ECG-based Seizure Prediction Utilizing Transfer Learning with CNN

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***Abstract*—Clinically, electroencephalography (EEG) is the most common tool used to diagnose epilepsy. However, if considering practicality and convenience, electrocardiogram (ECG) is more suitable for use in non-medical institutions. Its problem that needs to be overcome is the improvement of accuracy. Therefore, this study attempted to apply transfer learning strategy to develop a seizure prediction system based on ECG for detecting interictal and preictal periods. We trained a nonpatient specific epilepsy prediction model based on Convolutional Neural Network (CNN), and then used transfer learning to fine-tune parameters with the goal of reducing the model development time and improving the performance for each specific patient. ECG data were obtained from two open-source datasets, the Siena Scalp EEG database and Zenodo, including 13 and 14 patients, respectively. The results show that the patient-specific model with six frozen layers achieved accuracy, sensitivity, and specificity of 100% for nine patients and required only 40 s of training time. By applying transfer learning, the model could directly use raw ECG signals, eliminating the time and manpower in extraction of features and greatly speeding up the training process. Furthermore, it achieved the purpose of personalized and accurate detection that could increase the practicality of seizure prediction in daily life.**

Keywords- electrocardiography (ECG); Convolutional Neural Network (CNN); seizure prediction; transfer learning.

I. INTRODUCTION

According to statistics report of the World Health Organization, epilepsy is one of the most common neurological diseases in the world, with about 50 million patients worldwide. It refers to the occasional, excessive, and disorderly discharge of brain neurons, resulting in limb movement disorders and perception, language, or other cognitive dysfunctions. Clinically, electroencephalography (EEG) is the most common tool used to diagnose epilepsy. However, its measurement environment is limited, and the operation requires the assistance of professionals. Besides, the interpretation of complex signals requires extensive work as well. Therefore, many researchers have used machine learning or deep learning technology to build an automatic epilepsy detection system (e.g., [7]). The recognition accuracies of those EEG models for epileptic seizures detection could reach more than 90%. However, if such signals were to be collected using a wearable device at home, various factors would have to be considered, including easy operation by a nonprofessional, and user comfort. Hence, some researchers have begun to investigate the potential of using other physiological signals, such as electrocardiogram (ECG), as an alternative (e.g., [6]). Because epileptic seizures often affect the autonomic nervous system, leading to effects on cardiovascular, respiratory, gastrointestinal, and urinary functions during or shortly after seizures, cardiovascular changes are gaining attention because of their ability to cause sudden unexpected death in epilepsy [8]. That means excessive neural activation associated with seizures affects central autonomic network function, regulates parasympathetic and sympathetic heart rhythm and contractility, and thereby reflects in heart rate and ECG waveforms [9][10]. Although they concluded that ECG is quite feasible in practice for at home monitoring, effectively improving the low accuracy of this method would be challenging. Therefore, this study attempted to apply transfer learning strategy to develop a seizure prediction system based on ECG for detecting interictal and preictal periods. We trained a nonpatient specific epilepsy prediction model based on Convolutional Neural Network (CNN), and then used transfer learning to fine tune parameters with the goal of reducing the model development time and improving the results for each specific patient.

The rest of this paper is organized as follows: Section 2 provides the classification method for CNN model. Section 3 describes the performance of the model and the comparison results of the different models. Section 4 includes conclusion and future.

II. MATERIALS AND METHODS

The followings describe the datasets, the analysis methodology and the evaluation metrics used in our study.

A. Datasets

ECG data were downloaded from two data sets: the Siena Scalp EEG database (including 13 patients; mean ± standard deviation age 42.6 ± 13.8 years) [3][5] and Zenodo (including 14 patients; mean ± standard deviation age 17.4 ± 9.6 years) [1]. For each patient, the diagnosis of epilepsy and classification were made by a doctor. All patients provided written informed consent approved by the Ethics Committee of the University of Siena.

B. Data Analysis

ECG signals were preprocessed using MATLAB in three steps: detrending, 80Hz lowpass filtering and 60Hz notch filtering. After preprocessing, the signals were truncated by using 10s overlapping windows with 8 s of overlap and divided into four epileptic states: seizure, preictal 20–10, preictal 30–20, and preictal 40–30. A total of 12,222 samples were obtained for each state (Figure 1).

C. Classification and Performance Evaluation

The CNN model was modified from the model of Wang et al. [7] and implemented using Python. It comprised four convolutional layers, five pooling layers, and three FC layers (Figure 2). Three approaches were used for training: recordwise (i.e., mixed datasets), subjectwise (i.e., cross dataset) and patient-specific (i.e., transfer learning). For all approaches, 10-fold cross-validation was used to evaluate the trained models. The optimized model was then validated on the testing dataset by calculating its accuracy, specificity, and sensitivity. These processes were performed five times.

