EEG Foundation Model for Heterogeneous Sensor Layouts Trained with Task-Switch Contrastive Learning

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***Abstract*—This paper presents a general-purpose foundation model for electroencephalography (EEG) data using self-supervised learning. Drawing on neuroscience research, we employ a suite of techniques to identify and label cognitively distinct segments of brain activity across large, unlabeled EEG datasets. These pseudo-labels are used to train a contrastive learning objective alongside a graph neural network encoder that, unlike existing approaches, handles arbitrary electrode configurations without discarding any channels. The resulting foundation model can serve as a starting point for downstream tasks, reducing the amount of labeled data required to build accurate, task-specific EEG models. Evaluated on a motor imagery benchmark, our approach produces statistically significant improvements over the baseline while allowing for flexible electrode configurations. This has significant implications for few-shot clinical modeling and adaptive brain-computer interfaces. Code is available at https://github.com/LeopoldEhrlich/EEG-SSL**

I. Introduction

Electroencephalography (EEG) is a non-invasive neuroimaging technique that measures the electrical potentials generated by clusters of cortical neurons, recorded via electrodes placed on the scalp [1]. Its noninvasiveness, low cost, and portability make EEG particularly well-suited for adaptive Brain-Computer Interface (BCI) applications. EEG biomarkers are increasingly studied in the context of depression, autism spectrum disorder, and attention-deficit hyperactivity disorder, where they may offer quantitative data to complement typical behavioural assessments [2]. Furthermore, EEG can be used in individuals with physical impairments, allowing the control of computers and adaptive devices for communication and mobility, greatly improving autonomy [3].

Current challenges in applying EEG to these problems center around data interpretation, where training an effective model for patient diagnosis becomes problematic due to the high cost of acquiring effective new labeled data. While vast quantities of data are already available, the hardware variability between devices makes it challenging to integrate multiple sources [4], [5]. This often necessitates specialized trials requiring new setups for every task, increasing the cost and complexity of developing new treatments using EEG.

In the context of adaptive technology, highly advanced EEG devices with many channels can be cost prohibitive and bulky. As such, wearable EEGs often have few channels, which can be located in positions other than those in a clinical device. For instance, configurations where electrodes are located in earpieces or headbands are very common in commercially available devices, compared to the clinical devices that often cover the whole head [6], [7]. Consequently, models trained on the standard 10-20 clinical layout are incompatible with these ergonomic consumer devices. This means that creating a model for one of these devices would necessitate the creation of new datasets specifically for the device, a significant barrier to the use of these more ergonomic devices in adaptive technology.

Self-supervised learning (SSL) is a technique where unlabeled data is used to train foundation models that contain broad insights on a class of data, which can then be refined into task specific models via fine-tuning on labeled datasets [8]. This has many benefits because it reduces the amount of labeled data one needs to procure. In the context of EEG data, this looks like pooling data across many existing recordings, tasks, and datasets, then training on unsupervised pseudo-labels of the data. This forms a solid foundation that can be tuned based on the smaller amount of specialized labeled data available. Often, this data is collected by recruiting participants, running experimental protocols to generate relevant brain states, and applying many hours of clinical expertise to annotate the datasets [9]. The specific approach to performing SSL on EEG data that this paper will focus on is BErt-inspired Neural Data Representations (BENDR).

BENDR is an architecture presented in 2021 that implements SSL on EEG data using a modified wave2vec setup [4]. Standard wav2vec is a speech recognition architecture that works by encoding waveforms into dimension reduced slices, then jumbling and learning to reconstruct the sequences [10]. It does this with a learned encoder block composed of five convolutional layers, then an attention based context network. The main difference in the BENDR paper's approach is that the convolutional encoder block uses 1D convolutions to reduce all channels into one dimension before the wav2vec

contextualizer. Since the wav2vec architecture only works on 1d timeseries data, this approach was used to allow compatibility without introducing extreme memory challenges from extending wav2vec into multiple dimensions. Kostas et. al report two main limitations of their approach, rather limited generalization ability to novel EEG data, and loss of data due to channel reduction [4]. We have two approaches to tackle these problems.

