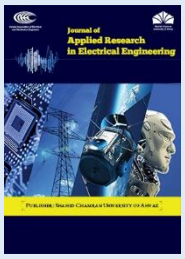
Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Epileptic Seizures Detection with Low Processing Load Using the R-R interval of ECG Signals and Deep Neural Network

Mostafa Ghaempour [1], Kourosh Hassanli [1,*], and Ebrahim Abiri [1]

[1]*Department of Electrical Engineering, Shiraz University of Technology, Shiraz, Iran*

* *Corresponding Author: hassanli@sutech.ac.ir*

Abstract: Early detection of seizure occurrence is important in improving the lives of patients with epilepsy. Although various methods have been presented so far, there are still challenges regarding the ease of using these methods. This paper aims to present an approach based on neural networks to detect epileptic seizures using ECG signals instead of EEG signals. In the proposed method, only single-lead ECG signals are used for detecting seizures, making them highly suitable for wearable instruments. In the proposed approach, light pre-processing is first performed to prepare raw ECG signals as labeled data. Then, R-R intervals are extracted and considered as features for classification. Without using other manual feature extraction methods, a combined structure of a convolutional neural network and a bidirectional long short-term memory network is employed for automatic feature extraction and classification. The proposed method was evaluated using a strict Leave-One-Subject-Out cross-validation on five patients, achieving a mean accuracy of 82.4%, sensitivity of 74.4%, specificity of 91.3%, and an aggregated AUC of 0.844. The model requires approximately 4500 trainable parameters, confirming its low computational load. This research demonstrates that a single-lead ECG signal, combined with a lightweight deep learning algorithm, can be effectively used in monitoring systems for epilepsy patients.

Keywords: Epileptic seizure, detection, deep neural network, ECG signals, R-R interval.

Article history
Received 15 July 2025; Revised 01 June 2026; Accepted 23 September 2026; Published online 11 October 2026.
© 2026 Published by Shahid Chamran University of Ahvaz & Iranian Association of Electrical and Electronics Engineers (IAEEE)
How to cite this article
M. Ghaempour , K. Hassanli , and E. Abiri, " Epileptic seizures detection with low processing load using the R-R interval of ECG signals and deep neural network," *J. Appl. Res. Electr. Eng.*, vol. 4, no. 2, pp. 289-297, 2025.
DOI: 10.22055/jaree.2026.50180.1249

Check for updates

1. INTRODUCTION

Epileptic seizures result from a series of abnormal nerve activities in the brain [1]. After a seizure, usually, a part or the whole body is affected [2]. Various types of epileptic seizures have affected the lives of about 60 million people worldwide [3, 4]. There are different types of epileptic seizures, Such as generalized and focal (partial) epilepsy [5]. These seizures may sometimes cause irreparable physical damage to the patient [6]; also, people with epileptic seizures sometimes avoid social activities and miss appropriate social situations [7]. Detecting seizures is necessary for these patients [8-10].

One of the oldest methods for monitoring the condition of epilepsy patients is the use of brain signals or Electroencephalography (EEG) signals [11-13]. Since 2016, significant researches have been done to detect epileptic seizures by deep-learning (DL) networks using EEG signals [4]. Networks such as convolutional neural networks (CNN) [14, 15] and Recurrent Neural Networks (RNN) [16] have been widely used in this field. In [11], the detection of epileptic seizures has been made using EEG signals. They have introduced a CNN, which is placed along with other processing stages.

Another method for monitoring the condition of epilepsy patients is to use heart signals of patients called Electrocardiography (ECG) signals [17-19]. Even though the EEG signals contain more information about seizures [20, 21], but there are some challenges in using them [22, 23], such as the low amplitude of the EEG signals [24] and the large number of channels required for processing [25]. Due to the ease of receiving ECG signals compared to EEG signals [26], using ECG signals will be more beneficial for portable applications [27].

In [9], automatic detection of epileptic seizures has been done through ECG, EEG, and monitoring of the patient. They pointed out that ECG signal analysis, especially heart rate

variability (HRV) analysis, seems to be a promising marker for brain damage. In [28], seizures have been detected in temporal lobe epilepsy patients using a single-lead-ECG. This research has presented a method for seizure detection by classifying the heart rate (HR) characteristics. Baghersalimi et al. in [29] have proposed a deep-neural network (DNN) for seizure detection, which is learned Real-Time. Their proposed DNN is a Residual 1-Dimensional CNN (Res1DCNN). In [30] an approach is introduced to detect and predict epileptic seizures with the help of a CNN using the ECG signal. The authors of [17] have predicted seizures based on HR value. They have been expressed, epilepsy often causes changes in the autonomic nervous system. In [31], the prediction of seizure probability using wearable technologies has been considered. They have mentioned that for some patients, HRV changes in the long term (monthly) follow patterns that can be used for daily seizure prediction. They have estimated the daily and hourly risk of seizures by combining a Long short-term memory (LSTM), the Random Forest Regression method, and the selected features. In [32], a method for estimating the Cardiac Sympathetic Index (CSI) is presented using 1D-CNN.

In many related studies that use DNN, a large part of the processing load is directed toward heavy pre-processing, optimization, and manual feature extraction [33]; while the neural networks themselves have high capabilities in selecting and purposefully extracting data features [34]. Therefore, by removing some of the conventional feature extraction steps in the time and frequency domains, the processing load of the final system can be reduced. According to the needs of epileptic patients, the advantages of ECG signals in identifying their condition, and the efficiency of DNN, this paper presents a combined CNN and bidirectional LSTM (CNN-BiLSTM) for detecting epilepsy seizures using single-lead-ECG. The main contribution of this paper is to introduce an algorithm with a low computational load that can detect the occurrence of seizures. The main focus of this article is to provide an optimal method with the least amount of pre-processing and feature extraction load, and the least trainable components associated with the neural network. This aim is achieved by creating a balance between using and not using manual feature extraction steps.

