

# EEGDM: EEG Representation Learning via Generative Diffusion Model

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**Abstract**—While electroencephalogram (EEG) has been a crucial tool for monitoring the brain and diagnosing neurological disorders (e.g., epilepsy), learning meaningful representations from raw EEG signals remains challenging due to limited annotations and high signal variability. Recently, EEG foundation models (FMs) have shown promising potential by adopting transformer architectures and self-supervised pre-training methods from large language models (e.g., masked prediction) to learn representations from diverse EEG data, followed by fine-tuning on specific EEG tasks. Nonetheless, these large models often incurred high computational costs during both training and inference, with only marginal performance improvements as model size increases. In this work, we proposed EEG representation learning framework building upon Generative Diffusion Model (EEGDM). Specifically, we developed structured state-space model for diffusion pretraining (SSMDP) to better capture the temporal dynamics of EEG signals and trained the architecture using a Denoising Diffusion Probabilistic Model. The resulting latent EEG representations were then used for downstream classification tasks via our proposed latent fusion transformer (LFT). To evaluate our method, we used the multi-event Temple University EEG Event Corpus and compared EEGDM with current state-of-the-art approaches, including EEG FMs. Empirical results showed that our method outperformed existing methods while being approximately 19× more lightweight. These findings suggested that EEGDM offered a promising alternative to current FMs. Our code is available at: <https://github.com/jhpuah/EEGDM>.

**Index Terms**—Electroencephalogram, diffusion model, representation learning, transformer, structured state-space model.

## I. INTRODUCTION

**E**LECTROENCEPHALOGRAPHY (EEG) provides a noninvasive technique for monitoring brain by recording electrical signals arising from neural activity and pathological processes, with high temporal resolution. Its effectiveness has led to widespread use in brain–computer interfaces (BCIs), neuroscience research, and neurological diagnostics [1], [2]. A key clinical application is the management and treatment of epilepsy, which approximately affect 50 million patients worldwide [3], where EEG recognition plays a critical role in diagnosis and pre-surgical planning. Numerous machine learning and deep learning models have been developed to detect interictal epileptiform discharges (IEDs) from EEG recordings, which often include various other brain activity (e.g., eye

movements, artifacts, and background activity, etc.), aiming to assist clinicians in decision-making. Despite showing initial promise, improving classification performance remains an active area of research for practical clinical adoption.

A major challenge behind the performance bottleneck in IED detection is the difficulty of learning robust and meaningful representations of EEG signals, due to limited high quality annotation and high signal variability across subjects, conditions, and brain activities [2], [4]. Recently, inspired by the success of large language models (LLMs), various EEG foundation models (FMs) [4], [5] have been proposed and achieved different degrees of success. Following the procedure of LLMs, EEG FMs are pretrained on large amount of unlabeled and diverse EEG data through self-supervised pre-training for representation learning using transformer architectures [6]. In most EEG FMs, the signals were tokenized into sequential tokens, with a subset masked to enable self-supervised training via masked token prediction [1], [2], [7]. These methods encouraged the models to learn the underlying relationships (through self- and cross-attention modules in transformer) between tokens and effectively capture meaningful representations without relying on labeled data. Subsequently, these FMs were fine-tuned on specific downstream tasks such as IED detection [2], sleep stage classification [8], and emotion recognition [9]. While they often outperformed traditional deep learning models, they incurred high computational costs during both training and inference, with only marginal performance improvements as model size increases.

Diffusion models [10] represent another class of self-supervised learning and generative models that have demonstrated remarkable success in image [10], [11] and audio generation [12], [13]. Recent studies suggested that diffusion models also hold strong potential for representation learning tasks [14]. Unlike masking-based methods, diffusion models achieve self-supervision by progressively corrupting input data with Gaussian noise in a forward process and learning to recover the original data through a reverse denoising process. Several approaches [15]–[17] have been proposed to leverage diffusion models for extracting representations for classification and segmentation of visual tasks. However, the generalization and applicability of diffusion models in EEG representation learning remains underexplored, as most existing works primarily employed them for signal generation and data augmentation, rather than for representation learning. Furthermore, it is also unclear whether the learned representation would be useful, and how to use it for downstream classification tasks. Hence, this work attempts to fill this gap.

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In this work, we proposed EEG Representation Learning Framework building upon Generative Diffusion Model (EEGDM). Specifically, we developed a neural architecture based on a structured state-space model for diffusion pre-training (SSMDP) to better capture the temporal dynamics of EEG signals and trained the architecture using a Denoising Diffusion Probabilistic Model (DDPM). The resulting latent EEG representations were then used for downstream classification tasks via our proposed latent fusion transformer (LFT). To evaluate our method, we used the Temple University EEG Event Corpus (TUEV) [18] and compared EEGDM with current state-of-the-art approaches, including EEG FMs.

The main contributions of this work are as follow:

- We presented EEGDM, a diffusion model-based framework for learning EEG signal representations and classification of multi-event EEG, extending diffusion model beyond signal generation and data augmentation.
- We developed structured state-space model diffusion pre-training (SSMDP) to capture the temporal dynamics of EEG signals and trained it via the forward and reverse process of DDPM for representation learning.
- We proposed LFT to leverage and fuse the latent representations from SSMDP for downstream classification tasks.
- We empirically compared our method with current state-of-the-art approaches on multi-event dataset TUEV to show its competitiveness and provided a detailed ablation study to analyze its components.

## II. RELATED WORKS

This section reviews the evolution of EEG representation learning, from classical supervised, unsupervised, and semi-supervised approaches to recent advances in self-supervised learning (particularly FMs and diffusion models) and their emerging potential for EEG, with an emphasis on the latter.

### A. Supervised and Unsupervised Approaches

EEG representation learning has often arisen as a byproduct of supervised approaches, such as the seminal common spatial pattern methods [19] and more recent deep neural network models [20]. Such representations have been examined across various neural architectures, including convolutional neural networks [21], graph neural networks [22], [23], and Transformers [24], [25], revealing findings that aligned with known brain activity patterns. When annotations are unavailable, unsupervised approaches, particularly autoencoders and their variants offered an alternative. Variational autoencoder (VAE) has shown effectiveness in learning robust representation in the regularized latent space, achieving transfer learning from motor execution signal to motor imaginary signals [26]. Another approach was metric learning, which embedded EEG signals into a vector space where similarity was defined by the proximity between samples, typically optimized using contrastive loss (e.g., [27]). However, these methods are constrained by the availability of annotation and often yield task-specific representations that lack generalizability.

