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# HengNet: An Ultra-lightweight Model with Two-level Reuse Algorithm for Seizure Detection and Prediction

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**Abstract**—Traditional models based on electroencephalographic (EEG) signals for seizure monitoring encounter difficulties in simultaneously optimizing accuracy, response latency, and computational load. These challenges hinder their deployment in edge computing environments, where real-time local inference is critical. To address these issues, we introduce a novel network architecture, designated as *HengNet*. This architecture integrates a Two-level Reuse Algorithm (TRA), which strategically reutilizes outputs from intermediate layers, considerably reducing the average computational load per inference—vital for scenarios requiring frequent inferences. When tested on the CHB-MIT dataset, this patient-specific model attains classification accuracies of 95.67% and 99.60% for seizure prediction and detection, respectively. Notably, it maintains an average computational load of merely 0.05 million multiply-accumulate operations (MACs) per inference and has a compact model size of 6.87 K parameters. These results represent a significant advancement compared with existing methods. Operating at a rate of 32 inferences per second, the computational load of the model for seizure prediction has been reduced by more than 19.4 times, and for seizure detection, by more than 6.4 times.

**Index Terms**—EEG Signals, Seizure Detection, Seizure Prediction, Two-level Reuse Algorithm, Ultra-lightweight.

## I. INTRODUCTION

Epilepsy, a chronic neurological disorder characterized by abnormal electrical activity in brain's neurons, affects approximately 60 million people worldwide [1]. Patients experiencing seizures may suffer from loss of consciousness or muscle control, potentially leading to serious accidents such as drowning or falls [2, 3]. Technologies for seizure prediction empower patients to adopt preventative measures, thereby mitigating the risks associated with seizures [4]. Moreover, seizure detection technologies can autonomously alert healthcare providers or emergency contacts when a seizure occurs [5], which serves as an essential safety measure for those living alone.

In this paper, we define the number of inferences executed per second as the inference frequency. We also introduce terms

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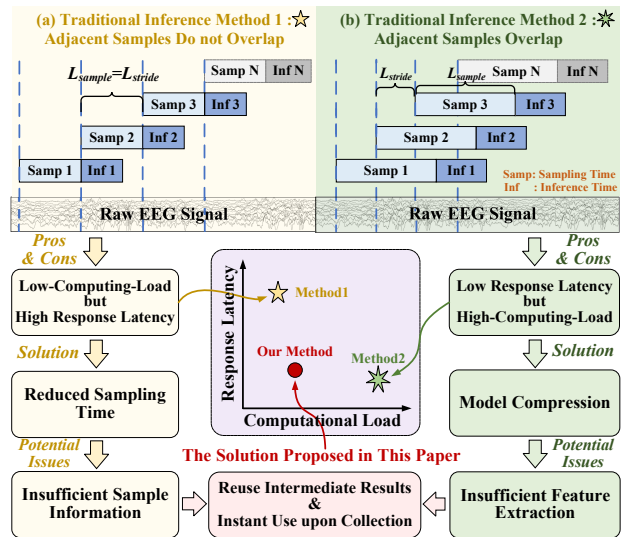


Fig. 1. Comparison of computational load and response latency across different inference methods.

such as the sample length  $L_{sample}$ , which is the duration of the sample window input to the model, and the sampling stride  $L_{stride}$ , the interval between the start of consecutive sample windows. A shorter  $L_{stride}$  corresponds to a higher inference frequency, thereby enhancing system responsiveness. We describe the delay from the onset of a seizure to the system's response as the response latency.

Regarding inference methodologies, as depicted in Figure 1(a), the traditional procedure involves sampling the electroencephalogram (EEG) signal, processing a sample of length  $L_{sample}$ , and ensuring that subsequent samplings commence after the prior sample concludes. This method minimizes data overlap and inference number, but it extends the sampling stride  $L_{stride}$ , which can increase response latency. The impact of latency is reduced through overlapping sampling techniques, illustrated in Figure 1(b), where the stride  $L_{stride}$  represents the non-overlapping segment between samples, reducing the sampling delay. The shorter response latency of Method 2, as shown in the figure, results from a reduced step size, which also imposes a higher computational load, increasing the complexity by  $L_{sample}/L_{stride}$  times compared to the