The first limitation of BENDR is how in the preprocessing setup, all datasets are truncated to 19 channels [4]. This means that during training, information is lost. Furthermore, the resultant model is fixed to this configuration. While the chosen 19 channels are common to most setups, this means that the model will not be effective on datasets that use smaller EEG setups, or that are localized to specific scalp regions and lack any of the 19 channels. This severely limits applicability to wearable adaptive BCI devices, as it necessitates more expensive and bulky hardware. Furthermore, in the case of larger static clinical sensor layouts that may have upwards of 200 electrodes, a significant amount of information is lost in the truncated channels. An ideal approach would natively support heterogeneous sensor configurations without information loss.

The second limitation is how the loss is set up based on priors from natural language that may not hold [4]. BENDR does contrastive learning like wav2vec, trying to unmix permutations of EEG time series sequences [11]. This approach is very sensible in the context of language processing as spoken sentences are known to be based on highly regular grammars with relatively few valid permutations relative to invalid ones along with having definite start and ends. In the context of EEG data, this might necessarily not be the case. While the wav2vec loss approach has been shown to be fairly effective in [4], it may prove beneficial to incorporate loss based on more strongly validated priors in EEG. The priors that we consider are based on models of task switching. We assume that segments where the focus is changing should bound states of consistent focus or mental state. We posit that an embedding space that where signals from the same cognitive state are closer than those separated by task switches may capture features useful in downstream performance.

The goal of this project is to investigate the viability of applying prior information from neuroscience to improve an existing framework for performing self-supervised learning on EEG data.

II. Methods

Our solutions to the two problems are to implement a GNN based encoder capable of reducing any number of channels to a 1D time series, and to implement a loss that rewards clustering embeddings that are bounded by the same two task switches.

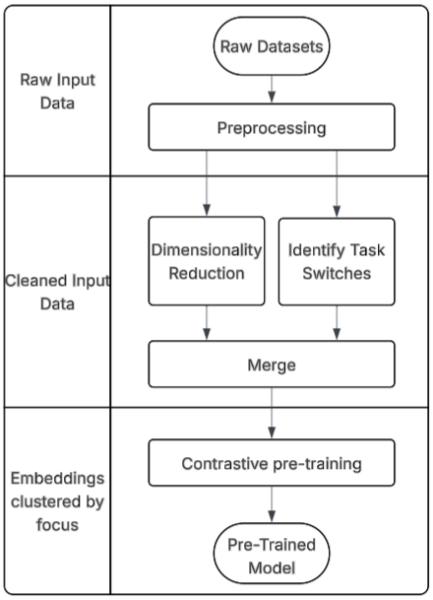

Fig. 1. Flowchart of the whole pre-training process

We implement our approaches as a part of a unified self-supervised learning pipeline. Broadly, the steps are to preprocess the data, identify the task switch labels offline, then train the full architecture using the contrastive losses. Then, downstream labeled datasets are used to prepare fine tuned models, which are evaluated.

Our approach for arbitrary sensor configurations is manifested as a modified encoder block, and our task-switch loss clustering is added as a term in the loss.

A. Data

Since this project is aimed at integrating across many datasets, we chose to source our data from OpenNeuro repositories. This has the advantage of the unified BIDS format, making metadata simple to automatically parse. We filtered datasets for EEG channels, which were selectively extracted. Then, we made note of the sensor configuration, grouping datasets according to their hardware layouts. We assembled the pre-training corpus by aggregating across multiple datasets without preserving labels, and kept our downstream corpus separate.

There are many possible approaches to filtering and cleaning the data. Based on research which shows that excessive preprocessing is not beneficial to model performance, we chose a minimal scheme [12], [13]. First, we resample to a unified 256 Hz, then we apply a high-pass filter at 0.3 Hz and low-pass at 120 Hz.