The rest of the paper is organized as follows. Section 2.1 presents pre-processing steps to prepare the chosen dataset. Section 2.2 describes the R-R interval (RRI) extraction as the only manually extracted feature. Section 2.3 explains the RRI data normalization step to guide network training to more important features. The proposed CNNLSTM networks structures are explained in Section 2.4. The results of the proposed networks are presented in Section 3, and in Section 4, a discussion about the comparison of these methods with the other researches is done. Finally, in section 5, the conclusion is made.

2. METHODS

2.1. Pre-processing Steps

In this research, the Post-Ictal dataset has been used [35]; A diverse group of patients with partial epilepsy is reported in this dataset. It contains the recorded ECG signals related to five epilepsy patients in seven separate records, which include a total of 10 seizures. This dataset can be used to obtain interictal and ictal signals since the ECG recording was taken several minutes before and after the seizure. The free annotated ECG recordings upon which this study was based can be found in [36].

To achieve more accurate and realistic results, the data must be prepared before feature extraction and network training. For this purpose, the following pre-processing steps, shown in Fig. 1, have been done on the recorded ECG signals.

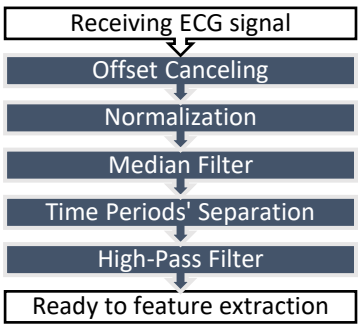
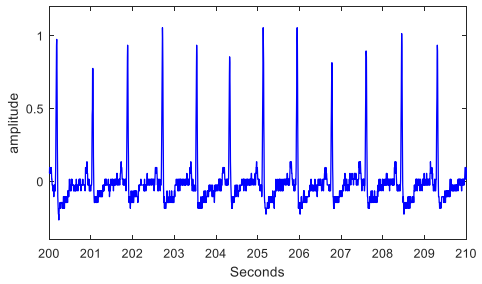
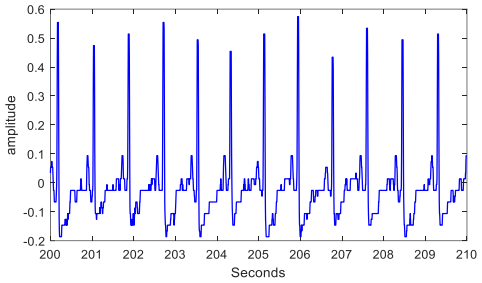


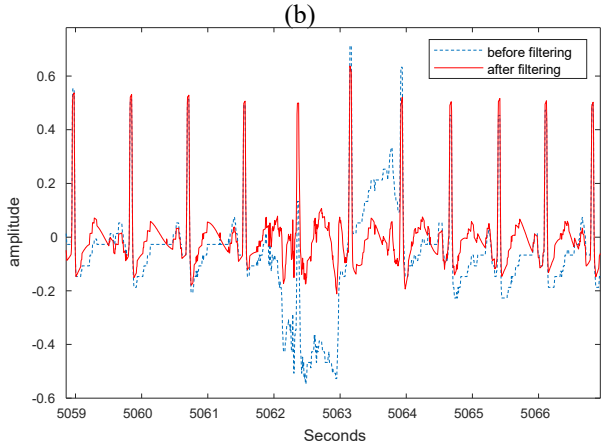
Fig. 1: The required pre-processing steps to prepare ECG data.



(a)



(b)



(c)

Fig. 2: (a) The ECG signal before applying median filter and (b) the ECG signal after applying the filter. (c) The effect of the high-pass filter on the ECG signal.

First, the signal offset has been removed by calculating the average of samples and subtracting it from the amplitude of each signal. This offset occurs due to the difference between the ground potential of the device and the potential of two leads in the human body. The next stage involves normalizing the ECG signals to be within the range of -1 and +1.

One of the things that can lead to errors in identifying R waves is unexpected noises which cause sudden changes in the signal. A median filter can make the signal behavior smoother. Fig. 2(a) shows ECG signal before applying the median filter, and Fig. 2(b) is related to the effect of the filter. The median filter window length is ten samples.

The average duration of each seizure in the collection of recordings is 80 seconds. Data are labelled according to the time related to the start and end of the seizure. One to two minutes after seizure onset is labelled as ictal data and 30 Minutes before or 50 minutes after the seizure as interictal data.

Finally, applying a high-pass filter with a cut-off frequency of 2 Hz removes some low-frequency fluctuations in the ECG data. As shown in Fig. 2(c), these fluctuations interfere with the correct acquisition of the PQRST waves of ECG signal.

2.2. Feature extraction

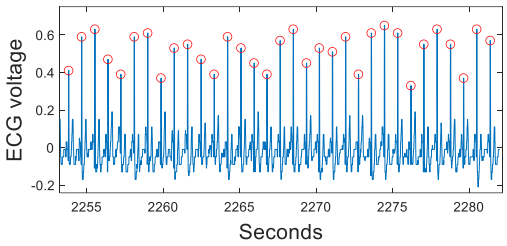
RRI feature can help identify the characteristics of ECG signals with the help of the changes at the time of the R waves. Firstly, R waves are determined using the local maximum extraction method and considering the minimum time between the R waves and the minimum height of their amplitude. Algorithm 1 demonstrates how to extract R peaks using a simple method. Since the data has been normalized, the algorithm has set the minimum time and height values at the same value for all available recordings. For these ECG records, the minimum time interval is 0.2 seconds and the corresponding minimum sample height is 0.25 units. The location of R waves is shown as red points in Fig. 3(a). The diagram of the RRI amplitude per time is shown in Fig. 3(b).