III. RESULTS

Effectiveness of the three training approaches for establishing a CNN-based epilepsy prediction model was investigated. The results for recordwise training revealed that the performance for classifying interictal and three preictal states were all greater than 97%; the training times for all three models were approximately 2 h (Table I). The results for subjectwise training revealed that the performance for classifying interictal and three preictal states were greater than 78%; the training times were approximately 2 h. A comparison of the results for recordwise and subjectwise training revealed that if the novel subject data were not used for model training, the test accuracy, sensitivity, and specificity decreased but the training time remained constant. Finally, the results for patient-specific transfer learning differed from those for recordwise and subjectwise training (Table II). The models with 12 frozen layers and used to classify interictal and three preictal states achieved performance of greater than 94% with training times of approximately 1 min. Models with nine and six frozen layers classifying interictal and three preictal states achieved performance of 100% with training times of approximately 40 s and 45 s, respectively. Those with three frozen layers achieved performance of 97% with training times of approximately 50 s. In summary, freezing 9 layers led to the highest accuracy (i.e., 100%) and the shortest training time (~40 seconds), which further indicated that transfer learning was superior to recordwise or subjectwise learning.

We then compared the accuracy rates of our model with those of models reported by other studies on epileptic seizure prediction using ECG data (Table III). De Cooman et al. [11] proposed a support vector machine with transfer learning approach for seizure detection using single lead ECG data from 24 temporal lobe epilepsy patients. Their personalized approach resulted in an overall sensitivity of 71% with an average decrease in false detection rate of 37%. Baghersalimi et al. [12] designed a standard federated learning framework in the context of epileptic seizure detection using a deep learning-based approach, which operates across a cluster of machines. They evaluated the accuracy on the EPILEPSIAE database consisting of one-lead ECG from 29 patients. Their framework achieved a sensitivity of 81.25%, a specificity of 82.00%, and a geometric mean of 81.62%. The comparison result shows that ours had the best accuracy, specificity, and sensitivity.

IV. CONCLUSION AND FUTURE WORK

EEG is currently the main tool used to diagnose epileptic seizures. Many studies have utilized deep learning technology for prediction of epileptic seizures (e.g., [2]); however, if considering practicality and convenience, ECG is more suitable for use in nonmedical institutions, while the problem that needs to be overcome is the improvement of accuracy [4]. Therefore, this study used three different training methods to evaluate ECG-based classification models. Recordwise training was used to test the architecture of our model. The performance could reach more than 97%. Subjectwise training was used to simulate practical situations, i.e., the test data are independent and unrelated to the training data. The performance was over 78%. Due to the sharp drop in model performance, we applied transfer learning approach to develop a patient-specific model. The results show that the training effect of freezing 6 layers was the best: the accuracy, specificity, and sensitivity for 9 subjects all reached 100%, and the training time was less than 40 seconds. By applying transfer learning, the model could directly use raw ECG signals, eliminating the time and manpower in extraction of features and greatly speeding up the training process. Furthermore, it achieved the purpose of personalized and accurate detection that could increase the practicality of seizure prediction in daily life. For future practical applications, such as wearable devices employed for seizure prediction, studies on more or larger datasets should be conducted to validate the reliability of the model.

ACKNOWLEDGMENT

This study was supported in part by the National Science and Technology Council (MOST 111-2221-E-130-001-MY3), Taiwan.

REFERENCES

[1] 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, pp. e0204339, April 2018.

[2] H. Daoud and M. A. Bayoumi, “Efficient epileptic seizure prediction based on deep learning,” IEEE Trans. Biomed. Circuits Syst., vol. 13, pp. 804–813, October 2019.

[3] P. Detti, G. Vatti, and M. D. L. Zabalo, “EEG synchronization analysis for seizure prediction: A study on data of noninvasive recordings,” Processes, vol. 8, pp. 846, June 2020.

[4] K. Fujiwara et al., “Epileptic seizure prediction based on multivariate statistical process control of heart rate variability features,” IEEE Trans. Biomed. Eng., vol. 63, pp. 1321–1332, June 2016.

[5] A. L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals,” Circulation, vol. 101, pp. 215–220, June 2000.

[6] A. Jahanbekam et al., “Performance of ECG-based seizure detection algorithms strongly depends on training and test conditions,” Epilepsia Open, vol. 6, pp. 597–606, July 2021.