Datasets in the BIDS format [14] were exclusively considered, as this format facilitated the use of scripts for automated processing. This allowed automation of training

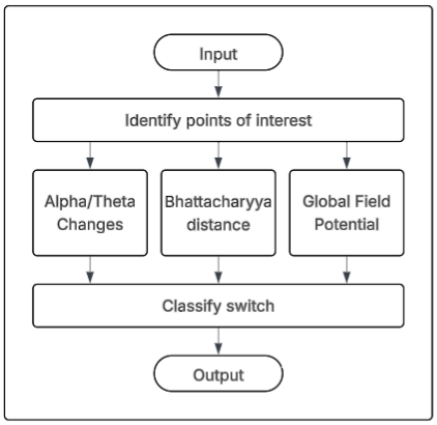

Fig. 2. Flowchart of the task-switch detection process

configuration specification and data cleaning for new datasets.

Due to constrained time and compute, two datasets are currently used. Pre-training is done on the SRM Resting-state EEG dataset [15], and downstream evaluation is on the PhysioNet Motor Imagery Dataset [16].

B. Task-Switch Detection

A task switch refers to a transition between distinct cognitive task sets, during which attentional control, working memory, and response mappings are reorganized. Accurate localization of these change points is challenging due to noise contamination, inter-subject variability, and the multi-scale nature of neural dynamics. To address these challenges, we propose a multi-stage detection pipeline integrating statistical divergence, spectral features, and microstate analysis.

1) Initial Candidate Selection via Spectral Divergence: The first stage of our algorithm focuses on detecting abrupt shifts in the frequency spectrum, a critical feature for identifying task switches in EEG signals. Following the methodology proposed by Chen et al. [17], we quantify the statistical divergence between adjacent signal segments using the Bhattacharyya distance (D_B), which measures the degree of overlap between two probability distributions. This metric has been demonstrated to outperform other similarity measures in capturing EEG state transitions [17]. We define a 500-ms sliding window and compute the Power Spectral Density (PSD) for two contiguous segments. For two normalized spectral distributions P and Q, the distance is calculated as follows:

$$D_B(P, Q) = -\ln\left(\sum_i \sqrt{P_i Q_i}\right)$$

A candidate switch point is identified at time t if D_B exceeds a dynamic threshold:

$$Threshold_t = \mu_{10s} + 3\sigma_{10s}$$

Here, μ_{10s} and σ_{10s} represent the mean and standard deviation of the distance scores over the preceding 10-second baseline, ensuring the detection of statistically significant deviations from the steady-state spectral profile.

2) Validation of Oscillatory Power Dynamics via Dual-Window Search: The algorithm validates each candidate from the first step against the power dynamics of the alpha (8-13 Hz) and theta (4-8 Hz) bands, which can denote cognitive state transitions [17]. For both bands, we first compute the squared Hilbert envelope to represent the energy trend. Specifically, the EEG signal is band-pass filtered, and the analytic signal is obtained via the Hilbert transform. To obtain a robust global estimate, the envelopes are averaged across all N channels before being squared:

$$E^2_{band}(t) = \left(\frac{1}{N}\sum_{i=1}^{N} |H(V_{i,band}(t))|\right)^2$$

Here, $H(\cdot)$ denotes the Hilbert transform. The verification process employs a sliding dual-window comparison within a local search range of ± 800 ms centered at the initial candidate point, excluding boundary regions shorter than $2W$ to ensure valid pre and post-transition windows. We utilize an observation window W of 200 ms and a sliding step of 40 ms. At each step t, the average power in the pre-transition window $\bar{E}^2_{pre}$ (defined as $[t, t+W]$) and the post-transition window $\bar{E}^2_{post}$ (defined as $[t+W, t+2W]$) is calculated to determine the relative power change ratio:

$$\Delta\text{Ratio} = \frac{\bar{E}^2_{post} - \bar{E}^2_{pre}}{\bar{E}^2_{pre} + \epsilon}$$

To ensure numerical stability during ratio calculation, a small constant $\epsilon = 10^{-10}$ is introduced to the denominator. A candidate transition point then must meet two further criteria:

1) The relative power shifts must meet the magnitude requirements $|\Delta Ratio_\alpha| \geq 30\%$ and $|\Delta Ratio_\theta| \geq 20\%$.
2) Second, cognitive shifts require anti-correlated oscillations, a requirement formalized by the polarity constraint: $\Delta Ratio_\alpha \cdot \Delta Ratio_\theta < 0$.