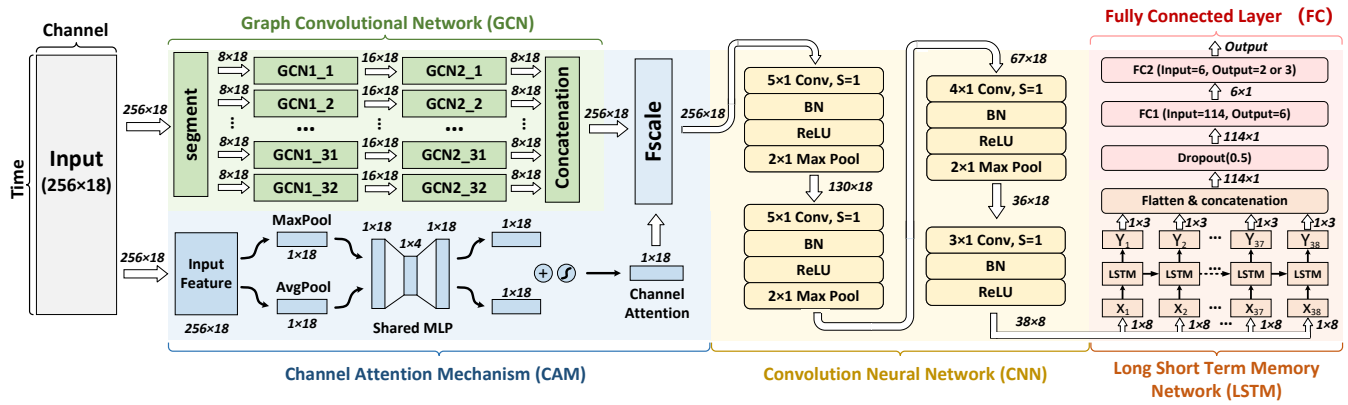


Fig. 2. Architecture of the seizure monitoring model *HengNet*.

previous method.

The model must be lightweight to enable real-time seizure monitoring on edge devices while extending battery life. Some studies have focused on designing lightweight models by employing techniques such as model pruning and quantization to reduce both computational load and parameter [6–9]. Although these model compression methods can lower resource consumption, they often do so at the expense of the models’ ability to capture complex features, resulting in decreased accuracy [10]. Some post-processing methods have been used in seizure monitoring tasks to reduce the computational load of models [11–13]. Traditional models often face difficulties in perfectly balancing accuracy, response latency, and computational load. Enhancing any two of these aspects typically results in a trade-off with the third [14].

In this study, we introduce a novel neural network architecture named *HengNet*, accompanied by a Two-level Reuse Algorithm (TRA). This algorithm boosts computational efficiency by reutilizing intermediate results produced during the inference process. This approach facilitates the concurrent optimization of response latency and computational efficiency while maintaining high accuracy levels.

## II. METHOD

### A. Structure of *HengNet*

In this study, we introduce the *HengNet* epilepsy monitoring model, meticulously engineered for the prediction and detection of epileptic seizures. In the seizure detection task, we consolidate the pre-ictal, inter-ictal, and post-ictal stages into a unified non-seizure stage category, enabling the model to delineate between seizure and non-seizure stages based on input EEG data. For the task of seizure prediction, *HengNet* executes a tripartite classification, segregating the EEG data into pre-ictal, inter-ictal, and post-ictal categories. As shown in Figure 2, the architecture of *HengNet* comprises five principal components: a graph convolutional network (GCN) block, a channel attention mechanism block, a convolutional neural network (CNN) block, a long short-term memory (LSTM) block, and a fully connected block. The model processes EEG samples with a duration of 1 second.

GCN are a subset of convolutional neural networks tailored to process and leverage the structural properties of graph-

formatted data. In the context of EEG monitoring, each electrode is conceptualized as a graph node, with electrode interconnections serving as edges of graph, thus forming the overall graph topology. This study employs a multifaceted graph construction strategy utilizing Pearson correlation coefficients, Spearman’s rank correlation coefficients, and Euclidean distances. This integrative approach ensures a precise depiction of the inter-nodal relationships within the EEG data, subsequently boosting the model’s ability to extract relevant features.

The channel attention mechanism layer functions as a feature enhancer, amplifying the influence of pivotal channels to focus the model’s analysis on critical EEG information. Concurrently, the CNN and LSTM blocks collaboratively extract temporal and spatial features from the EEG sequences. The fully connected layer compresses the feature tensor, tailoring its output to provide binary or ternary classifications dependent on specific task demands. This structured approach not only optimizes the model’s diagnostic accuracy but also enhances its utility in clinical and real-time monitoring applications.

