90	99.00
Zubair et al., (2016)	–	–	92.70
Yang et al., (2020)	–	–	98.63
Yang et al., (2018)	–	–	97.80
Martis et al., (2012)	–	–	98.11
Martis et al., (2013)	–	–	93.48
Our Study	**98.00**	**98.00**	**99.34**

Conclusion

Our proposed method is not only able to denoise and compress ECG signals but also can classify each heartbeat with an excellent accuracy of 99.34%. Based on the result of our proposed compression and classification algorithms, an automatic wearable tool can be developed for continuous monitoring of ECG signal. This tool can be a promising solution to detect early-stage heart diseases which can lower the death rate caused by cardiac diseases.