The algorithm employs a greedy search strategy within the local range around the candidate time point, terminating immediately upon detecting the first window pair that fulfills these criteria. This approach prioritizes the earliest detectable onset of the transition. The corresponding pre-transition window, defined by the interval $[t, t+W]$, is then designated as the coarse estimate of the task-switch period.

3) Temporal Refinement via Global Field Power (GFP): The final localization of task-switching points is refined using the Global Field Power (GFP), which quantifies the spatial dispersion of scalp potentials across N electrodes at time t:

$$GFP(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(V_i(t) - \bar{V}(t)\right)^2}.$$

EEG microstates are 60-120 ms long quasi-stable periods that may be consistent indicators of repeated cognitive processes [18]. Transitions between microstates typically occur at local GFP minima [18], [19]. These minima correspond to rapid large-scale neural reconfigurations [18].

Previous studies indicate that micro-task transitions are strongly associated with transient GFP reductions. [19] We hypothesize that large-scale changes in mental state or task may be associated with multiple microstate transitions. Consequently, we assume that these changes should satisfy the following properties:

1) they should coincide with prominent GFP minima within a broad temporal context;
2) they should be preceded by a sustained decline in global synchronization;
3) they should exhibit a short-term decay phase, consistent with microstates changing quickly in a short period of time.

As such, candidate points that do not satisfy these properties are discarded.

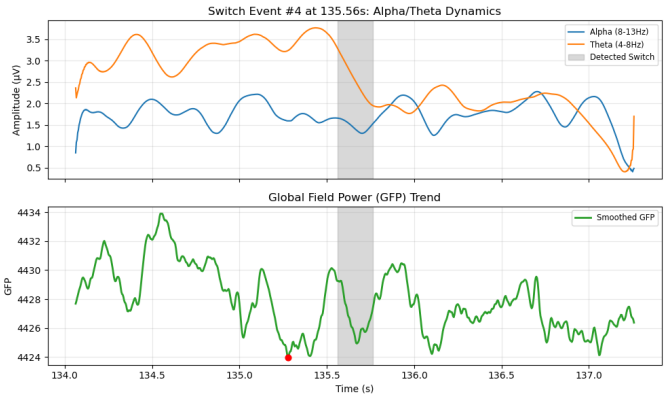

Fig. 3. Example of a detected task-switch event

Figure 3 illustrates a representative task-switch event detected by the proposed framework. During the validated transition interval, the theta-band power exhibits a pronounced decrease, whereas the alpha-band power shows a slight decline followed by a delayed rebound. This is a key indication of task switching. Meanwhile, the GFP signal presents a transient reduction and rapid recovery, indicating large-scale neural desynchronization and subsequent re-stabilization. The GFP minimum aligns closely with the detected transition window, supporting our microstate-based refinement strategy.

C. Graph and Convolution-based Encoder

The encoder transforms filtered EEG data into embeddings optimized during pre-training to capture underlying brain activity. This is done through 1D convolution over the time dimension, construction of a spatial graph linking adjacent electrodes, and application of a trained graph kernel over the adjacency matrix. Unlike BENDR, which assumes a fixed 20-channel layout, our encoder builds a separate graph neural network for each electrode configuration and projects all configurations into a shared latent space via an alignment layer. This design, following [20], accommodates arbitrary sensor layouts without discarding any channels. A high level overview of the convolutional and graph-based encoder process is shown in Fig. 4