Another line of research was semi-supervised learning that leverages a small amount of annotated data to train a model, while using the model itself to generate “pseudo-labels” for unannotated data, which can then be used as additional training data. For example, in [28], the empirical probabilities of the training data are used as pseudo-labels to calibrate model certainty and confidence, thereby addressing the scarcity of annotations in motor imagery classification. Another promising approach was self-supervised learning, which learns by corrupting and subsequently restoring the training data. Common corruption strategies included masking, adding noise, or combining both. These techniques have been successfully applied to various EEG tasks, such as sleep stage classification [29], evoked response enhancement [30], and motion intention recognition [31]. Recently, self-supervised pretraining methods, particularly mask prediction with transformers and diffusion models, have demonstrated strong potential across multiple domains. However, only a few pioneering studies have begun to explore their effectiveness in EEG representation learning.

### B. EEG FMs

Inspired by LLMs, EEG FMs employed token-based and masking-based self-supervised pretraining on diverse and large amount unannotated data with transformer architectures before finetuning the pretrained model on labeled data in supervised manners. The pre-training allowed EEG FMs to grasp the underlying structure of EEG from various problem domains and experimental paradigms, thus addressing the annotation scarcity issue and reducing the risk of overfitting [32]. Prior to pre-training, the raw EEG signal was usually preprocessed and then segment into patches. A tokenizer, usually a variant of vector-quantized (VQ) VAE [33], was trained to encode these patches into discrete representations, known as tokens. The VQ encoder first projected a patch to a vector representation, then the representation was replaced by the most similar entry (token) from a codebook. The VQ decoder then reconstructed a target from the token, either the original patch itself (in CBraMod [6] and Gram [7]) or a transformation of the original patch, such as Fourier spectrum (in LaBraM [2]). This process ensured that the tokens in the codebook capture semantically meaningful information about the original patches.

Subsequently, self-supervised pretraining operated on the sequence tokenized by the VQ encoder and the codebook. Initially, a subset of a sequence is masked by randomly replacing some of the tokens with a “mask token”. The masked sequence is then processed by a transformer-based model to predict the index of the replaced tokens in the codebook. The neural architecture of the model varies: LaBraM [2] used a classic transformer, CBraMod [6] employed a criss-cross attention mechanism to model spatial and temporal dependencies in parallel, and Gram [7] used a masked autoencoder consisting of a layer-fusion encoder and a transformer-based decoder. Subsequently, the pretrained model can be finetuned for classification tasks. Usually, a trainable “class token” is concatenated into the input sequence to be processed by transformer. Then, a linear classification head was trained

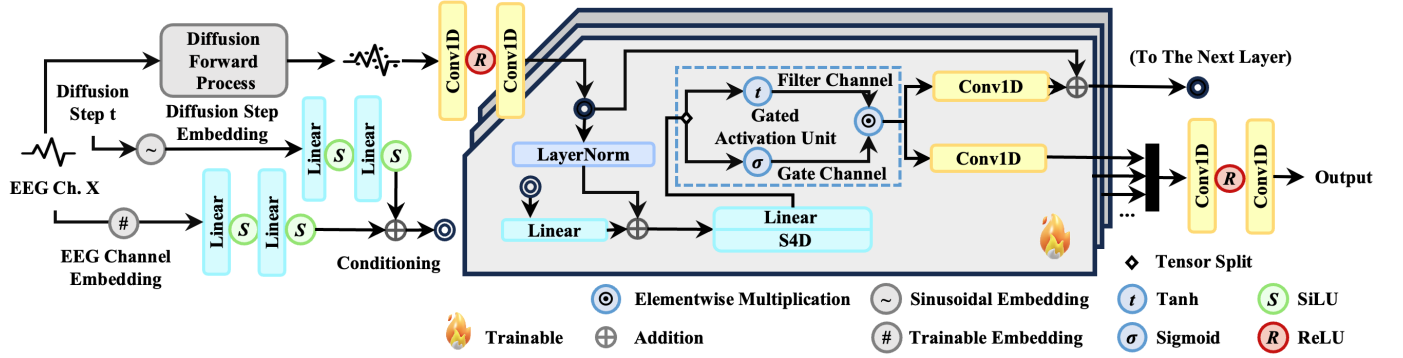


Fig. 1. Illustration of the proposed SSMDP for representation learning. The model learned to denoise and reversed a noised single-channel EEG signal by predicting the diffusion velocity, conditioned on diffusion step embedding and channel embedding, using S4D architecture. The latent activities and representations from the filter and/or gate channels were then leveraged for downstream classification.

to classify the processed class token to a label. While EEG FMs often outperformed classical deep learning models, they incurred high computational costs during both training and inference, with only marginal performance improvements as model size increases.

### C. Diffusion Model in Representation Learning

Diffusion models are closely related to denoising autoencoders [34], which are capable of producing meaningful representation in their latent space. In particular, denoising diffusion autoencoder [14] showed that the inner working of diffusion models was analogue to an autoencoder. Several works [16], [17] explored the efficiency of latent activities of diffusion models in image classification and achieved satisfactory results. [15] shows that even image segmentation is achievable with latent activities.

In addition to latent activities, the connection between conditional diffusion models and conditional probability distributions also led to alternative ways in representation learning. Diffusion classifier [35] showed that any conditional diffusion model can be converted into a classifier without any additional training. Joint diffusion model [36] unified this generator-classifier duality: the model was explicitly trained to minimize both classification loss and generative loss, and hence it can perform both tasks in a single model. These finding presented a promising direction for generalization to EEG representation learning and classification tasks, despite underexplored.

### D. Diffusion Models for EEG Signals

There is limited work on adapting diffusion models to EEG signal representation learning. Early works have primarily used EEG signals as conditioning inputs to generate other modalities, such as images [37] and audio [38], rather than learning representations of the EEG itself. A more relevant line of research [39], [40] integrates diffusion models within an autoencoder framework, so that the reconstruction errors from the diffusion model can help formulate a more informative latent space, thereby enhancing performance in imagined speech classification [39] and driving behavior classification [40]. Inspired by image super-resolution (e.g. [41]), [42]

proposed a diffusion model that can generate high-resolution EEG from low-resolution EEG, to migrate the data scarcity issue for classification task and improve spatial resolution for signal source localization. [43] applied a conditional diffusion model to generate clean EEG signal under the guidance of noisy EEG signals, hence suppressing EEG artifacts such as electrooculography artifacts.

