ECG-based Seizure Prediction Utilizing Transfer Learning with CNN

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- Her research interest lies in the biosignal processing (particularly in EEG and MEG), machine/deep learning (specifically in SVM and CNN), neuroscience (especially in Parkinson disease and depression).

INTRODUCTION

- Clinically, **EEG** is the most common tool used to diagnose epilepsy. However, its measurement environment is limited, and the operation requires the assistance of professionals.
- Excessive neural activation associated with seizures affects central autonomic network function, and thereby reflects in heart rate and **ECG** waveforms. However, how to improve the low accuracy of using ECG would be a challenge.
- Therefore, this study attempted to apply **transfer learning strategy** to develop a seizure prediction system based on ECG for detecting interictal and preictal periods.

MATERIALS AND METHODS

Datasets

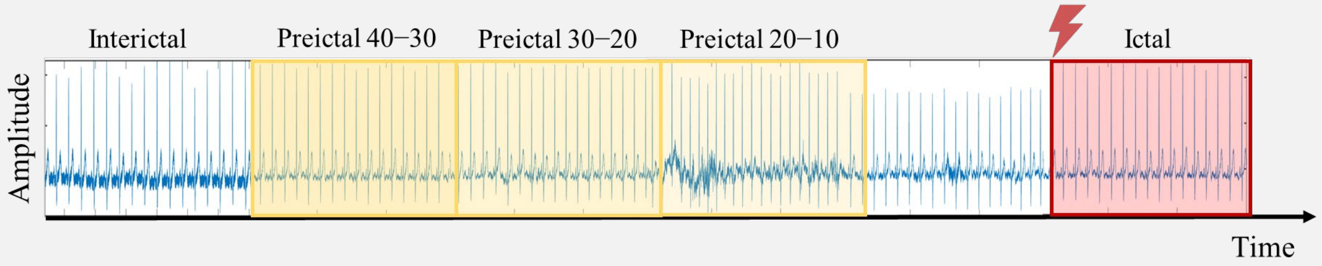
ECG data were downloaded from the Siena Scalp EEG database (including 13 patients) and Zenodo (including 14 patients)

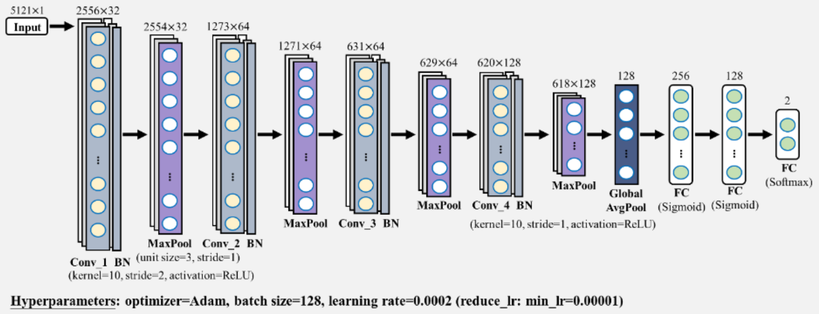
Data Analysis

ECG signals were preprocessed in three steps. After preprocessing, the signals were truncated and divided into four epileptic states.

Classification

Recordwise, subjectwise and patient-specific approaches were used for training. 10-fold cross-validation was used to evaluate the models.



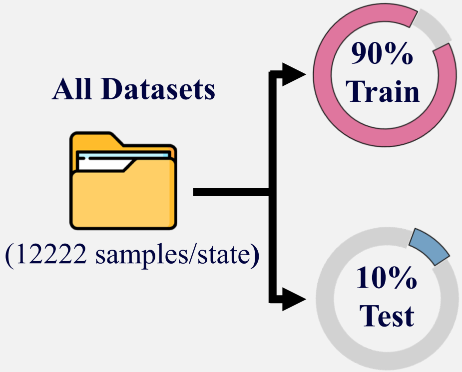


(modified from the model of Wang et al., 2021)

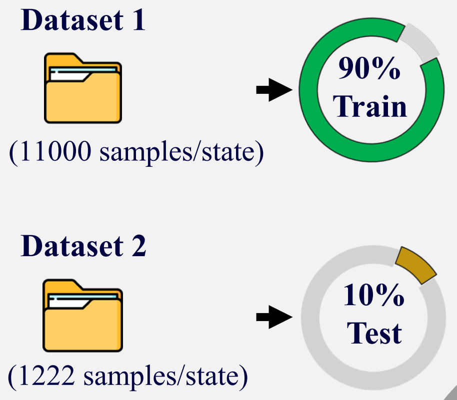
RESULTS I

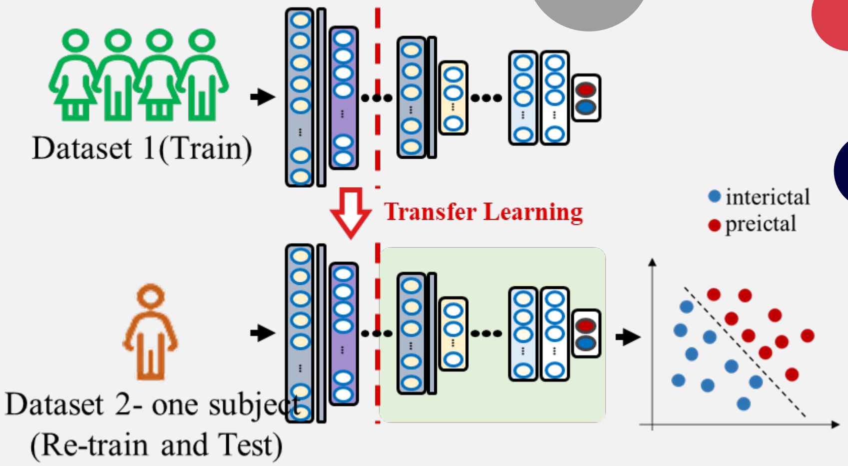
Performance of the recordwise and subjectwise training approaches.

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



- All greater than **97%**
- Greater than **78%**





RESULTS II

Performance of the patient-specific transfer learning approach.

NO.	# of frozen layers	preictal 20-10 Acc (%)	Sen (%)	Spe (%)	Time (sec)	preictal 30-20 Acc (%)	Sen (%)	Spe (%)	Time (sec)	preictal 40-30 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

The training effect of patient-specific was the best as freezing 9 layers.

CONCLUSION

- EEG is currently the main tool used to diagnose epileptic seizures. Many studies have utilized deep learning technology for prediction of epileptic seizures.
- 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.
- Therefore, this study used three different training methods to evaluate ECG-based classification models.
- 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.

THANKS!

Do you have any questions?

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