[7] X. Wang et al., “One dimensional Convolutional Neural Networks for seizure onset detection using long-term scalp and intracranial EEG,” Neurocomputing, vol. 459, pp. 212–222, October 2021.

[8] F. Leutmezer et al., “Electrocardiographic Changes at the Onset of Epileptic Seizures,” Epilepsy, vol. 44, March 2003.

[9] M. Zijlmans, D. Flanagan, and J. Gotman, “Heart rate changes and ECG abnormalities during epileptic seizures: prevalence and definition of an objective clinical sign,” Epilepsy, vol. 43, August 2002.

[10] T. Yamakawa et al., “Wearable epileptic seizure prediction system with machine-learning-based anomaly detection of heart rate variability,” Sensors, vol. 20, no. 14, pp. 3987, May 2020.

[11] T. De Cooman et al., “Personalizing heart rate-based seizure detection using supervised SVM transfer learning,” Front. Neurol., vol. 11, pp. 145, February 2020.

[12] S. Baghersalimi et al., “Personalized real-time federated learning for epileptic seizure detection,” IEEE J. Biomed. Health Inform., vol. 26, no. 2, pp. 898-909, February 2022.

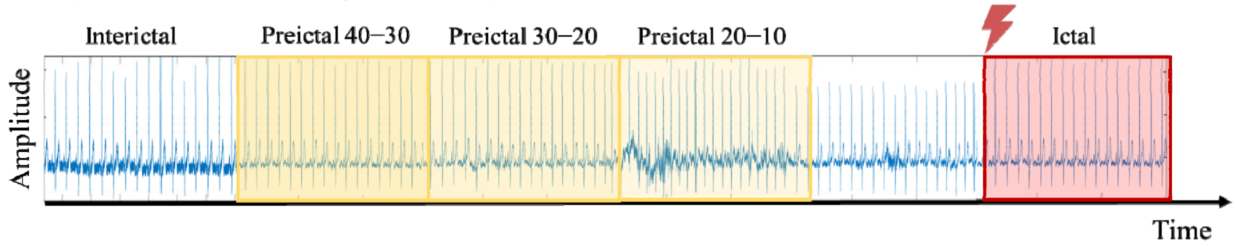

Figure 1. Illustration of four epileptic states in ECG signals.

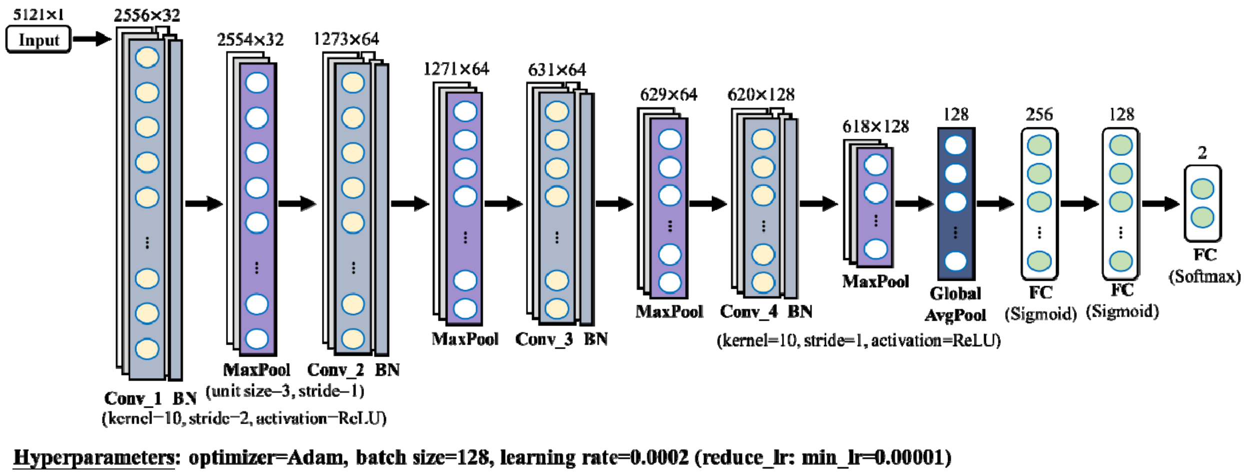

Figure 2. CNN architecture for classification of preictal and interictal periods.

TABLE I. PERFORMANCE OF THE RECORDWISE AND SUBJECTWISE TRAINING APPROACHES.

