Epileptic Disease Predictive Model with Limited Clinical Data Resource

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ABSTRACT

While end-to-end approach to multi-channel electroencephalogram (EEG) learning has shown significant promise, their applicability is often constrained in resource-limited clinical scenarios. When provided with a single-channel EEG, how can we effectively capture representative features that are robust to multi-channels and scalable across varied clinical tasks, such as seizure prediction? In this paper, we present ***SplitSEE***, a structurally **Split**table architecture designed for effective epileptic disease prediction using **S**ingle-channel **EE**Gs. The key concept behind *SplitSEE* consists of 1) high-capacity temporal-frequency feature encoding, 2) a task-free self-supervised learning framework without label supervision, and 3) a splittable architectural design evaluated in an advanced split federated deployment manner. *SplitSEE* has the following properties: (a) *Effectiveness*: it learns informative features solely from single-channel EEG and has even outperformed baselines. (b) *Robustness*: it shows the capacity to adapt across different channels with low performance variance. Superior performance is also achieved with our real clinical dataset. (c) *Scalability*: Our experiments show that with just *one fine-tuning epoch*, *SplitSEE* achieves high and stable performance using partial model layers. We develop a federated learning version of *SplitSEE* with only *one-layer federated deployment*, showing its great potential in real-world clinical scenarios. Moreover, an evaluation of our real clinical dataset also confirms the performance and potential of *SplitSEE*. The source code is available at: https://anonymous.4open.science/r/SplitSEE/

CCS CONCEPTS

• **Computing methodologies → Machine learning approaches**; • **Applied computing → Health care information systems**.

KEYWORDS

EEG data, representation learning, self-supervised learning

1 INTRODUCTION

Epilepsy is a brain disorder characterized by the transient occurrence of unexpected seizures, resulting from excessive or hypersynchronous neuronal activity [10]. About 1.0 % of the world's population, 80 million people, are affected by this disease, and about half of them experience severe seizures. They cannot predict when they will have a seizure, and unexpected changes in behavior, loss of muscle control, and sudden blackouts can significantly impact their daily lives. Therefore, reliable seizure prediction systems are becoming increasingly important. As a major brain monitoring tool, an electroencephalogram (EEG) reveals the activities of millions of neurons in response to various body states or event stimuli in real-time with millisecond precision [7, 20]. While end-to-end approaches to multi-channel EEG learning have shown significant promise [4, 18], there are some limitations in practical uses.

- Applying conductive gel and managing the complex setup make routine multi-channel data acquisition challenging.
- Continuous wear is impractical or patients to wear multi-channel EEGs all day because it can disrupt natural conditions.
- Recent developments in portable monitoring devices have proposed advancements using fewer sensors.

Given these challenges, ***single-channel EEG modeling*** has become increasingly prominent. Consequently, our research focuses on the following question: *How can we develop an effective seizure prediction model using only single-channel EEGs and how our model is disruption-reduced, cost-effective, and portable monitoring-friendly?* However, single-channel EEG studies has the following challenges:

No spatial (multiple channels) information, and Transient and temporally unpredictable features. Some studies are heuristics that aim to develop general-purpose time series frameworks

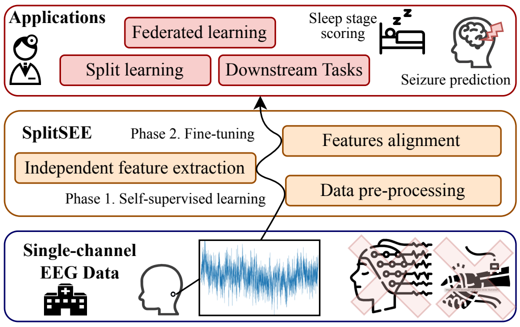

Figure 1: *SplitSEE* is a framework designed for single-channel EEG, eliminating the need for multi-channel or multi-data sources. It can learn task-free features and easily fine-tune to clinical tasks. More effectively, it can deploy on edge device by split federated fashion.

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suitable for EEGs [9]. However, EEGs generally lack recognizable patterns, e.g., trend and seasonality. The eventful features are transient and temporally unpredictable. For instance, a spontaneous K-complex waveform often exhibits bursts within 0.5∼1.5 seconds [5]. Researchers utilize the spectrogram to simultaneously capture temporal frequency features and their correlations [6, 7, 19]. But the trade-off between the time and frequency resolution is a long-standing problem [14, 15].

Insufficient labels. Existing deep methods rely heavily on a supervised learning framework, necessitating vast amounts of high-quality labeled data for model training [5, 12]. However, in a clinical setting, procuring labels is time-consuming and infeasible [13, 16]. Furthermore, training on a limited amount of labeled data tends to be task-specific, often with an overfitting issue and low generalization capability [24].