The RRI can be used as a feature for classifying. In this paper, the goal is to use a deep learning method for data classification with the help of the RRI feature. No manual extraction of multiple features from RRI is performed here; rather, only RRI data are used. If other time-domain and frequency-domain features were to be extracted manually from RRI, the processing load would increase significantly, and some data features might remain unknown or ignored. The approach of directly using raw ECG data as the neural network input would also increase the trainable components of the network, which can increase the computational load. Therefore, to optimize the computational load, a balance must be created. In this paper, the RRI data have been extracted and used directly as the neural network input. This approach achieves optimal system performance with acceptable accuracy.

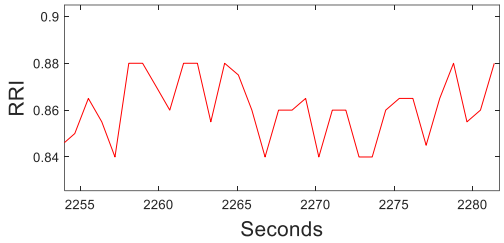
Algorithm 1: R-waves-extract

Input: ECG samples, **Output:** extracted R waves

```
for each sample
do
    Measure the sample value difference with the before and after samples
    if the sample is bigger than the previous one
        if the sample is equal to or larger than the 1, 3, 5, 7, and 9 next ones
            if the time interval from the previous peak is greater than the specified minimum time.
                if the sample's value is greater than the specified minimum height
                    Report the sample as an R peak
                end if
            end if
        end if
    end if
end for
```



(a)



(b)

Fig. 3: (a) Determining the R waves of the ECG signal and (b) the diagram of RRI changes.

2.3. RRI segmentation and normalization

RRI signals were segmented into non-overlapping windows of length 6 samples. To ensure the model learns the pattern of RRI changes rather than absolute RRI values, each window was independently normalized to zero mean and unit variance using z-score normalization: $(x - \mu)/\sigma$, where μ and σ are the mean and standard deviation of the samples within that window. This per-window normalization removes patient-specific baseline heart rate differences while preserving the relative temporal dynamics that characterize ictal versus inter-ictal states.

2.4. The Proposed neural network

A key characteristic of CNNs is their ability to extract salient feature maps from raw input data. Furthermore, LSTM-based RNNs excel at capturing temporal dependencies. To leverage both advantages, this study proposes a hybrid CNN-BiLSTM architecture for seizure detection.

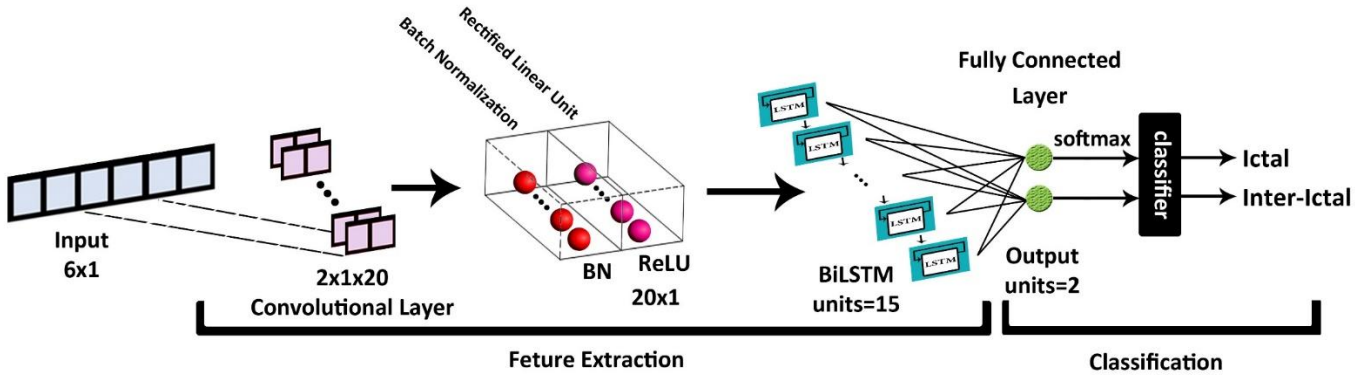


Fig. 4: The structure of the proposed 9-layer network for detecting seizures using the RRI feature

The architecture of the proposed model is illustrated in Fig. 4. The network begins with a sequence input layer that accepts univariate time series data with a length of 6 time steps. This is followed by a one-dimensional convolutional layer containing 20 filters of size 2. This layer extracts local patterns and short-term features from the input signal.

A batch normalization layer is then added to accelerate training and enhance numerical stability. A Rectified Linear Unit (ReLU) activation layer then introduces non-linearity, enabling the model to learn complex representations.

To capture dependencies, a BiLSTM layer with 15 hidden units is incorporated. A dropout layer with a dropout probability of 0.3 is placed before the final classification stage to mitigate overfitting. This is followed by a fully connected layer with two neurons, corresponding to the two output classes (ictal and interictal). Finally, a softmax layer and a classification layer produce the probability distribution over the classes and the detected label, respectively. The network has 4.5k trainable parameters and requires approximately 27k FLOPs for inference.