Several works [44]–[46] quantitatively evaluated the similarity between the generated and real signals, and used the synthesized data for augmentation in various downstream tasks, such as imagined motor activity detection and major depressive disorder classification. Nonetheless, the generalization and applicability of diffusion models in EEG representation learning remain underexplored. Moreover, the optimal strategies for leveraging the learned representations are still unclear. These open questions motivate the present work.

## III. METHODOLOGY

We first present the preliminaries of key components (diffusion models, state-space models, and transformers) that EEGDM builds upon, followed by our EEGDM.

### A. Preliminaries

1) *Diffusion Model*: A diffusion model consists of a forward process and a reverse process. The forward process gradually transforms a target data distribution into a standard Gaussian distribution, while the reverse process learns to denoise step by step to reconstruct the original data. After training, the reverse process can be used for generation by gradually transforming a sample from the Gaussian distribution into one that resembles the target data distribution.

The forward process models the trajectory of a data point  $\mathbf{x}_0$  drifts and diffuses from its original distribution  $p(\mathbf{x}_0)$  to the Gaussian distribution  $\mathcal{N}(0, I)$ . This process is split into  $T$  diffusion steps, where each step is an intermediate distribution dependent on the original data and a noise schedule  $\bar{\alpha}$ :

$$p(\mathbf{x}_t|\mathbf{x}_0) = \underbrace{\sqrt{\bar{\alpha}_t}\mathbf{x}_0}_{\text{Drifting term}} + \underbrace{\sqrt{1-\bar{\alpha}_t}\epsilon}_{\text{Diffusing term}} \quad (1)$$

where  $t = 1, 2, 3, \dots, T$ ,  $\epsilon \sim \mathcal{N}(0, I)$ , and  $\bar{\alpha}_t \in (0, 1)$  is a set of strictly decreasing hyperparameters controlling the noise schedule.

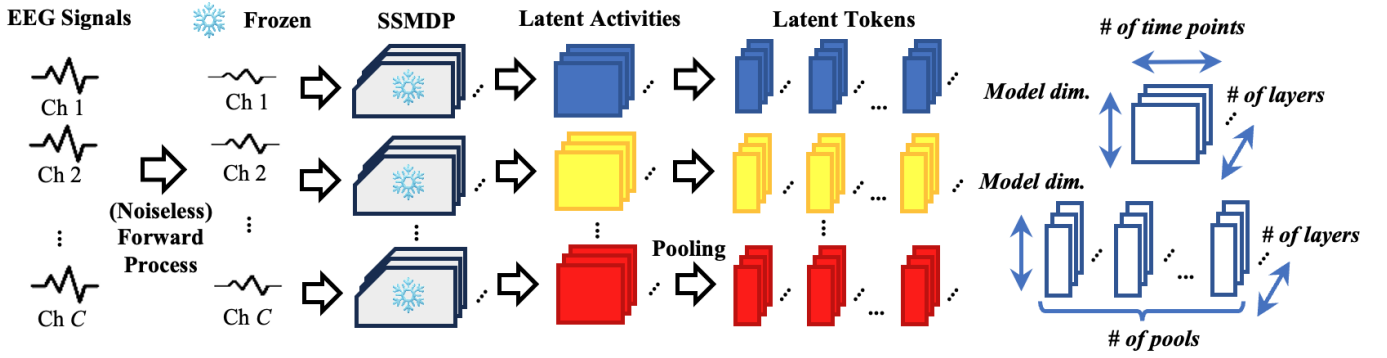


Fig. 2. Given the latent activities and representations from SSMDP of each EEG channel, we obtained the latent activities as a four-dimensional tensor: (# of channels, # of layers, # of time points, # of gate channels per layer). The latent activities are then pooled along the time dimension, reducing the dimensionality to (# of channels, # of layers, # of pools, # of gate channels per layer). Colors indicate the latent activities from different channels.

The reverse process starts from a pure Gaussian distribution  $q(\mathbf{x}_T)$ . The model is trained to perform denoising, under the assumption that each transition step in the reverse process is also Gaussian. This assumption becomes increasingly valid as the number of diffusion steps  $T$  grows large. The reverse process is modeled as:

$$q_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu(\mathbf{x}_t, t), \sigma_t^2) \quad (2)$$

parameterized by the mean  $\mu$  and variance  $\sigma_t^2$ .  $\sigma_t^2$  is assumed to be a function of  $\bar{\alpha}_t$  and not dependent on  $\mathbf{x}_t$ . Previous works have found that instead of predicting  $\mu$ , predicting added noise [10] or velocity [47]:

$$v_t = \sqrt{\bar{\alpha}_t}\epsilon - \sqrt{1 - \bar{\alpha}_t}\mathbf{x}_0 \quad (3)$$

gives better results in general.

A deep neural network  $\Phi$  is trained to approximate the chosen target  $v_t$  with a training loss  $\mathcal{L}$  to maximize the evidence lower bound (ELBO) of  $q_\theta(\mathbf{x}_0)$ , which is typically simplified to minimize the mean square error (MSE) between the prediction and the actual target (e.g. velocity) of every diffusion step [10]:

$$\mathcal{L}_{\text{MSE}} = \mathbb{E}_{t \sim [1, T]} [\|v_t - \Phi(\mathbf{x}_t, t)\|^2] \quad (4)$$

Diffusion models have no restriction on the architecture of the backbone model  $\Phi$ , some popular choices include U-Net [48] and transformer [49]. Conditional diffusion models accept extra input  $c$  known as “conditioning” that provide supplementary information about the target  $\mathbf{x}_0$ , such as its class label. This effectively turns the outcome of the reverse diffusion process into conditional distributions  $q_\theta(\mathbf{x}_0|c)$ , allowing for a finer control over the generation outcome [50].

2) *Structured State-Space Model*: Structured state-space models [51] (SSMs) are a class of neural networks that originate from the state-space representation of a dynamic system in control theory.