Computational efficiency and clinical/portable monitoring scalability. Existing methods are typically designed is an end-to-end fashion and require the deployment of a large model in a clinical scenario [13, 18]. Facing newly collected data, de-novo model training is often needed. However, in real-world clinical settings, not only are the computing resources of user devices limited, but also those available in hospitals.

2 PROPOSED METHOD

To address above challenges, we propose ***SplitSEE***, a **Split**table self-supervised learning framework tailored for **S**ingle-Channel **EE**G representation, which has the following contributions:

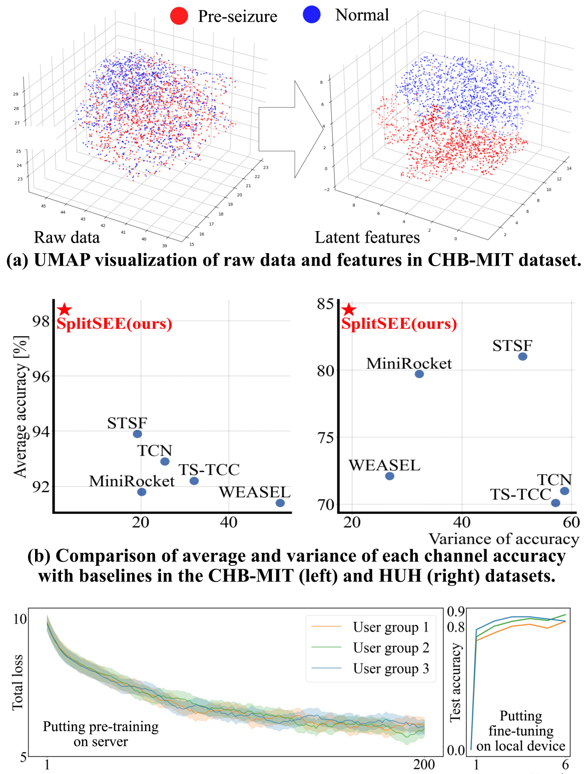
Temporal frequency independent learning with domain alignment. *SplitSEE* involves (i) two domain-specific feature learning modules and (ii) cross-domain alignment. The domain-specific modules independently learn features of both time and frequency. (iii) The multi-granularity learning for each module ensures the effective capture of local features and global semantic information.

Task-free self-supervised learning. The driving force behind *SplitSEE* is self-supervised learning (SSL). SSL has recently drawn attention to data representation by employing rich unlabeled data and its scalability for downstream tasks [3, 6, 9, 17]. We propose a three-step contrastive learning framework, which (i) facilitates two independent feature learning modules, and (ii) further serve as the objective of domain alignment, unifying the time and frequency feature spaces for a given EEG observation.

Splittable neural architecture evaluated in one-layer-oriented federated deployment manner. *SplitSEE* contains a "pre-training to fine-tuning" training strategy. Architecturally, the structure of *SplitSEE* is splittable: only selected networks are employed for fine-tuning and serving downstream tasks, eliminating the need for end-to-end model re-training. This design has potential as a clinical distributed architecture. Hence, we provide a split federated learning [23] version of *SplitSEE*, wherein pre-training can be handled on the server, with fine-tuning executed locally.

3 EXPERIMENT AND RESULT

We evaluate *SplitSEE* on epileptic seizure prediction task involving two public CHB-MIT [11], HUH [22], and our hospital dataset with TS-TCC [9], TCN[1], MiniRocket [8], STSF [2], and WEASEL [21].



(a) UMAP visualization of raw data and features in CHB-MIT dataset.

(b) Comparison of average and variance of each channel accuracy with baselines in the CHB-MIT (left) and HUH (right) datasets.

(c) Results of split federated version in our dataset.

Figure 2: Experimental results.

Effectiveness. Figure 2 (a) shows a uniform manifold approximation and projection (UMAP) visualization of the features extracted by *only self-supervised pre-training without any label supervision* in a 3D space. A clear boundary can be found in two datasets, highlighting the high effectiveness of capturing an informative representation from different feature domains.

Robustness. Figure 2 (b) shows comparison results on the average accuracy among channels and its variance. A smaller variance implies that the accuracies are closely grouped around the mean. In all databases, our method not only achieves the highest average accuracy but also shows the least variance.

Scalability. Figure 2 (c) shows the result obtained with a split federated version of *SplitSEE*. We randomly divide our hospital dataset into three user groups, and conduct an experiment. During the fine-tuning phase, the single-layer linear classifier achieved high performance across all user groups within just a few steps of training.

4 CONCLUSION

We propose ***SplitSEE***, a structurally Splittable framework designed for effective single-channel EEG representation learning. *SplitSEE* learns informative features solely from single-channel EEG and has even outperformed baselines on epileptic seizure prediction task. Future directions include verifying the effectiveness of the proposed method in more fundamental neurological problems.

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