Epilepsy detection with artificial neural network based on as-fabricated neuromorphic chip platform

Liu, Yihe; Chen, L.; Li, X. W.; Wu, Yuancong; Liu, S.; Wang, Junjie; Hu, Shaogang; Yu, Qi; Chen, Tupei; Liu, Yang

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Y. H. Liu,[1] L. Chen,[2] X. W. Li,[2] Y. C. Wu,[1] S. Liu,[1] J. J. Wang,[1] S. G. Hu,[1] Q. Yu,[1] T. P. Chen,[3] and Y. Liu[1,a)]

AFFILIATIONS

[1] State Key Laboratory of Electronic Thin Films and Integrated Devices, University of Electronic Science and Technology of China, Chengdu 610054, People's Republic of China
[2] Beijing Microelectronics Technology Institute (BMTI), Beijing 100076, People's Republic of China
[3] School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798

[a)] **Author to whom correspondence should be addressed:** yliu1975@uestc.edu.cn

ABSTRACT

Epilepsy is a serious neurological condition caused by a sudden abnormality of brain neurons. An accurate epilepsy detection based on electroencephalogram (EEG) signals can provide vital information for diagnosis and treatment. In this study, we propose a lightweight automatic epilepsy detection system with artificial neural network based on our as-fabricated neuromorphic chip. The proposed system utilizes a neural network model to achieve high-accuracy detection without the need for epilepsy-related prior knowledge. The model uses a filter module and a convolutional neural network to preprocess the raw EEG signal and uses a long short-term memory recurrent neural network and a fully connected network as the classifier. In the examination, the classification accuracy of the normal cases and seizures approaches 99.10%, and the accuracy of the normal cases, and interictal and seizure cases can reach 94.46%. This design provides possible epilepsy detection in wearable or portable devices.

I. INTRODUCTION

At the present time, artificial intelligence (AI) technology has achieved breakthrough development and has been applied to many fields, especially in biomedicine.[1–7] In the field of mathematics, AI technology can be used to solve problems of linear fractional order ordinary differential equations.[6,7] AI technology can also be applied to the field of devices: memristor-based neural network systems can realize the discriminative task.[4] In the field of biomedicine, AI technology can assist doctors in diagnosing diseases. Epilepsy is a serious neurological condition caused by a sudden abnormality of brain neurons, and it has affected nearly 1% of the world population. Electroencephalogram (EEG) contains temporal and spatial information of brain and is widely used for clinical detection of epilepsy. Even for experienced neurologists, the visual assessment of the EEG recordings is tedious and cumbersome. Therefore, advanced, accurate, and automatic detection methods may have a significant impact on the prediction and treatment of epilepsy, especially wearable or portable epilepsy detection equipment. In recent years, some research studies implemented the automatic epileptic seizure detection using machine learning algorithms and artificial intelligent algorithms.[8–10] These algorithms include classification methods, such as support vector machines (SVM),[11–15] K nearest neighbor (K-NN),[16,17] neural networks,[18,19] and decision tree (DT),[20] and feature extraction methods, such as convolutional neural network (CNN)[18–22] and Wavelet packet decomposition (WPD).[12]