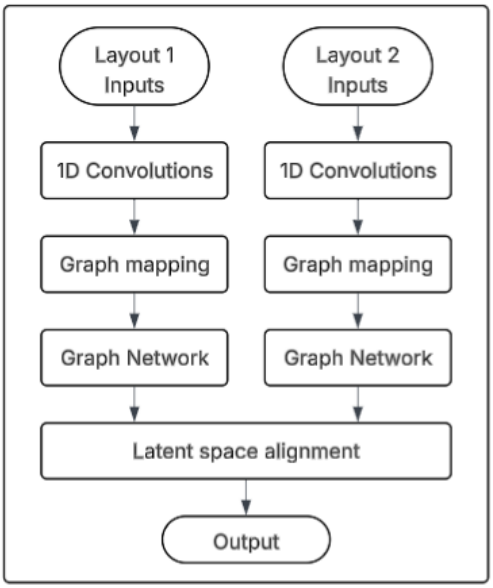

Fig. 4. High level overview of the convolutional and graph based encoder

1) Architecture: The encoder consists of two main components: a convolutional neural network that extracts temporal features, and a graph neural network to gather spatial information while improving robustness across datasets. The raw EEG files from the filtered datasets are first passed through a series of CNN blocks with large kernel sizes and pooling layers for dimensionality reduction. Each CNN block consisted of a 1d convolutional layer followed by batch normalization, PReLu activation layer, a 1d average pooling layer, and a dropout layer. The chosen sequence was modeled based on the structure of EEGnet [21]. However, our CNN omitted depthwise convolutions and extracted only temporal features.

The node-feature matrix is then passed to the graph neural network, which consists of neighborhood based adjacency matrix, graph convolutions, batch normalization, PRelu activation, and SAGPooling. The adjacency matrix was constructed by assigning a binary value of 1 to electrode pairs in close spatial proximity and 0 otherwise, such that spatially neighboring nodes contribute most strongly to the feature updates of each node. SAGPooling was incorporated to further reduce dimensionality by scoring nodes according to their learned importance and retaining the most informative nodes for downstream processing [22]. The overall architecture is

shown in Fig. 5

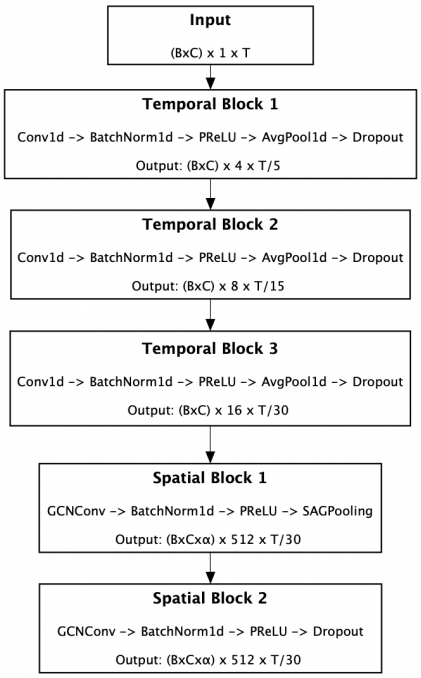

Fig. 5. The flowchart illustrates the architecture for the GNN approach. B is the batch size, C is the number of electrodes, T is the temporal dimension, and α is the parameter that determines the percentage of nodes which are kept after the SAGPooling layer.

D. Loss

The contrastive loss has the task of taking a sampling of embeddings from N different clusters, then reconstructing both the clusters and the order of the clusters. Our approach differs from that in BENDR by including this clustering alongside the ordering, rather than focusing solely on the ordering.

Our total loss combines three terms:

$$\mathcal{L} = \alpha_{\text{InfoNCE}}\,\mathcal{L}_{\text{InfoNCE}} + \alpha_{\text{cluster}}\,\mathcal{L}_{\text{cluster}} + \beta\,\|Z\|_2^2 \qquad (1)$$

By default, we use the weights $\alpha_{\text{InfoNCE}} = 1.0$, $\alpha_{\text{cluster}} = 0.5$, $\beta = 1.0$.

The first term is the BENDR contrastive objective inherited from wav2vec 2.0; the second encourages embeddings from the same cognitive state to cluster together; and the third is an L2 penalty on the raw latent features to prevent norm collapse, a common failure in contrastive learning where encoders learn to produce arbitrarily large-magnitude embeddings instead of geometrically meaningful ones [10].