SSMs project a continuous-time input  $x(\tau)$  to a continuous-time output  $y(\tau)$  and a hidden state  $h(\tau)$  with matrices  $\mathbf{A}, \mathbf{B}, \mathbf{C}$  and  $\mathbf{D}$ :

$$h'(\tau) = \mathbf{A}h(\tau) + \mathbf{B}x(\tau) \quad (5a)$$

$$y(\tau) = \mathbf{C}h(\tau) + \mathbf{D}x(\tau) \quad (5b)$$

In practice, continuous-time data are often unavailable, so SSMs are typically computed using their discrete-time approximations:

$$h_k = \bar{\mathbf{A}}h_{k-1} + \bar{\mathbf{B}}x_k \quad (6a)$$

$$y_k = \mathbf{C}h_k + \mathbf{D}x_k \quad (6b)$$

The matrices in Eq. (6a) can be trained directly or obtained by applying a discretization rule with trainable step size  $\Delta$  on Eq. (5a), like zero-order hold:

$$\bar{\mathbf{A}} = \exp(\Delta\mathbf{A}), \quad \bar{\mathbf{B}} = (\Delta\mathbf{A})^{-1}(\exp(\Delta\mathbf{A}) - \mathbf{I})(\Delta\mathbf{B}) \quad (7)$$

This approach preserves the continuous-time structure of SSMs, enabling the adjustment of  $\Delta$  to operate the model at different sampling rates without retraining [51]. However, in practice, this advantage may be diminished if the SSM is used alongside components that are inherently dependent on the sampling rate.

Unrolling the formulae in Eq. (6) will eliminate  $h_k$ , which results in the convolution form of SSMs that can be trained efficiently:

$$\begin{aligned} \bar{\mathbf{K}} &= (\bar{\mathbf{C}}\bar{\mathbf{B}}, \bar{\mathbf{C}}\bar{\mathbf{A}}\bar{\mathbf{B}}, \bar{\mathbf{C}}\bar{\mathbf{A}}^2\bar{\mathbf{B}}, \dots, \bar{\mathbf{C}}\bar{\mathbf{A}}^{L-1}\bar{\mathbf{B}}) \\ y &= \bar{\mathbf{K}} * x \\ \Leftrightarrow y_k &= \sum_{i=0}^k \bar{\mathbf{C}}\bar{\mathbf{A}}^i\bar{\mathbf{B}}x_{k-i}, k = 0, 1, 2, \dots, L-1 \end{aligned} \quad (8)$$

However, in practice, the calculation of  $\bar{\mathbf{A}}^i$  in Eq. (8) is a performance bottleneck. The S4D [52] overcomes this by constraining  $\mathbf{A}$  to be a diagonal matrix with special initialization schemes.

3) *Transformer*: Transformers [49] are a class of neural network that implemented attention mechanisms. The attention mechanisms learn the dependencies between two sequences of tokens  $\mathbf{S}_1 \in \mathbb{R}^{L_1 \times H_1}$  and  $\mathbf{S}_2 \in \mathbb{R}^{L_2 \times H_2}$  and produce a new sequence with the same dimensions as  $\mathbf{S}_1$ . Here,  $L_i$  denotes the length of sequence and  $H_i$  denote the dimension of a token. If  $\mathbf{S}_1 = \mathbf{S}_2$ , the attention mechanism is termed “self attention”, otherwise it is termed “cross attention”.

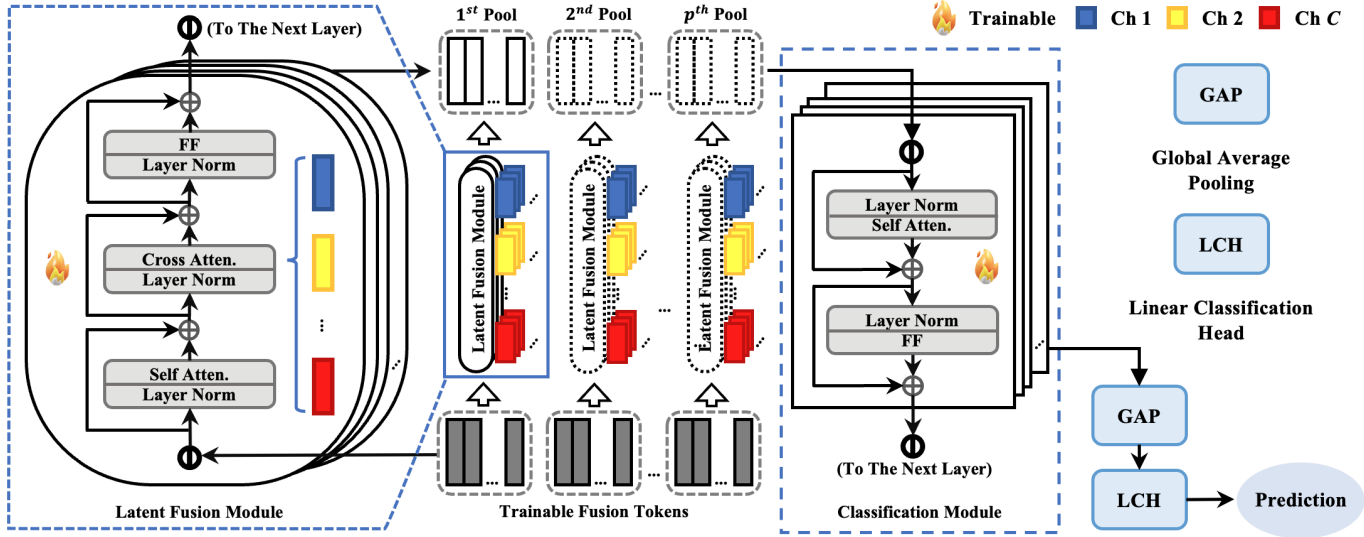


Fig. 3. Architecture of the proposed LFT. LFT comprises two main modules: latent fusion and classification modules. Left: The latent fusion module processes tokens from one pool at a time, with each block handling tokens from a single layer. Trainable fusion tokens are passed sequentially between blocks, integrating nonisomorphic representations from different layers via cross-attention. Middle: To capture time-invariant representations, the same fusion model is applied to every pool. Right: The classification module fused representations from all pools. Subsequently, LFT applies global average pooling followed by a linear classification head to generate predictions.

In attention mechanism, each token of input sequences is first linearly projected to a subspace with dimension  $H$  to obtain query  $\mathbf{Q}$ , key  $\mathbf{K}$ , and value  $\mathbf{V}$  matrices:

$$\begin{aligned} \mathbf{Q} &= \mathbf{S}_1 \mathbf{W}_Q, \quad \mathbf{K} = \mathbf{S}_2 \mathbf{W}_K, \quad \mathbf{V} = \mathbf{S}_2 \mathbf{W}_V, \\ \mathbf{Q} &\in \mathbb{R}^{L_1 \times H}, \quad \mathbf{K}, \mathbf{V} \in \mathbb{R}^{L_2 \times H} \end{aligned} \quad (9)$$

Here,  $\mathbf{W}_i$  indicates a trainable matrix. The attention mechanism then calculates:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \left( \frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{H}} \right) \mathbf{V} \quad (10)$$

The attention mechanism produces a new matrix with the same dimension as  $\mathbf{Q}$ . Each row in this new matrix is a different weighted average of the rows in  $\mathbf{V}$ , where the weight is divided by the scaled dot production between the corresponding row in  $\mathbf{Q}$  and all rows in  $\mathbf{K}$ . This is similar to a simplified cosine similarity, with the denominator replaced by a constant. Through the attention mechanism, information from different parts of  $\mathbf{V}$  can be dynamically selected and routed to different parts of the output.