### B. TRA: Two-level Reuse Algorithm

To simultaneously enhance the computational efficiency, accuracy, and response latency of the model, we further introduce TRA. By reusing intermediate results within the network, TRA increases the inference frequency to reduce response latency without significantly increasing computational load. We set  $L_{stride}$  to 8 frames (31.25 ms) and the sample length  $L_{sample}$  to 10 s. Given the CHB-MIT dataset’s sampling rate of 256Hz [15], the inference frequency is 32 times per second. Each sample can be divided into 10 one-second windows, and each window can be further divided into 32 groups of 8 frames each.

As shown in Figure 3, Figure 3(a) illustrates the first-level reuse strategy—Window result reuse. Between the  $T$  and  $T + 256$  timestamps, 9 Windows (Window2 to Window10) in the sample contain identical data. Therefore, at the  $T + 256$  timestamp, the model can reuse the inference results of Window2 to Window10 from the  $T$  timestamp (Result2 to Result10). The model only needs to perform inference on the data in Window11, and the result, Result11, is combined with Result2 to Result10 through voting to produce the final

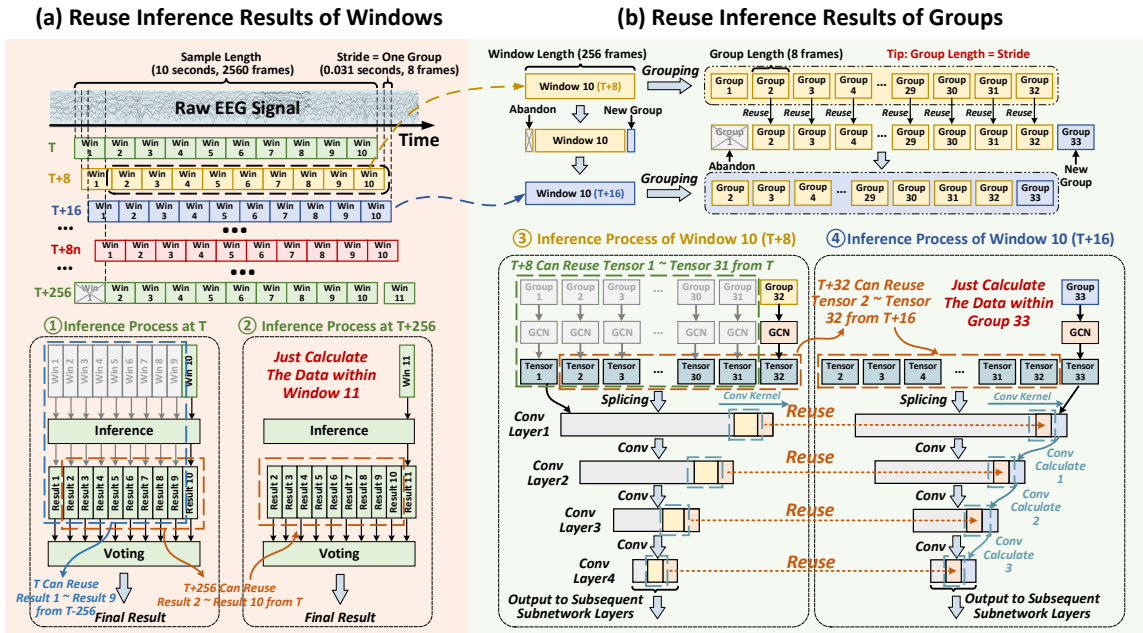


Fig. 3. Two-level Reuse Algorithm (TRA) workflow. (a) Reuse inference results of windows. (b) Reuse inference results of groups.

output at the  $T + 256$  timestamp. Although the inference at  $T + 256$  involves data from Window2 to Window11, actual computation is only required for Window11. It is also important to note that the inference results for Window1 to Window9 at  $T$  timestamp (Result1 to Result9) are derived from the  $T - 256$  timestamp.