WPD and local detrended fluctuation analysis (L-DFA) is proposed to analyze and diagnose a variety of epilepsies automatically, and finally, EEG signals are classified by SVM.[12] The pyramid of difference of Gaussian filtered signals is used to detect the key points at multiple scales in the EEG signals, and the local binary pattern (LBP) of these key points is calculated and treated as a feature set.[11] Finally, the feature set is classified by the SVM classifier, and the classification accuracy (Acc) of the normal, interictal, and ictal cases can reach 98.8%. The Taylor–Fourier filter (TFF) is used to extract features from the EEG signals. The classifiers, such as K-NN and least square SVM, are employed for the classification of normal, seizure-free, and seizure, with an accuracy rate of 94.88%.[15] Lahmiri and Shmuel calculated the Hurst exponent of the EEG signal on different scales to obtain the generalized Hurst exponent (GHE) as the feature of the EEG signal and uses K-NN for classification.[16] The accuracy of the binary classification between the interictal and ictal cases reaches 100%. The system proposed in Ref. 17 uses a feature extraction network based on a local graph structure (LGS), and then the EEG signals are classified using discrete wavelet transform (DWT) and K-NN methods, achieving 97.2% binary classification accuracy rate. Most epilepsy detection systems designed based on traditional machine learning require experienced designers to manually design the EEG signal features. Compared with the former traditional machine learning method, the neural network algorithm has better fault tolerance and robustness to process the actual epileptic seizure signals, and it is easier to realize the hardware requirements of energy saving and portability.[18–22] The system proposed uses a four-layer CNN to extract EEG features and a DT as the classifier.[20] The accuracy of the two classifications is 98.65%, and the network parameter is 78.8k. Li *et al.* proposed a channel embedding spectrum time squeezing and excitation network (CE-stSENet) for the feature extraction of the EEG signals, which is mainly composed of CNN, fully connected (FC), and maxpolling.[21] Finally, the features are sent to the exponential linear unit (ELU) for classification. The network structure of the system is complex, the amount of parameters is huge, and the accuracy of the three classifications can reach 99.36%. The algorithms mentioned above are all implemented in software, and there are also some articles on the hardware of the epilepsy automatic detection system. A novel bit-serial data processing unit (DPU) is proposed and used to simulate neurons to design a low-power and low-cost neural network processor for epilepsy seizure diagnosis.[23] Both Application Specific Integrated Circuit (ASIC) and Field-Programmable Gate Array (FPGA) are used to implement the epileptic seizure prediction system. The EEG signal is sent to the Finite Impulse Response (FIR) band pass filter for preprocessing and is classified using the Extreme Learning Machine (ELM) classifier.[24] The epileptic seizure detection algorithm is implemented in FPGA. The total on-chip power of the algorithm is 0.16 W, and the dynamic power is 1 mW. The system classification accuracy rate can reach 98.5%. A low power SVM training, feature extraction, and classification algorithms are hardware implemented in a neural seizure detection application, and sequential minimal optimization (SMO) algorithm is used as the training algorithm, and the total power consumption of the ASIC is 14.91 mW (including SMO, feature extraction, and classifier).[13] The system achieves up to 96.77% sensitivity and 90.36% accuracy.

The design of automatic epilepsy detection systems based on traditional machine learning mostly requires relevant epilepsy knowledge and artificial identification of the EEG signal features. In this work, we propose an artificial neural network model for epilepsy detection using our as-fabricated neuromorphic chip platform. This experiment uses different band combinations of the EEG signals as input for epilepsy detection. It provides evidence for judging whether each band signal has a strong correlation with epilepsy and provides conditions for further reducing the network scale and hardware cost. The proposed lightweight neural network system has a small amount of parameters and achieves a high classification accuracy. The neuromorphic chip was fabricated with a 55 nm CMOS technology. The classification accuracy for the normal cases and seizures can approach up to 99.10%, and the accuracy of the normal cases, interictal, and seizure cases can reach 94.46%. The system proposed in this paper performs the task of epilepsy detection excellently without prior knowledge of the epilepsy disease. This design provides possible epilepsy detection in wearable or portable devices.

II. METHOD

As shown in Fig. 1, the system utilizes the filter in MNE library[25] and the two dimensional CNN (2D-CNN) to preprocess the raw EEG signals and extract features. Then, the bidirectional long short-term memory (Bi-LSTM) and FC layer are realized in the as-fabricated chip for classification.