Multi-head attention (MHA) is a commonly used variation of the attention mechanism. In MHA, attention is calculated on  $h$  different sets of  $\mathbf{Q}$ ,  $\mathbf{K}$  and  $\mathbf{V}$ , then the outputs are concatenated and linearly projected back to the desired dimension.

$$\begin{aligned} \mathbf{h}_i &= \text{Attention}(\mathbf{Q}_i, \mathbf{K}_i, \mathbf{V}_i) \\ \text{MHA}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) &= [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \mathbf{h}_3 \quad \dots \quad \mathbf{h}_h] \mathbf{W}_O \end{aligned} \quad (11)$$

## B. EEGDM

Building upon the aforementioned components, EEGDM comprises two main modules: (1) SSM-Based Diffusion Pretraining (SSMDP) for EEG representation learning, and (2) LFT for downstream classification of multi-event EEG signals.

We detail the neural architectures and training procedures of each component in the following subsections.

1) *SSM-Based Diffusion Pretraining*: Our diffusion pretraining module was built upon SSMs, which were designed for capturing the temporal dynamics of EEG signals. EEG signals were first subjected to a forward diffusion process, progressively injecting noise into the signals. Our model then learned to reverse this process step by step, denoising the input and learning meaningful latent representations. The architecture preserved fine-grained temporal structures while capturing long-range dependencies across time steps.

A known limitation of SSMs was their unidirectional nature: they model each output  $y_k$  as a function of current and past inputs  $x_{0:k}$ , while completely ignoring future inputs  $x_{k+1:L}$ . To model bidirectional dependencies, we adopt a dual-SSM setup, wherein one SSM processed the original sequence in the forward direction and another processes the reversed sequence, as suggested in prior work [13]. SSMDP is illustrated in Fig. 1. In this work, SSMDP consisted of 20 layers of SSMs, each layer contained 128 gate channels and 128 filter channels. Each channel, either gate or filter, had its own trainable bidirectional SSM with 128-dimensional hidden state. The SSMs were initialized with diag-lin scheme (see [52]).

SSMDP processed signals from each EEG channel individually, and twenty-two (TUEV has 22 channels) 128-dimensional trainable channel embeddings were included to encode the spatial context of input signals, while the diffusion step was embedded through sinusoidal embedding [49]. The sum of these two embeddings is fed to the backbone model as conditioning, as a means to inform the model about the differences in spatial coordinate and noise level.

2) *Latent Fusion Transformer*: The LFT employed a transformer-based architecture to integrate the latent representations generated by the SSMDP, illustrated in Fig. 3. Due to

the large dimensionality of these representations, subsequent processing became computationally demanding. For example, the diffusion backbone used in our setup produces latent activities with a dimensionality 2560 times larger than the original input (20 layers  $\times$  128 gate channels). To reduce this burden, the latent activities were pooled based on windowing (e.g., average pooling and standard deviation pooling), illustrated in Fig. 2.

Subsequently, a decoder-only transformer named as the latent fusion module aggregated the SSM latent representations into a structured sequence. We defined latent fusion tokens that are prepended to the per-channel and per-pool latent representations, and the transformer's self-attention mechanism jointly processed the sequence, enabling the modeling of inter-channel and inter-pool dependencies and fusion into context-aware features. These fused representations were then passed to the classification module, an encoder-only transformer, which captured inter-token dependencies and performed EEG event classification using a linear classification head with softmax activation.

The LFT implemented had 20 decoder blocks in the latent fusion module and 8 encoder blocks in the classification module, each equipped with 8-headed attention. The embedding dimension of the attention mechanism was 128, and the hidden dimension of the multilayer perceptron is 512.

### 3) Training Procedures:

a) *Signal Embedding*: EEG data typically exhibits a wide dynamic range with occasional extreme values, which can hinder model training. To address this, we apply the  $\mu$ -law companding algorithm:

$$u(x) = \begin{cases} \text{sgn}(x) \frac{\ln(1+\mu|x|)}{\ln(1+\mu)}, & \text{if } |x| > 1 \\ x, & \text{otherwise.} \end{cases} \quad (12)$$

where  $x$  denotes the normalized signal and  $\mu = 255$ . This nonlinear transformation compressed large-amplitude values more than smaller ones, effectively suppressing outliers and enhancing numerical stability. In addition to signal embedding, we included learnable embeddings EEG channel and sinusoidal embeddings for diffusion timestep to provide spatial and noise-level context to the model, as shown in Fig. 1.

b) *Pretraining of SSMDP*: We adopted DDPM and modified the noise schedule as EEG signals are approximately Gaussian-distributed [53] and typically exhibit low signal-to-noise ratios. To preserve signal integrity across diffusion steps, we adopt a less aggressive noise injection scheme compared to standard DDPM configurations. Specifically, the total diffusion timestep  $T$  was set to 50 (in contrast to the typical 1000), and we employ the cosine noise schedule [11]:

$$\bar{\alpha}_t = \frac{f(t)}{f(0)}, \quad \text{where } f(t) = \cos\left(\frac{\frac{t}{T} + 0.008}{1.008} \cdot \frac{\pi}{2}\right)^2. \quad (13)$$

c) *Fine-tuning of LFT*: During fine-tuning, each EEG channel was processed by SSMDP, and the outputs from all gate channels across all layers were collected as *latent activities*.

As illustrated in Fig. 2, given an EEG segment with  $C$  channels and  $L$  samples, processed by a backbone model with  $n$

layers and  $H$  gate channels, the resulting latent activities form a tensor of shape  $(C, n, L, H)$ . We divided the time axis ( $L$ ) into  $p$  segments and performed pooling (e.g., using standard deviation), yielding latent tokens with shape  $(C, n, p, H)$ . The gate dimension  $H$  serves as the embedding dimension, so each token summarized latent activity within a local window of  $L/p$  samples for a specific channel and layer.