3. RESULTS

In this section, the results of the network training and evaluation are presented. To investigate the effect of input data dimensions, window lengths from 2 to 7 RRI samples were examined. Subsequently, a sensitivity analysis over hyperparameters (learn rate, drop factor, maximum epochs, min batch size) was conducted. The final evaluation used Leave-One-Subject-Out (LOSO) cross-validation on 5 patients. To address class imbalance during training, we applied random oversampling to duplicate minority-class samples until both classes were equal. This was done only on the training set, leaving test subjects unchanged for unbiased evaluation. It should be mentioned that the training of the desired neural network is done with the help of the MATLAB platform [37]. The training was performed on a system with a 12th Gen Intel Core i5-12400F processor (2.50 GHz), 32 GB RAM, and a 64-bit operating system.

3.1. Hyperparameters Effects

The analysis of window length was performed on patient 2 as a representative case, with window lengths from 2 to 7 RRI samples evaluated. Accuracy for window lengths 2, 3, 4, 5, and 7 were 63.83%, 68.13%, 64.71%, 61.35%, and 62.69%, respectively. The best performance was achieved at a window length of 6, with Accuracy = 68.70%, Sensitivity = 70.45%, Specificity = 67.61%, and AUC = 0.783. Following window length selection, a systematic hyperparameter grid search was conducted to optimize the training configuration, examining initial learning rates of 0.005, 0.01, and 0.05; learning rate drop factors of 0.3, 0.5, and 0.8; epochs of 50, 100, and 200; and minimum batch sizes of 10 and 20, resulting in 54 distinct configurations. Adam's algorithm is used to train the networks [38]. The best configuration was identified as an initial learning rate of 0.005, drop factor of 0.8, 200 epochs, and a minimum batch size of 20, yielding an accuracy of 73.91%.

3.2. Per-Patient Performance

The heatmap of 5 patients is presented as an overall performance summary in Fig. 5. Fig. 6 presents the Accuracy, Sensitivity, Specificity, Precision, F1-score, and AUC for each of the five patients separately, with 95% confidence intervals (CI) computed via bootstrap resampling (1000 iterations). The results demonstrate substantial inter-subject variability. Patients 3 and 5 achieved excellent performance (AUC: 0.979 and 0.961, respectively), while Patients 1 and 2 showed moderate performance (AUC: 0.779 and 0.811). Patient 4, with the fewest ictal samples, exhibited lowest sensitivity (0.500).

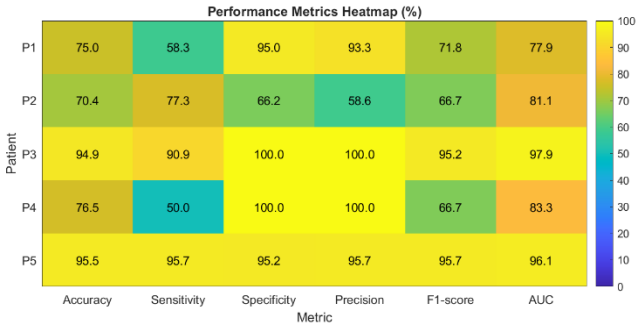


Fig. 5: Performance heatmap.

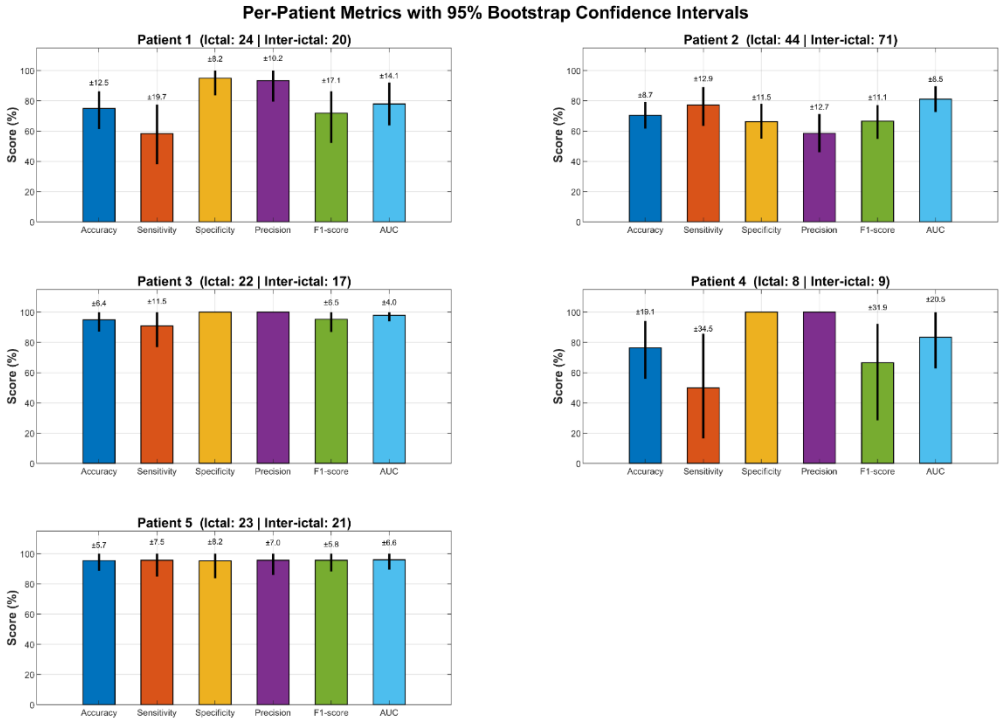


Fig. 6: Per-patient metrics (±95% CI).