Bonn University dataset[26] is used to verify the epilepsy detection system. The dataset samples the EEG signal at a frequency of 173.6 Hz, and the recording time for each single-channel EEG segment is 23.6 s, containing 4097 data points. The frequency ranges from 0.53 to 40 Hz, including the low frequency signals related to epilepsy. Bonn University dataset contains three categories: normal (set A, set B), interictal (set C, set D), and ictal (set E). In order to improve the robustness and the training accuracy, we expand the dataset. The method is to divide each group of single-channel data into seven groups with a 5.9 s time window. There is an overlap of 2.95 s between each two sets of adjacent data. 2450 sets of data are used for training, 700 sets of data are used for verification, and 350 sets of data are used for examination.

As shown in Fig. 2, the system for detecting epilepsy mainly includes three parts: the first part is the preprocessing module, where the MNE filter is used to divide the single-channel raw data (size $= 1 \times 1024$) into five frequency bands (5×1024).

The second part is used for feature pre-extraction of the EEG waveforms. As shown in Fig. 2(a), the CNN layer is used to pre-extract the high-dimensional features of the EEG signal while

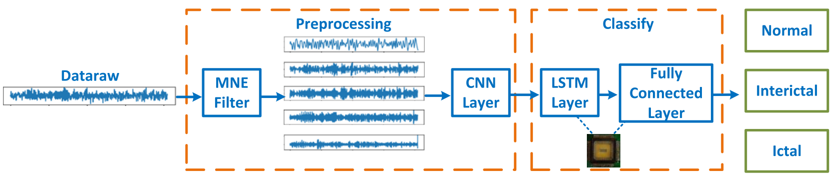

FIG. 1. Block diagram of the automatic epilepsy detection system.

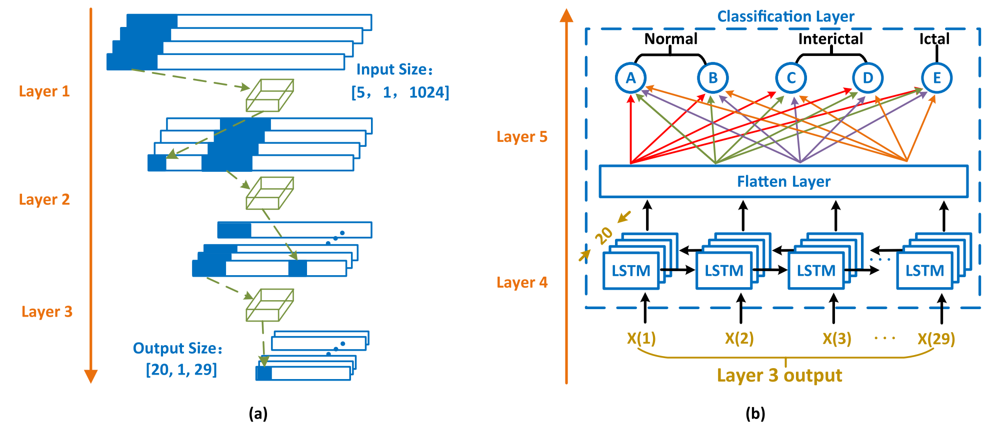

FIG. 2. The network structure in the automatic epilepsy detection system: (a) schematic of CNN structure and (b) schematic of LSTM and FC.

TABLE I. List of the proposed neural network parameters.

Layer	Type	Input size	Kernel size	Output size
1	Conv2D+max-pooling	$1 \times 5 \times 1024$	$1 \times 5 \times 5 \times 5$ (conv) 3×1 (pooling)	$5 \times 1 \times 254$
2	Conv2D+max-pooling	$1 \times 5 \times 254$	$1 \times 10 \times 5 \times 5$ (conv) 3×1 (pooling)	$10 \times 1 \times 62$
3	Conv2D	$1 \times 10 \times 62$	$1 \times 20 \times 5 \times 5$	$20 \times 1 \times 29$
4	Bi-LSTM	20×29	⋯	1×160
5	FC	1×160	⋯	1×3

preserving the timing information. It is also for shortening the length of the EEG signal in the time dimension, reducing the model parameters of the classification layer and the training time. After preprocessing, the data dimension is reduced from 5×1024 to 20×29. The third part is the classification layer composed of one layer of Bi-LSTM and one layer of FC, as shown in Fig. 2(b). EEG high-dimensional features containing timing information are input to the Bi-LSTM layer, and finally, the fully connected layer outputs in the form of determination. The neural network model parameters used in this paper are given in Table I.