Latent fusion was performed using a decoder-only transformer (Fig. 3). For each temporal pool, there were  $n$  groups of  $C$  latent tokens (each of dimension  $H$ ) that represented activity across EEG channels. Since each group encoded different information, we assign a dedicated decoder block to each group.  $N$  trainable latent fusion tokens were passed sequentially through these decoder blocks: first through the block for the first group, then the second, and so on. Within each decoder block, fusion tokens acted as queries, and the corresponding latent tokens served as keys and values. This design condensed the  $C$ -channel information into  $N$  context-rich fusion tokens for each temporal pool. In this work,  $C = 22$ ,  $n = 20$ ,  $L = 1000$ ,  $H = 128$ ,  $p = 5$ , and  $N = 16$ .

The resulting fusion tokens from all  $p$  temporal pools were concatenated and passed to an encoder-only transformer (Fig. 3). This transformer captured dependencies across pools and fusion tokens. Its output were then global average pooled and fed into a linear classification head to predict event classes. The classification module was trained in a supervised manner, representing the fine-tuning phase of the EEGDM framework.

## IV. EXPERIMENT

The experimental details include: (1) dataset preprocessing, (2) training configurations and hyperparameters, and (3) evaluation methodology and baseline comparisons.

### A. Dataset Preprocessing

The TUEV [18] dataset is a multi-event dataset from the largest the TUH EEG Corpus [54] for the detection and classification of epileptic events from EEG recordings including other brain activities such as eye movements, artifacts, background. The recordings were sampled at 250 Hz sampling rate and referenced using transverse central parietal (TCP) montage. The recordings in the dataset were labelled with the following annotations: spike and slow wave (SPSW), generalized periodic epileptiform discharge (GPED), periodic lateralized epileptiform discharge (PLED), eye movement (EYEM), artifact (ARTF), and background (BCKG).

We followed the same preprocessing steps of LaBraM [2] and NeuroLM [5]: 0.1 Hz - 75 Hz band pass filtering with a 50 Hz notch filter, resampling to 200 Hz, and finally scale down the signal amplitude (in  $\mu$ V) by 100 to ensure that most values are between -1 and 1. The recordings were then segmented to 5-second samples. The training data were divided into two sets, 80% training set and 20% validation set.

### B. Training Configurations and Hyperparameters

The SSMDP was trained with batch size 108 for 100 epochs using AdamW optimizer. The prediction target was velocity



TABLE I  
COMPARATIVE ANALYSIS (%) ON MULTI-EVENT TUEV

Model	Size	Kappa	BAcc	WF1
<i>Training from Scratch</i>				
SPaRCNet [55]	0.79M	42.33 ± 1.81	41.61 ± 2.62	70.24 ± 1.04
ContraWR [56]	1.6M	39.12 ± 2.37	43.84 ± 3.49	68.93 ± 1.36
FFCL [57]	2.4M	37.32 ± 1.88	39.79 ± 1.04	67.83 ± 1.20
CNN-Trans [58]	3.2M	38.15 ± 1.34	40.87 ± 1.61	68.54 ± 2.93
ST-Trans [59]	3.5M	37.65 ± 3.06	39.84 ± 2.28	68.23 ± 1.90
<i>Fine-tuning of Pretrained Parameters</i>				
BIOT [1]	3.2M	52.73 ± 2.49	52.81 ± 2.25	74.92 ± 0.82
LaBraM-Base [2]	5.8M	64.33 ± 0.87	67.25 ± 1.02	82.01 ± 0.87
LaBraM-Large [2]	46M	66.22 ± 1.36	65.81 ± 1.56	83.15 ± 0.40
LaBraM-Huge [2]	369M	66.80 ± 1.85	66.95 ± 1.54	84.01 ± 0.38
CBraMod [6]	4.0M	67.72 ± 0.96	66.71 ± 1.07	83.42 ± 0.64
Gram-B [7]	6.0M	65.28 ± 1.79	73.26 ± 0.93	86.14 ± 0.80
Gram-M [7]	47.19M	66.77 ± 2.27	74.06 ± 1.26	86.74 ± 1.17
Gram-L [7]	251.28M	<u>71.30 ± 3.33</u>	<u>74.87 ± 1.51</u>	<b>88.24 ± 1.58</b>
<i>Freezing of Pretrained Parameters</i>				
MMM [9]	0.36M	23.22 ± 1.55	52.69 ± 0.71	68.20 ± 1.93
BENDR [8]	157.14M	39.64 ± 1.48	50.09 ± 2.24	75.35 ± 1.07
EEGPT-Tiny [4]	4.7M	50.85 ± 1.73	56.70 ± 0.66	75.35 ± 0.97
EEGPT [4]	25M	63.51 ± 1.34	62.32 ± 1.14	81.87 ± 0.63
NeuroLM-B [5]	254M	42.85 ± 0.48	45.60 ± 0.48	71.53 ± 0.28
NeuroLM-L [5]	500M	44.14 ± 9.96	41.32 ± 12.35	73.87 ± 4.00
NeuroLM-XL [5]	1696M	45.70 ± 4.98	46.79 ± 3.56	73.59 ± 2.19
<b>EEGDM (Ours)</b>	12.8M	<b>74.23 ± 1.36</b>	<b>75.57 ± 1.47</b>	<u>86.88 ± 0.66</u>

(see Eq. (3)). The learning rate, weight decay,  $\beta_1$  and  $\beta_2$  were 1e-4, 0, 0.99 and 0.999, respectively. Exponential moving average (EMA) was applied to the model with decay rate of 0.999. Gradients were clipped by their norm with threshold of 1. The seeds of the random number generators (RNGs) were set to 0 during training. The model size of SSMDP was 5.9M parameters.

The LFT was trained using the cross-entropy loss function, regularized with a label smoothing factor of 0.1. A batch size of 256 was used, distributed evenly across the available GPUs. The AdamW optimizer was employed with a weight decay of 0.05, and momentum parameters  $\beta_1 = 0.9$  and  $\beta_2 = 0.98$ . No layer-wise parameter tuning was applied; therefore, the learning rate and weight decay were kept uniform across all layers. Latent fusion tokens and bias terms were exempted from weight decay. The initial learning rate was set to  $10^{-5}$  and scheduled using a cosine annealing one-cycle policy, with a peak learning rate of  $5 \times 10^{-4}$  and a warm-up period of 5 epochs. To stabilize training, exponential moving average (EMA) was applied with a decay rate of 0.999. Additionally, gradients were clipped by their global norm, with a threshold of 3. The model size of LFT was 6.9M parameters.