3.3. Aggregated Performance

Fig. 7 shows the aggregated confusion matrix across all patients. The model correctly classified the majority of both ictal and inter-ictal instances. Fig. 8(a) illustrates the mean aggregated metrics with their 95% CIs across the 5 patients. The mean results were: Accuracy = 82.4% (67.8–97.1), Sensitivity = 74.4% (49.7–99.2), Specificity = 91.3% (73.6–100), Precision = 89.5% (67.8–100), F1-score = 79.2% (60.6–97.8), and AUC = 87.3% (76.0–98.5). Notably, the higher specificity compared to sensitivity indicates a conservative detection strategy, which is clinically desirable to minimize false alarms. Fig. 8(b) displays the aggregated Receiver Operating Characteristic (ROC) curve with a mean AUC of 0.844, confirming the model's discriminative ability between ictal and inter-ictal states across patients.

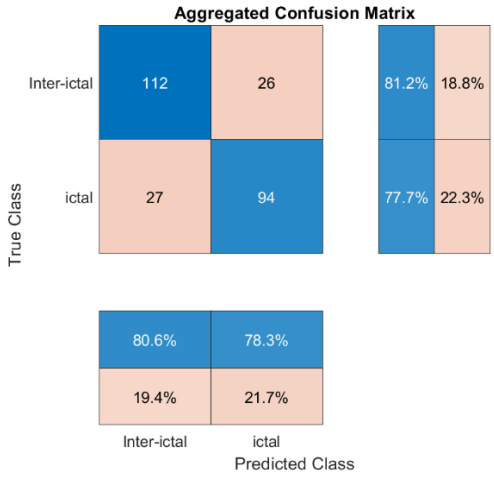
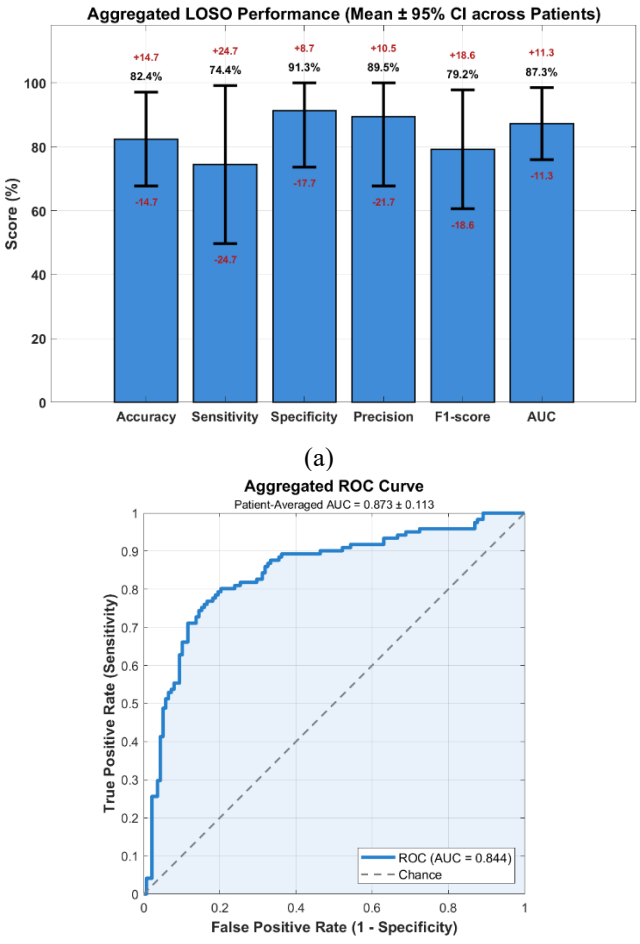


Fig. 7: Overall confusion matrix.



(a)

(b)

Fig. 8: (a) Aggregated metrics (±95% CI across patients) and (b) aggregated ROC curve.

4. DISCUSSION

Table 1 compares the results of the proposed seizure detection method with other works that use ECG signals. The size of the dataset and the variety of epilepsy types can affect the generalizability of the results. [39] use a dataset related to infants with unspecified seizure type. In [18], [29], and [40] focal and general seizures were studied, while this paper focuses on focal seizures. In [28], seizures are of the temporal lobe type. The pre-processing steps of the various researches are illustrated in the Table, which are a criterion for the processing load of the system. In most of the methods, filters have been used for data preparation by removing unwanted noises and fluctuations in the ECG signals.

In most research, the RRI feature has been manually extracted first. Also, most of them have manually extracted many other features in the time-domain and frequency-domain using the extracted RRI feature. In [18], 10 features, in [28], some various features and in [39], 62 features are extracted. However, this paper uses only the RRI feature as input to the CNN-BiLSTM network, significantly reducing the manual feature extraction processing load. [29] also avoided manual feature extraction by using a Res1DCNN.

Different methods of machine learning (ML) and DL have been used for the final classification of data. [28] and [39] have performed the desired classification with the help of a Support Vector Machine (SVM) algorithm. [40] has used an event-dependent approach to determine HR behavior for seizure detection. [18] has done its classification by considering the cut-off values and [29] using a Res1DCNN. The proposed method employs a 9-layer CNN-BiLSTM with only 4500 trainable parameters, offering a lightweight architecture.

As shown in Table 1, the proposed method achieves a high specificity (91.30%) compared to other studies, which indicates a low false alarm rate, a clinically desirable characteristic for seizure detection systems. However, the sensitivity (74.40%) is lower than those reported in [18] (93.1%) and [29] (81.25%), suggesting room for improvement in detecting all seizure events. The accuracy (82.40%) is comparable to that of [28, 29] and higher than [39, 40].

It should be noted that direct comparison is challenging due to differences in datasets (number of patients, seizure types, recording conditions), evaluation protocols, and reported metrics. The proposed method was evaluated on a relatively small cohort of 5 patients with focal seizures due to the limited availability of accessible ECG databases containing seizure events, which may limit the generalizability of the findings. Future work should validate the approach on larger, more diverse datasets including generalized seizures.