To further reduce the computational load during high-frequency inference, we introduce a second-level reuse strategy—the Group reuse strategy. As shown in Figure 3(b), during each inference, only the newly acquired Group needs to be input into the GCN and 1D-CNN for computation. Between the  $T + 8$  and  $T + 16$  timestamps, 31 groups (Group2 to Group32) in the sample contain identical data. Therefore, at the  $T + 16$  timestamp, the network can reuse the computed results for Group2 to Group32 in Window10 from the  $T + 8$  timestamp (Tensor2 to Tensor32). Similarly, the inference results for Group1 to Group31 at the  $T+8$  timestamp (Tensor1 to Tensor31) are derived from the  $T$  timestamp. Except for the initial inference process during system startup, the inference results for the first 9 Windows at the  $T$  timestamp can always be reused from the  $T - 256$  timestamp. Additionally, within the final Window, the network can consistently reuse the computed results for the first 31 groups from the  $T - 8$  timestamp. Thus, inference calculation is only required for one Group to complete the inference for the current 10-second data segment.

### III. EXPERIMENTS

#### A. Dataset

In this study, we used the CHB-MIT dataset, an EEG signal database specifically designed for patients with refractory epilepsy. The dataset comprises EEG recordings from 23 cases, using either 18 or 23 leads, with a sampling resolution of 16 bits and a sampling rate of 256 Hz. To maintain consistency

TABLE I  
PERFORMANCE EVALUATION OF THE MODEL PROPOSED IN THIS PAPER FOR PATIENT-SPECIFIC SEIZURE DETECTION AND PREDICTION.

Patient ID	Detection			Prediction		
	Acc(%)	Sen(%)	Spe(%)	Acc(%)	Sen(%)	Spe(%)
Chb01	100.00	100.00	100.00	99.46	99.88	99.27
Chb02	99.98	100.00	99.98	97.16	97.87	96.80
Chb03	99.99	100.00	99.99	98.38	100.00	97.53
Chb04	100.00	100.00	100.00	95.59	96.65	95.14
Chb05	99.97	100.00	99.97	92.16	97.71	89.41
Chb06	100.00	100.00	100.00	91.77	98.86	88.58
Chb07	99.96	99.68	100.00	97.98	99.83	97.03
Chb08	99.25	99.43	99.22	98.96	99.93	98.51
Chb09	99.99	100.00	99.99	96.04	99.93	94.23
Chb10	100.00	100.00	100.00	91.90	99.02	87.66
Chb11	99.99	100.00	99.99	92.12	94.24	90.98
Chb12	97.38	95.60	97.55	96.07	88.97	99.05
Chb13	99.99	99.88	100.00	98.84	100.00	98.34
Chb14	99.96	100.00	99.96	92.69	88.87	94.67
Chb15	99.74	97.74	99.99	88.94	90.05	88.40
Chb16	99.95	100.00	99.95	93.78	93.51	93.90
Chb17	99.90	100.00	99.89	98.01	99.65	97.09
Chb18	99.62	100.00	99.59	98.25	97.91	98.43
Chb19	99.15	100.00	99.07	99.66	99.46	99.74
Chb20	96.42	85.89	97.86	97.64	99.09	96.88
Chb21	100.00	100.00	100.00	90.99	99.26	87.56
Chb22	99.64	100.00	99.62	94.82	96.09	94.07
Chb23	99.83	100.00	99.80	99.10	99.81	98.74
Avg	99.60	99.05	99.67	95.67	97.24	94.87

in electrode configuration across all participants, we used an 18-lead setup.

We characterized the EEG of a patient during a seizure as the ictal stage, those recorded 20 minutes before a seizure as the pre-ictal stage, those recorded 20 minutes after a seizure as the post-ictal stage, and the signals during all other times as the inter-ictal stage. In this study, due to the limited sample

TABLE II  
PERFORMANCE COMPARISON OF THE PROPOSED MODEL WITH OTHER PATIENT-SPECIFIC BASELINES USING THE CHB-MIT DATASET AT AN INFERENCE FREQUENCY OF 32 TIMES PER SECOND.