Recordwise training				
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Time
Preictal 10-20	98.96(± 0.05%)	99.09(±0.11%)	98.82(± 0.15%)	1hr48min40sec
Preictal 20-30	98.13(± 0.08%)	98.50(± 0.16%)	97.77(± 0.08%)	1hr54min39sec
Preictal 30-40	99.89(± 0.04%)	99.94(± 0.06%)	99.84(± 0.05%)	1hr44min26sec
Subjectwise training				
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Time
Preictal 10-20	85.88(± 0.68%)	83.24(± 0.32%)	88.52(± 1.57%)	1hr51min21sec
Preictal 20-30	84.90(± 0.87%)	82.66(± 1.18%)	87.13(± 0.89%)	1hr33min47sec
Preictal 30-40	83.33(± 1.54%)	78.51(± 3.39%)	88.15(± 1.24%)	1h37min58sec

TABLE II. CLASSIFICATION ACCURACY, SENSITIVITY, AND SPECIFICITY (MEAN VALUES) OF THE PATIENT-SPECIFIC INTERICTAL AND PREICTAL CLASSIFICATION TRANSFER LEARNING MODELS.

NO.	# of frozen layers	preictal 20-10				preictal 30-20				preictal 40-30			
		Acc (%)	Sen (%)	Spe (%)	Time (sec)	Acc (%)	Sen (%)	Spe (%)	Time (sec)	Acc (%)	Sen (%)	Spe (%)	Time (sec)
2	3	100	100	100	42	99.5	98.8	100	39	98.5	100	97	56
	6	100	100	100	40	100	100	100	37	100	100	100	45
	9	100	100	100	35	100	100	100	46	100	100	100	41
	12	100	100	100	104	97.5	94.4	100	112	100	100	100	102
4	3	100	100	100	46	100	100	100	46	100	100	100	39
	6	100	100	100	35	100	100	100	37	100	100	100	36
	9	100	100	100	38	100	100	100	32	100	100	100	34
	12	100	100	100	111	100	100	100	109	100	100	100	90
5	3	100	100	100	44	100	100	100	43	100	100	100	44
	6	100	100	100	43	100	100	100	36	100	100	100	35
	9	100	100	100	36	100	100	100	35	100	100	100	31
	12	100	100	100	58	100	100	100	81	100	100	100	76
7	3	100	100	100	50	100	100	100	51	100	100	100	40
	6	100	100	100	46	100	100	100	41	100	100	100	37
	9	100	100	100	34	100	100	100	39	100	100	100	32
	12	100	100	100	94	97.5	95.6	100	76	100	100	100	93
8	3	100	100	100	43	100	100	100	49	100	100	100	46
	6	100	100	100	38	100	100	100	45	100	100	100	36
	9	100	100	100	36	100	100	100	36	100	100	100	36
	12	100	100	100	109	94.9	94.1	95.6	112	100	100	100	107
9	3	100	100	100	38	100	100	100	49	100	100	100	42
	6	100	100	100	36	100	100	100	38	100	100	100	37
	9	100	100	100	37	100	100	100	31	100	100	100	30
	12	100	100	100	88	100	100	100	110	100	100	100	108
10	3	100	100	100	59	100	100	100	48	100	100	100	46
	6	100	100	100	45	100	100	100	38	100	100	100	36
	9	100	100	100	45	100	100	100	38	100	100	100	33
	12	100	100	100	73	100	100	100	78	100	100	100	59
11	3	100	100	100	42	100	100	100	45	100	100	100	41
	6	100	100	100	41	100	100	100	38	100	100	100	35
	9	100	100	100	40	100	100	100	33	100	100	100	35
	12	100	100	100	71	100	100	100	75	100	100	100	56
13	3	100	100	100	49	100	100	100	56	100	100	100	46

6	100	100	100	37	100	100	100	39	100	100	100	37
9	100	100	100	39	100	100	100	35	100	100	100	38
12	100	100	100	107	100	100	100	57	100	100	100	71

TABLE III. PERFORMANCE OF DIFFERENT SEIZURE PREDICTION SYSTEMS BASED ON CNNS WITH ECG SIGNALS.

Study	Dataset	Input	Model	Training Type	ACC(%)	SEN(%)	SPE(%)
De Cooman et al. [11]	Self-recorded	HRI and HR peaks	SVM+TL	P-spc	-	71%	-
Baghersalimi et al. [12]	EPILEPSIA	Raw data	Res1DCNN+FL	P-spc	81.62%	81.25%	82.00%
			1DCNN+FL		76%	69.25%	82%
			MLP+FL		74.00%	77%	71.50%
This study	Siena EEG+ Zenodo	Raw data	1D-CNN+TL	P-spc	99.94%	99.86%	100%

 ISBN: 978-1-68558-046-9