Despite these limitations, the proposed method demonstrates that a lightweight CNN-BiLSTM using only RRI features can achieve competitive specificity and accuracy with significantly lower manual feature extraction and computational load. Therefore, this approach can be considered a building block for future large-scale implementation in wearable epilepsy monitoring devices.

Table 1: Specifications of the proposed method compared to the other works based on ECG signal

Reference	dataset	Seizure type	pre-processing	Feature extraction	Detection algorithm	Results
[39]	208-hour dataset of 14 newborns	Unspecified infantile seizures	Filter to remove the average value	Time and frequency domain features (62 features)	SVM	SEN 60% SPE 60%
[40]	Hospitalization of three epileptic patients for 14, 13, and 9 nights	Focal and General seizures	Unknown	HR feature	Event dependent	SEN 75% SPE 70.4%
[18]	126 seizures from 43 patients	Focal and General seizures	Median filter	10 HRV time and frequency domain features	cut-off values	SEN 93.1%
[28]	17 patients, 127 focal seizures	Temporal lobe epilepsy	Unknown	Time-frequency HRV characteristics	SVM	ACC 81.89%
[29]	EPILEPSIAE DATABASE	Focal and General seizures	50 Hz low-pass filtering, linear reduction, normalization	No feature extraction	Res1DCNN	SEN 81.25% SPE 82%
The proposed method	Physionet post-ictal data 5 patients	Focal seizures	Median filter high pass filter Normalization	RRI feature	9-layer CNN-BiLSTM	SEN 74.40% SPE 91.30% ACC 82.40%

5. CONCLUSION S

This research provides solutions for monitoring the condition of epilepsy patients. Due to the advantages of using the single-lead ECG signal, it is chosen as an optimal and valuable criterion for constructing epilepsy monitoring systems. These benefits include ease of receiving ECG signals from the patient's body and lower processing requirements compared to EEG signals, which require multiple channels for processing.

The use of ECG signals allows pre-processing and manual feature extraction steps to be minimized. In this research, instead of using various stages of feature extraction, only RRI feature extraction is used. These data are then normalized and used as input to the neural network. For this purpose, a combined CNN-BiLSTM neural network with 4500 trainable parameters was used. Evaluated using a Leave-One-Subject-Out cross-validation on five patients, the proposed network achieved an average accuracy of 82.4%, sensitivity of 74.4%, and specificity of 91.3%. Thus, the proposed method can be considered promising for use in wearable monitoring systems for epileptic seizure detection as part of a larger future framework.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Mostafa Ghaempour: Conceptualization, Data curation, Formal analysis, Methodology, Resources, Software, Writing - original draft, Writing - review & editing. **Kourosh Hassanli**: Conceptualization, Investigation, Project administration, Supervision, Validation, Writing - review & editing. **Ebrahim Abiri**: Investigation, Supervision, Validation, Visualization.

Declaration Of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

REFERENCES

[1] J.-J. Fan, W. Shan, J.-P. Wu, and Q. Wang, "Research progress of vagus nerve stimulation in the treatment of epilepsy," *CNS Neuroscience & Therapeutics*, vol. 25, no. 11, pp. 1222–1228, 2019. DOI: https://doi.org/10.1111/cns.13209.

[2] J. M. Rho and D. Boison, "The metabolic basis of epilepsy," *Nature Reviews Neurology*, vol. 18, no. 6, pp. 333–347, 2022. DOI: https://doi.org/10.1038/s41582-022-00651-8.

[3] T. Kim, P. Nguyen, N. Pham, N. Bui, H. Truong, S. Ha, and T. Vu, "Epileptic seizure detection and experimental treatment: A review," *Frontiers in Neurology*, vol. 11, Art. no. 701, 2020. DOI: https://doi.org/10.3389/fneur.2020.00701.

[4] A. Shoeibi *et al.*, "Epileptic seizures detection using deep learning techniques: A review," *International Journal of Environmental Research and Public Health*, vol. 18, no. 11, Art. no. 5780, 2021. DOI: https://doi.org/10.3390/ijerph18115780.

[5] J. J. Falco-Walter, I. E. Scheffer, and R. S. Fisher, "The new definition and classification of seizures and epilepsy," *Epilepsy Research*, vol. 139, pp. 73–79, 2018. DOI: https://doi.org/10.1016/j.eplepsyres.2017.11.015.

[6] X. Qiu, F. Yan, and H. Liu, "A difference attention ResNet-LSTM network for epileptic seizure detection using EEG signal," *Biomedical Signal Processing and Control*, vol. 83, Art. no. 104652, 2023. DOI: https://doi.org/10.1016/j.bspc.2023.104652.

[7] A. C. Modi, A. D. Patel, C. A. Mara, M. Schmidt, J. R. Tenney, and J. Stevens, "Pilot randomized controlled clinical trial of an adherence social norms intervention for adolescents with epilepsy," *Epilepsy & Behavior*, vol. 140, Art. no. 109082, 2023. DOI: https://doi.org/10.1016/j.yebeh.2022.109082.

[8] L. Kuhlmann, K. Lehnertz, M. P. Richardson, B. Schelter, and H. P. Zaveri, "Seizure prediction—ready for a new era," *Nature Reviews Neurology*, vol. 14, no. 10, pp. 618–630, 2018. DOI: https://doi.org/10.1038/s41582-018-0055-2.