E. InfoNCE

InfoNCE is a contrastive loss that frames each masked time step as a classification problem. To understand it concretely: suppose a 10-second EEG segment from an eyes-open resting recording is fed into the model. The encoder f_θ produces a latent sequence $Z \in \mathbb{R}^{d \times T_e}$ one d-dimensional vector per time step. A random binary mask (rate 6.5%, span 10) replaces some of those latent vectors with a learned placeholder token [23]. The Transformer contextualiser g_ϕ then processes the full sequence (including masked positions) and produces context vectors $C \in \mathbb{R}^{d \times T_e}$. The model's task at each masked position t is: given the context c_t at that position, retrieve the correct original latent z_t from a pool of candidates.

$$\mathcal{L}_{\text{InfoNCE}} = -\mathbb{E}\left[\log \frac{\exp(\cos(c_t, z_t)/\kappa)}{\sum_j \exp(\cos(c_t, z_j)/\kappa)}\right] \qquad (2)$$

The denominator sums over the correct z_t plus 20 randomly sampled distractors drawn from other positions in the same batch. Each candidate is scored by its cosine similarity to c_t, scaled by temperature $\kappa = 0.1$. Cosine similarity measures the angle between two vectors regardless of their magnitude, so the model must encode direction rather than magnitude. The temperature sharpens the distribution: at $\kappa = 0.1$, a candidate that is 10% more aligned with c_t than a distractor receives exponentially more probability mass, forcing the encoder to make more precise distinctions. This formulation follows wav2vec 2.0 and is equivalent in practice to a 21-way cross-entropy problem, computed with PyTorch's nn.CrossEntropyLoss [10].

Intuitively, if a participant transitions from eyes-open to eyes-closed during a recording, InfoNCE encourages the latent at any eyes-closed time step to be geometrically close to context vectors from neighbouring eyes-closed time steps, but not from eyes-open steps drawn as distractors. However, InfoNCE enforces this only locally in time: the 20 distractors are drawn from the same recording, so the model learns temporal coherence but not necessarily any broader structure about what kinds of brain states are similar [4].

F. Cluster Contrastive Loss

The cluster loss extends the contrastive objective across time by using the task-switch labels derived in Section 2.3. Where InfoNCE asks the model to identify a specific latent from nearby time steps, the cluster loss is a more abstract approach. It attempts to identify whether two windows, possibly far apart in the recording or even from different recordings, belong to the same cognitive state.

Concretely, consider a recording with three detected stable segments, say, a pre-task rest, an arithmetic block, and a post-task rest. Each stable segment receives a cluster label (0, 1, 2). Windows inside transition periods receive $y_i = -1$ and are excluded. For any window i with label $y_i \geq 0$, the model summarizes its latent sequence by means of a pooling and normalization of L2: $p_i = \text{mean}_t(Z_i)/\|\cdot\|_2$. This

collapses the temporal dimension into a single unit-norm vector representing that window's overall cognitive state.

To define what it means for two windows to be similar, we maintain a per cluster memory bank $\mathcal{M}_k \in \mathbb{R}^{d\times M}$ ($M = 1000$ embeddings per cluster) implemented as a circular buffer that stores p_i vectors from previous batches [24]. The loss for window i is:

$$\mathcal{L}_{\text{cluster}} = -\frac{1}{N_+} \sum_{i:y_i\geq 0} \log \frac{\exp(\bar{s}_i^+/\tau_c)}{\exp(\bar{s}_i^+/\tau_c) + \sum_j \exp(s_{ij}^-/\tau_c)} \tag{3}$$

where $\bar{s}_i^+ = \text{mean}(p_i^\top \mathcal{M}_{y_i})$ is the average cosine similarity between window i and all stored embeddings from the same cluster y_i, and s_{ij}^- are cosine similarities to stored embeddings from every other cluster. The cluster temperature $\tau_c = 0.5$ is set higher than the InfoNCE temperature to allow softer gradients across the within-cluster distribution. This decision is reflective of the fact that two windows in the same cognitive state are not identical, a resting brain state at minute 1 and minute 5 of the same recording share structure but are not point-wise the same.