Method	Task <sup>1</sup>	$L_{sample}(s)$	Accuracy	Sensitivity	Specificity	ACLPI (MACs)	Parameters
CE-stSENet 2020 [16]	D	4	95.96%	92.41%	96.05%	8.63 M	289.00 K
DMLSENet 2021 [17]	D	8	86.68%	93.71%	79.64%	6.54 M	371.37 K
EEGWaveNet 2021 [18]	D	4	98.39%	68.94%	99.25%	3.46 M	48.37 K
1D-CNN 2022 [6]	D	2	99.80%	97.10%	99.80%	3.70 M	113.80 K
Spiking Conformer 2024 [19]	D	5	97.10%	94.90%	99.30%	0.32 M	9.90 K
HengNet without TRA	D	10	99.60%	99.05%	99.67%	16.36 M	6.87 K
HengNet (Ours)	D	10	99.60%	99.05%	99.67%	0.05 M	6.87 K
AdderNet-SCL 2022 [20]	P	4	/	94.90%	/	10.73 M	120.06 K
GCN 2022 [21]	P	4	92.00%	96.51%	/	0.97 M	15.50 K
Spiking Conformer 2024 [19]	P	5	93.10%	96.80%	89.50%	2.10 M	40.30 K
HengNet without TRA	P	10	95.67%	97.24%	94.87%	16.36 M	6.87 K
HengNet (Ours)	P	10	95.67%	97.24%	94.87%	0.05 M	6.87 K

<sup>1</sup> In task, D presents Detection and P presents Prediction.

size utilized for model training, an oversampling strategy was employed to enrich the dataset. Specifically, an 80% overlap was applied to the data collected during the ictal stage, while a 50% overlap was used for the pre-ictal and post-ictal stages.

### B. Metrics

We evaluate the performance of *HengNet* and TRA with the following metrics.

- The Average Computational Load per Inference (ACLPI) denotes the average quantity of computational resources demanded for each inference carried out by the model.
- Parameters (Para) is the total number of parameters involved in the model's inference process.
- Accuracy (Acc) is the proportion of correct predictions made by the model across all test samples.
- Specificity (Spe) is the proportion of negative samples correctly identified by the model.
- Sensitivity (Sen) is the proportion of positive samples correctly identified by the model.

### C. Results

To evaluate the performance of the *HengNet* model on the CHB-MIT dataset, we employed a five-fold cross-validation method. Table I presents the performance of *HengNet* in seizure detection and seizure prediction tasks. In the seizure detection task, the model achieved an average accuracy, sensitivity, and specificity of 99.60%, 99.05%, and 99.67%, respectively. In contrast, in the seizure prediction task, the model also demonstrated high accuracy with an average accuracy of 95.67%, sensitivity of 97.24%, and specificity of 94.87%. These results reflect the exceptional diagnostic accuracy and reliability of the *HengNet* model in both tasks.

We also assessed the performance of the *HengNet* model presented in this paper and the TRA with respect to classification accuracy and computational efficiency by comparing the performance of *HengNet* models with and without TRA. Notably, the TRA method proposed herein demonstrates its advantages primarily in high-frequency inference scenarios where low response latency is of paramount importance. Since a higher inference frequency results in faster response times

to sensitive events, we set the inference frequency at 32 times per second in our experiments to maintain the same latency level between our model and the baseline model.

As illustrated in Table II, in the seizure detection task, the computational load and parameters of the *HengNet* model without TRA are 16.36 million MACs and 6.87 K, respectively. Compared with the baseline model, *HengNet* demonstrates a remarkable advantage in parameter. However, its computational load is significantly higher than that of the baseline model. When *HengNet* is combined with TRA, since the model can reuse the intermediate results of the neural network in the previous stage, each inference merely requires an increase in the calculation amount by 0.05 million MACs, while the calculation amount of the baseline model is over 6.4 times that of *HengNet*. In the seizure prediction task, the same model as in the detection task was employed. Compared with a baseline model specifically designed for seizure prediction, the method presented in this paper resulted in a reduction of more than 19.4 times in ACLPI. Although ACLPI and the parameters decreased significantly, the accuracy of *HengNet* was not affected. This indicates that *HengNet* with TRA can significantly enhance computing efficiency while maintaining high accuracy and low response latency.

## IV. CONCLUSION AND DISCUSSION

This paper introduces a seizure monitoring model architecture, *HengNet*. Experiments demonstrate that *HengNet* achieves accuracies of 99.6% and 95.67% in the seizure detection and prediction tasks, respectively. To minimize the ACLPI during high-frequency inference scenarios, we introduced a TRA. This algorithm optimizes accuracy, inference delay, and computational efficiency by enhancing the utilization of intermediate results within model. At an inference frequency of 32 times per second, the ACLPI of *HengNet* is reduced to only 0.05 million MACs, achieving a computational efficiency that is six times higher than the baseline model of seizure detection and nineteen times higher compared to the baseline model of seizure prediction. With a total parameters of just 6.87 K, *HengNet* is particularly well-suited for deployment on wearable devices in edge computing scenarios.

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