[9] B. Olmi, L. Frassineti, A. Lanatà, and C. Manfredi, "Automatic detection of epileptic seizures in neonatal intensive care units through EEG, ECG and video recordings: A survey," *IEEE Access*, vol. 9, pp. 138174–138191, 2021. DOI: https://doi.org/10.1109/ACCESS.2021.3118227.

[10] T. Nguyen and C. J. Wusthoff, "Clinical manifestations of neonatal seizures," *Pediatrics International*, vol. 63, no. 6, pp. 631–635, 2021. DOI: https://doi.org/10.1111/ped.14654.

[11] M. Sahani, S. K. Rout, and P. K. Dash, "FPGA implementation of epileptic seizure detection using semisupervised reduced deep convolutional neural network," *Applied Soft Computing*, vol. 110, Art. no. 107639, 2021. DOI: https://doi.org/10.1016/j.asoc.2021.107639.

[12] S. Y. Shah, H. Larijani, R. M. Gibson, and D. Liarokapis, "Random neural network based epileptic seizure episode detection exploiting electroencephalogram signals," *Sensors*, vol. 22, no. 7, Art. no. 2466, 2022. DOI: https://doi.org/10.3390/s22072466.

[13] K. Komal, F. Cleary, J. S. G. Wells, and L. Bennett, "A systematic review of the literature reporting on remote monitoring epileptic seizure detection devices," *Epilepsy Research*, vol. 201, Art. no. 107334, 2024. DOI: https://doi.org/10.1016/j.eplepsyres.2024.107334.

[14] A. A. E. Shoka, M. M. Dessouky, A. El-Sayed, and E. E.-D. Hemdan, "An efficient CNN based epileptic seizures detection framework using encrypted EEG signals for secure telemedicine applications," *Alexandria Engineering Journal*, vol. 65, pp. 399–412, 2023. DOI: https://doi.org/10.1016/j.aej.2022.10.014.

[15] W.-L. Mao, H. I. K. Fathurrahman, Y. Lee, and T. W. Chang, "EEG dataset classification using CNN

method," in *Journal of Physics: Conference Series*, vol. 1456, no. 1, 2020, Art. no. 012017. DOI: https://doi.org/10.1088/1742-6596/1456/1/012017.

[16] S. Mao and E. Sejdić, "A review of recurrent neural network-based methods in computational physiology," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 10, pp. 6983–7003, 2023. DOI: https://doi.org/10.1109/TNNLS.2022.3145365.

[17] L. Billeci, D. Marino, L. Insana, G. Vatti, and M. Varanini, "Patient-specific seizure prediction based on heart rate variability and recurrence quantification analysis," *PLoS ONE*, vol. 13, no. 9, Art. no. e0204339, 2018. DOI: https://doi.org/10.1371/journal.pone.0204339.

[18] J. Jeppesen, A. Fuglsang-Frederiksen, P. Johansen, J. Christensen, S. Wüstenhagen, H. Tankisi, E. Qerama, A. Hess, and S. Beniczky, "Seizure detection based on heart rate variability using a wearable electrocardiography device," *Epilepsia*, vol. 60, no. 10, pp. 2105–2113, 2019. DOI: https://doi.org/10.1111/epi.16343.

[19] J. Jeppesen, K. Lin, H. M. Melo, J. Pavei, J. L. B. Marques, S. Beniczky, and R. Walz, "Detection of seizures with ictal tachycardia, using heart rate variability and patient adaptive logistic regression machine learning methods: A hospital-based validation study," *Epileptic Disorders*, vol. 26, no. 2, pp. 199–208, 2024. DOI: https://doi.org/10.1002/epd2.20196.

[20] K. M. Hassan, M. R. Islam, T. T. Nguyen, and M. K. I. Molla, "Epileptic seizure detection in EEG using mutual information-based best individual feature selection," *Expert Systems with Applications*, vol. 193, Art. no. 116414, 2022. DOI: https://doi.org/10.1016/j.eswa.2021.116414.

[21] S. E. Sánchez-Hernández, R. A. Salido-Ruiz, S. Torres-Ramos, and I. Román-Godínez, "Evaluation of feature selection methods for classification of epileptic seizure EEG signals," *Sensors*, vol. 22, no. 8, Art. no. 3066, 2022. DOI: https://doi.org/10.3390/s22083066.

[22] L. Yang, Q. Liu, Z. Zhang, L. Gan, Y. Zhang, and J. Wu, "Materials for dry electrodes for the electroencephalography: Advances, challenges, perspectives," *Advanced Materials Technologies*, vol. 7, no. 3, Art. no. 2100612, 2022. DOI: https://doi.org/10.1002/admt.202100612.

[23] H. Gelbard-Sagiv, S. Pardo, N. Getter, M. Guendelman, F. Benninger, D. Kraus, O. Shriki, and S. Ben-Sasson, "Optimizing electrode configurations for wearable EEG seizure detection using machine learning," *Sensors*, vol. 23, no. 13, Art. no. 5805, 2023. DOI: https://doi.org/10.3390/s23135805.

[24] A. Delorme, "EEG is better left alone," *Scientific Reports*, vol. 13, no. 1, Art. no. 2372, 2023. DOI: https://doi.org/10.1038/s41598-023-27528-0.

[25] X. Wei, L. Zhou, Z. Chen, L. Zhang, and Y. Zhou, "Automatic seizure detection using three-dimensional CNN based on multi-channel EEG," *BMC Medical Informatics and Decision Making*, vol. 18, Suppl. 5, Art. no. 111, 2018. DOI: https://doi.org/10.1186/s12911-018-0693-8.

[26] Y.-H. Chen *et al.*, "Soft, comfortable polymer dry electrodes for high quality ECG and EEG recording," *Sensors*, vol. 14, no. 12, pp. 23758–23780, 2014. DOI: https://doi.org/10.3390/s141223758.