The neural network model used in this article is programmed and trained under the python-based PyTorch™ framework. The training algorithm is based on adaptive moment estimation and uses the CrossEntropyLoss as the loss function. For optimization, we employ dynamic learning rate and early stop in training. The network parameters of the CNN, Bi-LSTM, and FC layers are quantized into eight-bit integers. Then, the model is mapped to the hardware to carry out classification. Figure 3 shows the illustration of the processing element (PE) array in the neural network. Input data can be transmitted horizontally, and weight data ("Weight") are transmitted vertically. The calculation results support both vertical and diagonal transmission.

In order to ensure the consistency of the internal data format in the operation of the neural network, the upper and lower saturation data truncation method is adopted. The control module manages the data flow according to the flag bit and generates a handshake signal for data communication between PEs. The PE array is connected to a row of multiplexers (DMUX). The input of DMUX comes from the calculation result of the PE unit.

The design of PE unit is shown in Fig. 4. The PE array has two working modes: matrix (vector) multiplication and matrix (vector) dot product. In matrix (vector) multiplication mode, PE alone serves as a multiplying and accumulating unit, and the result is output by the "Mul_{out}" port. For the second working mode, each PE is used as an independent multiplication unit and completes the multiplication operation of an input feature ("Xin") and a weight ("Weight") without accumulation, and the result is output by the "Sum_{out}" port. "$Diag_{in}$" and "Col_{in}" represent the results from the diagonal and vertical PE, respectively.

The operators in the above two working modes of the PE array and the non-linear mapping functions, such as Sigmoid, Tanh, and hardware-softmax provided by the non-linear activation function module, are used to complete the acceleration operation of the LSTM and FC layers in the epilepsy automatic detection system.

III. EXPERIMENT AND RESULT

The examination utilizes the filtering module in the MNE library to filter the EEG data raw into five bands of δ (0–3 Hz), θ (4–7 Hz), α (8–13 Hz), β (14–30 Hz), and γ (above 30 Hz) band. The waveforms of different frequency bands are input to CNN for feature pre-extraction. In order to achieve better classification accuracy, one-dimensional CNN (1D-CNN) and two-dimensional CNN

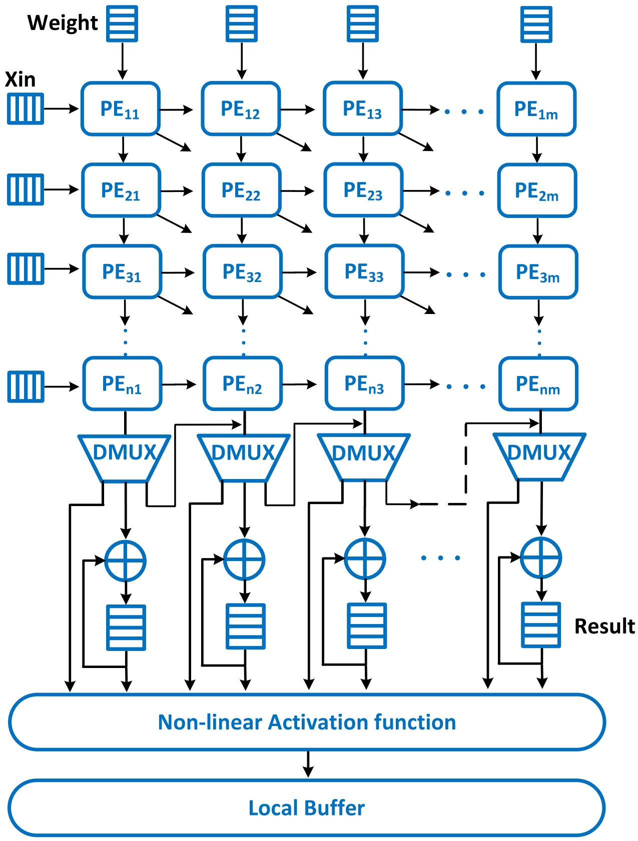

FIG. 3. Architecture of processing element array.