The LFT was trained for a maximum of 50 epochs, with early stopping applied if the validation Cohen’s kappa score did not improve for at least 3 consecutive epochs after epoch 20. Following training, the checkpoint with the highest validation score was selected for evaluation on the test set. The experiments were conducted on a server equipped with Intel Xeon CPUs and eight NVIDIA GeForce RTX 4090 GPUs.

TABLE II  
IMPACTS OF  $\mu$ -LAW (%)

Suppression	Kappa	BAcc	WF1
$\mu$ -law	<b>74.23 ± 1.36</b>	<b>75.57 ± 1.47</b>	<b>86.88 ± 0.66</b>
N/A	<u>72.50 ± 3.02</u>	<u>69.12 ± 1.81</u>	<u>85.79 ± 1.41</u>

TABLE III  
IMPACTS (%) OF DIFFERENT NOISE SCHEDULE

Scheduler	Kappa	BAcc	WF1
Cosine	<b>74.23 ± 1.36</b>	<b>75.57 ± 1.47</b>	<b>86.88 ± 0.66</b>
Linear	<u>70.97 ± 1.04</u>	<u>71.19 ± 0.92</u>	<u>85.07 ± 0.49</u>

### C. Evaluation and Baselines

The classification performance was evaluated using balanced accuracy (“BAcc”), Cohen’s kappa (“kappa”) and weighted F1 score (“WF1”). We reported the mean and standard deviation of performance across five independent runs. The selected baselines include deep learning models trained from scratch (SPaRCNet [55], ContraWR [56], FFCL [57], CNN-Trans [58], and ST-Trans [59]) and EEG FMs (MMM [9], BENDR [8], BIOT [1], EEGPT [4], LaBraM [2], CBraMod [6], Gram [7], and NeuroLM [5]).

## V. RESULTS & DISCUSSION

We evaluated our model on the multi-event TUEV EEG classification task and compared its performance against several strong baselines, including those training from scratch, EEG FMs that involved pre-training stage. In addition, we conducted ablation studies to investigate the contributions of key components in EEGDM, such as input noising strategies, latent activity extraction methods, the hierarchical structure captured in the learned latent representations, and latent fusion mechanisms. We also provided a sample of generated EEG signals as supplementary qualitative results. Moreover, we examined the model’s ability to generalize to EEG data sampled from different frequencies.

### A. Main Results

In Table I, we reported the mean and standard deviation of “kappa”, “BAcc”, and “WF1”, averaged over five runs with different random seeds. Detailed model sizes were also provided. In general, FMs exhibited a scaling law, with performance improving as model size increased. Furthermore, FMs that fine-tuned pre-trained parameters typically outperformed those that froze them for efficiency. However, freezing pre-trained parameters is often preferable due to lower training costs and improved efficiency, while still demonstrating the ability to represent richer and more universal EEG features. Our method achieved performance comparable to, and in most cases exceeding, that of the second-best baseline, Gram-L, while being approximately 19× more lightweight.

### B. Ablations

We examined and ablated the impacts of each component, reporting the mean and standard deviation of “kappa”, “BAcc”, and “WF1”.

TABLE IV  
IMPACTS OF DIFFERENT DIFFUSION TIME STEP (%)

Step	Kappa	BAcc	WF1
No	$74.23 \pm 1.36$	<b><math>75.57 \pm 1.47</math></b>	$86.88 \pm 0.66$
1	<b><math>74.46 \pm 1.39</math></b>	$74.87 \pm 1.83$	<b><math>86.94 \pm 0.68</math></b>
2	$73.73 \pm 1.16$	$74.83 \pm 1.55$	$86.66 \pm 0.55$
3	$69.05 \pm 1.63$	$69.89 \pm 1.49$	$84.34 \pm 0.81$

TABLE V  
IMPACTS OF POOLING STRATEGIES AND LATENT ACTIVITIES

Pool	Latent	Kappa	BAcc	WF1
Std	Gate	<b><math>74.23 \pm 1.36</math></b>	<b><math>75.57 \pm 1.47</math></b>	<b><math>86.88 \pm 0.66</math></b>
Std	Filter	$73.46 \pm 2.33$	$68.74 \pm 0.63$	$86.49 \pm 1.18$
Mean	Gate	$71.66 \pm 1.13$	$57.71 \pm 1.89$	$85.24 \pm 0.57$
Mean	Filter	$69.83 \pm 1.92$	$68.33 \pm 3.17$	$84.46 \pm 1.05$

### 1) Signal Embedding and Noise Schedule of SSMDP:

Table II showed the impact of the  $\mu$ -law, demonstrating the importance of handling the wide dynamic range of EEG. In Section III-B3b, we discussed the necessity of using a cosine noise schedule during the forward process. Here, we compared it with a diffusion model trained using the original linear noise schedule [10], followed by training a classifier on its latent activities. As shown in Table III, the linear noise schedule negatively impacted the classifier’s performance.

2) *Latent Activities and Representations of SSMDP*: When extracting latent activities from SSMDP, we found that minimizing the effect of the diffusion forward process, by using a small diffusion step and zeroing the forward diffusion term, improved performance, as shown in Table IV and Table VI. Eliminating the forward process yielded the best results.

We also analyzed the performance of different latent activities of SSMDP and various pooling strategies. As shown in Table V, when the pooling strategy is fixed, models using the latent activities of the gate channels outperformed those using other activities. Interestingly, standard deviation pooling, although rarely reported in the literature, outperformed average pooling, presumably because it better captured variability in time-series data.

3) *Latent Fusion through LFT*: While the convolution kernels of the bidirectional SSMDP captured global context (see Eq. (8)), it is worth investigating whether the layers in SSMDP still exhibit a hierarchical structure, where shallow layers capture local patterns and deep layers capture global, high-level patterns [51]. To examine the internal hierarchy of the proposed SSMDP, we trained LFT using only a fraction of the SSMDP’s layers. Since this reduced the size of the latent fusion module in LFT, the depth of the classification

TABLE VI  
IMPACT OF NOISE INJECTION ON LATENT TOKENS (%)

Noise Injection?	Kappa	BAcc	WF1
No	<b><math>74.23 \pm 1.36</math></b>	<b><math>75.57 \pm 1.47</math></b>	<b><math>86.88 \pm 0.66</math></b>
Yes	$71.39 \pm 1.46$	$56.19 \pm 3.34$	$84.87 \pm 0.54$

TABLE VII  
IMPACTS OF USING LATENT ACTIVITIES FROM DIFFERENT LAYERS (%)