[27] J.-J. Wang, S.-H. Liu, C.-H. Tsai, I. Manousakas, X. Zhu, and T.-L. Lee, "Signal quality analysis of single-arm electrocardiography," *Sensors*, vol. 23, no. 13, Art. no. 5818, 2023. DOI: https://doi.org/10.3390/s23135818.

[28] T. De Cooman, C. Varon, B. Hunyadi, W. Van Paesschen, L. Lagae, and S. Van Huffel, "Online automated seizure detection in temporal lobe epilepsy patients using single-lead ECG," *International Journal of Neural Systems*, vol. 27, no. 7, Art. no. 1750022, 2017. DOI: https://doi.org/10.1142/S012906571750022X.

[29] S. Baghersalimi, T. Teijeiro, D. Atienza, and A. Aminifar, "Personalized real-time federated learning for epileptic seizure detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 2, pp. 898–909, 2022. DOI: https://doi.org/10.1109/JBHI.2021.3097768.

[30] M. Ghaempour, K. Hassanli, and E. Abiri, "An approach to detect and predict epileptic seizures with high accuracy using convolutional neural networks and single-lead-ECG signal," *Biomedical Physics & Engineering Express*, vol. 10, no. 2, Art. no. 025041, 2024. DOI: https://doi.org/10.1088/2057-1976/ad29a3.

[31] R. E. Stirling *et al.*, "Forecasting seizure likelihood with wearable technology," *Frontiers in Neurology*, vol. 12, Art. no. 704060, 2021. DOI: https://doi.org/10.3389/fneur.2021.704060.

[32] M. Kołodziej, A. Majkowski, P. Tarnowski, R. J. Rak, and A. Rysz, "A new method of cardiac sympathetic index estimation using a 1D-convolutional neural network," *Bulletin of the Polish Academy of Sciences: Technical Sciences*, vol. 69, no. 3, Art. no. e137054, 2021. DOI: https://doi.org/10.24425/bpasts.2021.137054.

[33] Z. Lou, L. Wang, K. Jiang, Z. Wei, and G. Shen, "Reviews of wearable healthcare systems: Materials, devices and system integration," *Materials Science and Engineering: R: Reports*, vol. 140, Art. no. 100523, 2020. DOI: https://doi.org/10.1016/j.mser.2019.100523.

[34] M. M. Taye, "Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions," *Computation*, vol. 11, no. 3, Art. no. 52, 2023. DOI: https://doi.org/10.3390/computation11030052.

[35] I. Al-Aweel, K. Krishnamurthy, J. Hausdorff, J. Mietus, J. Ives, A. Blum, D. Schomer, and A. Goldberger, "Postictal heart rate oscillations in partial epilepsy," *Neurology*, vol. 53, no. 7, pp. 1590–1590, 1999. DOI: https://doi.org/10.1212/WNL.53.7.1590.

[36] PhysioNet. "Post-Ictal Heart Rate Oscillations in Partial Epilepsy" [Online]. Available: https://physionet.org/content/pihr/1.0.0/.

[37] MathWorks. "MATLAB (Deep Learning Toolbox)" [Online]. Available: https://www.mathworks.com/products/deep-learning.html.

[38] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980, 2014.

[39] O. Doyle, A. Temko, W. Marnane, G. Lightbody, and G. Boylan, "Heart rate based automatic seizure detection in the newborn," *Medical Engineering & Physics*, vol. 32, no. 8, pp. 829–839, 2010. DOI: https://doi.org/10.1016/j.medengphy.2010.05.010.

[40] F. Massé, M. V. Bussel, A. Serteyn, J. Arends, and J. Penders, "Miniaturized wireless ECG monitor for real-time detection of epileptic seizures," *ACM Transactions on Embedded Computing Systems*, vol. 12, no. 4, Art. no. 47, 2013. DOI: https://doi.org/10.1145/2485984.2485990.

BIOGRAPHY



Mostafa Ghaempour received his B.Sc. degree in electrical engineering from Shiraz University of Technology, Shiraz, Iran, in 2020, and his M.Sc. degree from the same university in 2022. He is currently a Ph.D. candidate at Shiraz University of Technology, conducting his dissertation research. His research interests include embedded systems, wearable medical monitoring systems, hardware implementation of artificial neural networks, digital signal processing, image processing, logic circuit design, and system modeling.



Kourosh Hassanli was born in Shiraz, Iran, in 1977. He received the B.Sc. degree from Shiraz University, Shiraz, Iran, in 2000, the M.Sc. degree from the Iran University of Science and Technology, Tehran, Iran, in 2002, and the Ph.D. degree from the Isfahan University of Technology, Isfahan, Iran, in 2016, all in electrical engineering. He is currently an Assistant Professor at Shiraz University of Technology. His research interests include smart image sensors, data converters, low-voltage and low-power circuits, energy harvesting system design, and hardware implementation of artificial neural networks.



Ebrahim Abiri received his B.Sc. degree in electronics engineering from Iran University of Science and Technology (IUST) in 1992, M.Sc. degree from Shiraz University in 1996 and the Ph.D. degree in electronics from IUST in 2007. He is currently a full Professor in the department of electrical and electronics engineering, Shiraz University of Technology. He has authored and co-authored more than 160 published technical papers and 4 books. His-current research activities include analog and digital ICs design, semiconductors, and power-electronics.

Copyrights
© 2026 Licensee Shahid Chamran University of Ahvaz, Ahvaz, Iran. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution –NonCommercial 4.0 International (CC BY-NC 4.0) License (http://creativecommons.org/licenses/by-nc/4.0/).