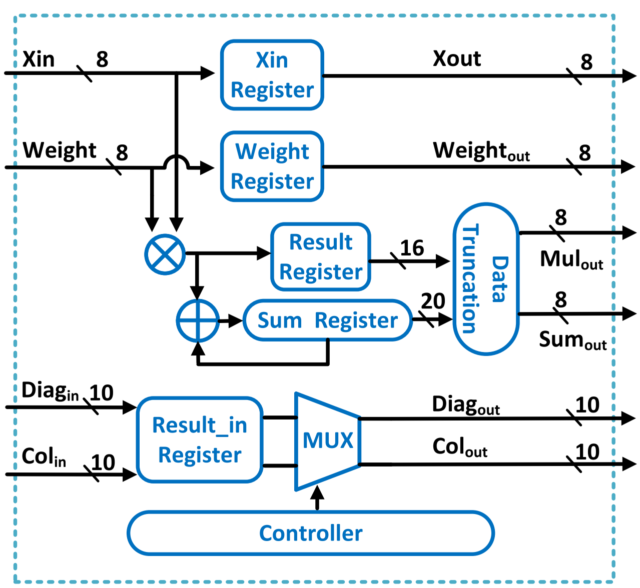

FIG. 4. Schematic illustration of the processing element.

(2D-CNN) are used to extract features for each frequency data, respectively. In order to improve the robustness of the system, all examinations utilizes the tenfold cross-validation method to obtain the classification accuracy. Figure 5 shows the accuracy of the system for 2D-CNN and 1D-CNN to preprocess the EEG signal. It can be observed that both 1D-CNN and 2D-CNN methods can achieve 100% accuracy in the two classification tasks (set A/E). However, the accuracy of using 2D-CNN to preprocess the EEG signal in other classification tasks is significantly better than 1D-CNN. The 2D-CNN-based model can achieve 100% accuracy in the two classification tasks (set A/E and set B/E) and an accuracy of 99.095% in the three classification tasks (set A/D/E).

In order to reduce the network size, this design uses different frequency bands as input, and the system classification accuracies are presented in Fig. 6. As can be observed, the data of three/four frequency bands as input to carry out the three-classification of set A/D/E is discussed in Fig. 5. As shown in Fig. 6, the EEG signals in the δ, α, and β bands contain more epilepsy-related information. When using only EEG data in the three frequency bands of δ, α, and β as input, the accuracy of the three classifications can also reach 98.38%. The accuracy is comparable to or even better that using four input bands.

When using the data of three frequency bands (δ, α, and β) as input, the network size can be further reduced. The system network parameters are dynamically quantized into eight-bit signed integer, and the network parameters of the Bi-LSTM and FC layer are mapped to the as-fabricated chip. As presented in Table II, the system is quantized and partially mapped on the as-fabricated chip. The accuracy of the system drops slightly. The accuracy of the two classifications is still above 99.10%. The accuracy of the three classifications of the system can reach 95.86% (set A/D/E) and 94.46% (set AB/CD/E), respectively.

A summary of epileptic seizure prediction by researchers is presented in Table III. As can be observed, the proposed system takes