Layers	Size	Kappa	BAcc	WF1
All	6.9M	<b><math>74.23 \pm 1.36</math></b>	<b><math>75.57 \pm 1.47</math></b>	<b><math>86.88 \pm 0.66</math></b>
First half	7.0M	$62.97 \pm 2.15$	$64.57 \pm 1.54$	$81.00 \pm 1.15$
Second half	7.0M	<u><math>71.60 \pm 1.14</math></u>	<u><math>68.40 \pm 1.92</math></u>	<u><math>85.60 \pm 0.52</math></u>
First quarter	6.9M	$59.63 \pm 2.49$	$58.75 \pm 3.13$	$78.88 \pm 1.43$
Second quarter	6.9M	$68.40 \pm 2.66$	<u><math>69.47 \pm 1.45</math></u>	$83.80 \pm 1.35$
Third quarter	6.9M	$68.32 \pm 1.22$	$64.39 \pm 1.37$	$83.96 \pm 0.63$
Forth quarter	6.9M	<u><math>70.48 \pm 2.21</math></u>	$65.78 \pm 1.46$	<u><math>84.71 \pm 1.16</math></u>

TABLE VIII  
IMPACTS OF DIFFERENT LATENT FUSION STRATEGY (%)

Fusion	Size	Kappa	BAcc	WF1
Base	6.9M	<b><math>74.23 \pm 1.36</math></b>	<b><math>75.57 \pm 1.47</math></b>	<b><math>86.88 \pm 0.66</math></b>
No	7.0M	$61.60 \pm 3.69$	$51.13 \pm 7.15$	$79.93 \pm 2.26$
Mean	7.0M	<u><math>65.05 \pm 1.41</math></u>	<u><math>59.40 \pm 8.67</math></u>	<u><math>82.08 \pm 0.83</math></u>

module was increased to compensate for the smaller model size. As shown in Table VII, evaluation metrics generally improved when deeper layers were used, indicating that latent activities from deeper layers are more effective than those from earlier layers. Furthermore, incorporating latent activities from earlier layers in addition to deeper ones further improved performance.

We also explored two alternative methods with no trainable parameters: “no fusion”, where the EEG channel ( $C$ ), layer ( $n$ ) and pool ( $p$ ) axes of latent tokens were simply flattened, and “mean fusion”, where latent fusion was performed by averaging along the layer ( $n$ ) dimension. Since replacing latent fusion removed a substantial part of the latent fusion module, we increased the depth of the classification module to match the total number of trainable parameters in the base model for a fair ablation. The results in Table VIII underscored the importance of our latent fusion.

### C. Additional qualitative and quantitative analyses

1) *Qualitative Result*: Fig. 4 showed an example of EEG generation through the reverse diffusion process of SSMDP, which appeared realistic.

2) *Generalization to Different Sampling Rates*: EEGDM preserved the time-continuous form of SSMs, enabling it to process EEG signals at different sampling rates. Table IX presented the performance of models trained on data with a 200 Hz sampling rate and tested on data with different sampling rates. The results showed that performance degraded slightly but largely remained intact. Nevertheless, this capability is unique to SSM-based method and not directly applicable in other EEG FMs.

## VI. CONCLUSION AND FUTURE WORK

This work presented EEGDM, a diffusion-based framework for self-supervised EEG representation learning. EEGDM comprises a structured state-space model SSMDP trained with DDPM to capture temporal dynamics with high granularity



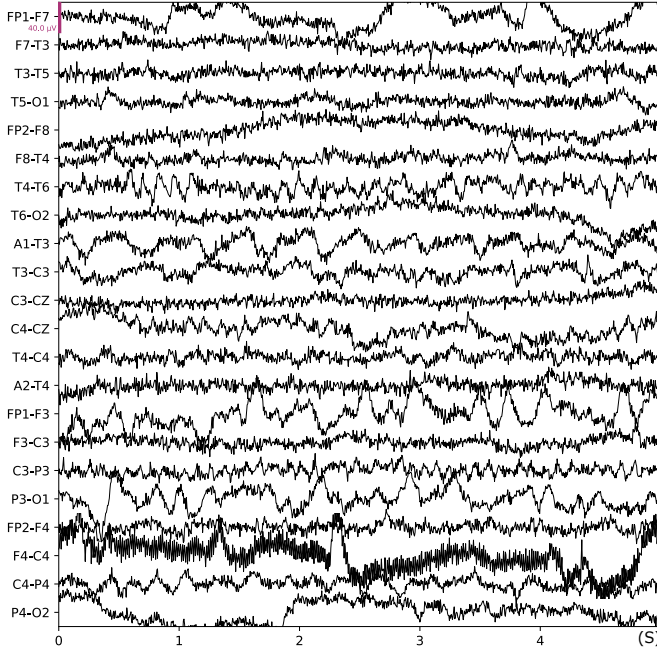


Fig. 4. EEG signals generated through the reverse process of SSMDP.

TABLE IX  
GENERALIZATION (%) EEGDM TO DIFFERENT SAMPLING RATE

Train	Test	Kappa	BAcc	WF1
<b>200 Hz</b>	<b>200 Hz</b>	<b>74.23 <math>\pm</math> 1.36</b>	<b>75.57 <math>\pm</math> 1.47</b>	<b>86.88 <math>\pm</math> 0.66</b>
200 Hz	190 Hz	70.26 $\pm$ 2.00	72.78 $\pm$ 1.38	85.17 $\pm$ 1.02
200 Hz	180 Hz	66.54 $\pm$ 1.60	68.36 $\pm$ 2.07	83.38 $\pm$ 0.81

and LFT for classification. Empirically, EEGDM achieved state-of-the-art performance on EEG event classification tasks when assessed using the TUEV dataset, despite having significantly fewer training samples and being approximately 19 $\times$  smaller than current EEG FMs. Comprehensive ablation studies validated the effectiveness of each component. The findings suggested that EEGDM was a highly competitive alternative for EEG signal processing, particularly compared to FMs that relied on masking-based pretraining, which typically required large and diverse datasets to learn effective self-supervised representations.

While this study evaluated EEGDM on clinical relevant TUEV, its potential generalizability to other EEG tasks worth further investigation. Moreover, This work opened several other directions for future research. On one hand, it is valuable to further reduce the model size of the SSMDP and LTF while maintaining performance, for clinical practicality and efficiency. On the other hand, it is natural to explore the scalability and robustness of EEGDM as a new class of EEG FMs trained with diffusion processes and capable of leveraging diverse EEG and other biosignal datasets. Furthermore, recent advances in discrete diffusion [60], which had shown promise in language models, represented another exciting direction worth exploring for EEG representation learning.

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