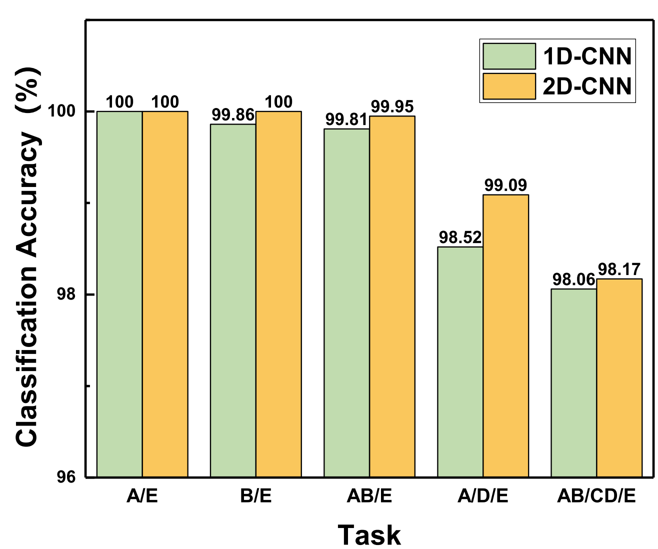

FIG. 5. Comparison of classification accuracy of system using 1D-CNN and 2D-CNN.

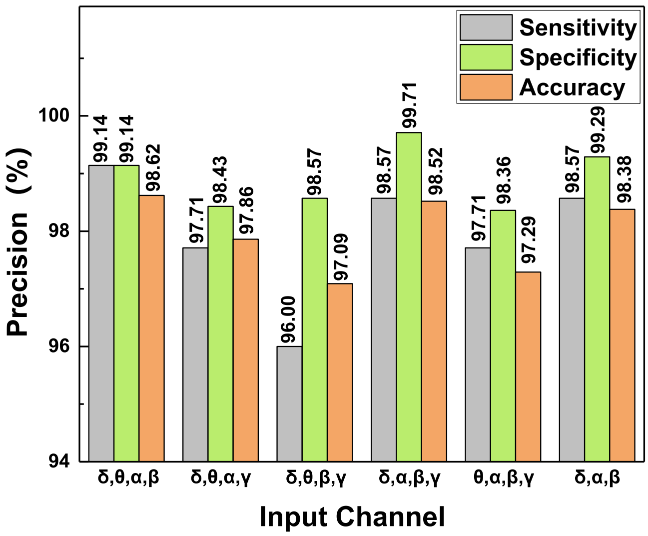

FIG. 6. Comparison of system classification accuracy with different frequency band data as input.

TABLE II. Classification accuracy of the measured system.

Task	Accuracy (%)	Sensitivity (%)	Specificity (%)
Set A/E	99.86	99.72	100
Set AB/E	99.10	98.66	100
Set A/D/E	95.86	95.00	99.00
Set AB/CD/E	94.46	95.29	98.38

advantages of a good accuracy both in two classifications and three classifications. The proposed neural network is constructed using a small amount of parameters of only 61.2 K. Furthermore, as the network can be mapped on the as-fabricated chip, the system has potential to be realized as a wearable or portable epilepsy detection device.

IV. CONCLUSION

This paper proposes a neural network system composed of 2D-CNN and LSTM for automatic detection of epileptic seizures based on the EEG signals. The system parameters and EEG signals are quantified, and part of the system parameters are mapped to the as-fabricated chip. By selecting frequency bands and quantization, only 61.2 K parameters are necessary. In the examination, the classification accuracy rate of the normal cases and seizures can approach 99.10%, and the classification accuracy rate of the normal, interictal, and ictal cases can be up to 94.46%. This design provides the possibility for the realization of wearable or portable epilepsy detection equipment.

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AUTHOR DECLARATIONS

Conflict of Interest

No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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TABLE III. Comparison between the proposed system and other systems in reference.

References	Platform	Model	2-class acc (%)	3-class acc (%)
[11]	CPU/GPU	LBP+SVM	100	98.8
[15]	CPU/GPU	TFF+SVM/K-NN	⋯	94.88
[20]	CPU/GPU	CNN+DT	98.65	⋯
[21]	CPU/GPU	CE-stSENet+ELU	99.8	99.36
[23]	FPGA+AISC	MLP	90	⋯
[24]	FPGA	FIR+ELM	98.5	⋯
This work	GPU+ASIC	CNN+LSTM	99.86	95.86

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