The loss pushes p_i toward the centroid of $\mathcal{M}_{y_i}$ while pulling it away from all other clusters' banks. Returning to the arithmetic example: the embedding of a window mid-way through the arithmetic block will be pulled toward stored embeddings of other arithmetic windows (same cluster), and pushed away from stored embeddings of both rest segments (different clusters). Over time, the latent space organizes so that windows from matching cognitive states are grouped together, regardless of when they occur in the recording.

EEG recordings are highly uneven in states: a 10-minute recording might contain 8 minutes of rest and only 2 minutes of a target task. In any given mini-batch, a rare cognitive state may appear in only one or two windows. Without a memory bank, the loss would have no meaningful positives or negatives for that state. By accumulating embeddings from the last $M = 1000$ windows of each state across all previous batches, the loss remains defined even when a state is sparsely represented in the current batch [24].

Together, the two losses operate at different scales of similarity. InfoNCE enforces temporal consistency; nearby time steps should have similar representations. The cluster loss enforces cognitive consistency; windows from the same task block should cluster together across temporal distance. The L2 regularization term $\beta\|Z\|_2^2$ prevents the encoder from satisfying both objectives by inflating embedding norms and overfitting, ensuring the geometry of the latent space carries meaningful information.

G. Downstream

For downstream training, annotated datasets are used to perform supervised learning on the pre-trained foundation. A standard supervised learning setup is employed, with hyperparameters and dropout as specified in [4]. 5-fold cross validation is used to acquire robust metrics of performance, identifying both accuracy and class balanced accuracy (BAC).

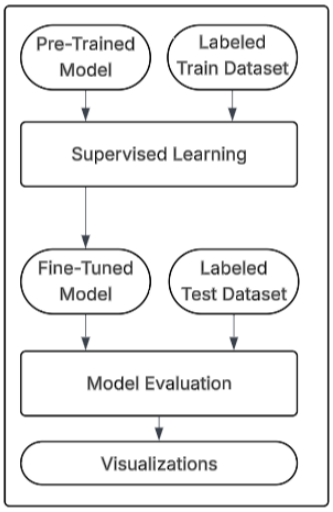

Fig. 6. Flowchart of the process for downstream training

III. Results

We trained four models on our downstream data and measured BAC and accuracy for each. First we trained with the baseline BENDR layout, then the BENDR layout using our custom GNN based contextualizer, then we trained one model for each of these incorporating our novel loss based on task switching.

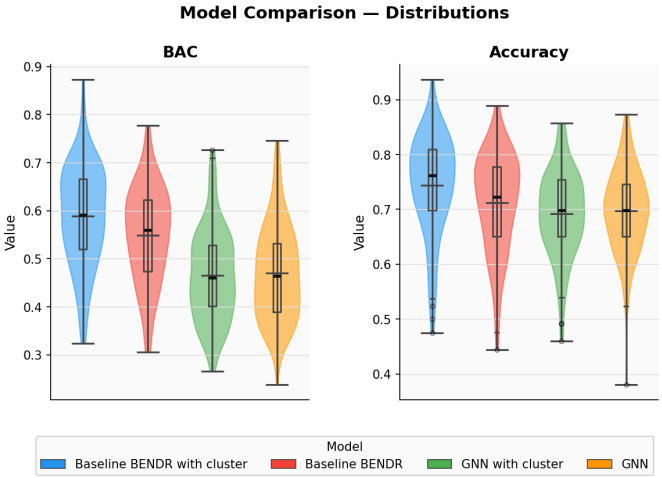

Fig. 7. BAC and accuracy for all four models

We used paired t-tests to assess what each model is statistically significant from each other on both BAC and accuracy, with the exception of adding cluster labels to the GNN. This showed no statistically significant improvement in

TABLE I
MODEL COMPARISON: MEAN ± STD

Model	BAC	Accuracy
BENDR with cluster	**0.5887 ± 0.1046**	**0.7441 ± 0.0906**
Baseline BENDR	0.5490 ± 0.0995	0.7120 ± 0.0894
GNN with cluster	0.4658 ± 0.0953	0.6915 ± 0.0780
GNN	0.4702 ± 0.0982	0.6970 ± 0.0762

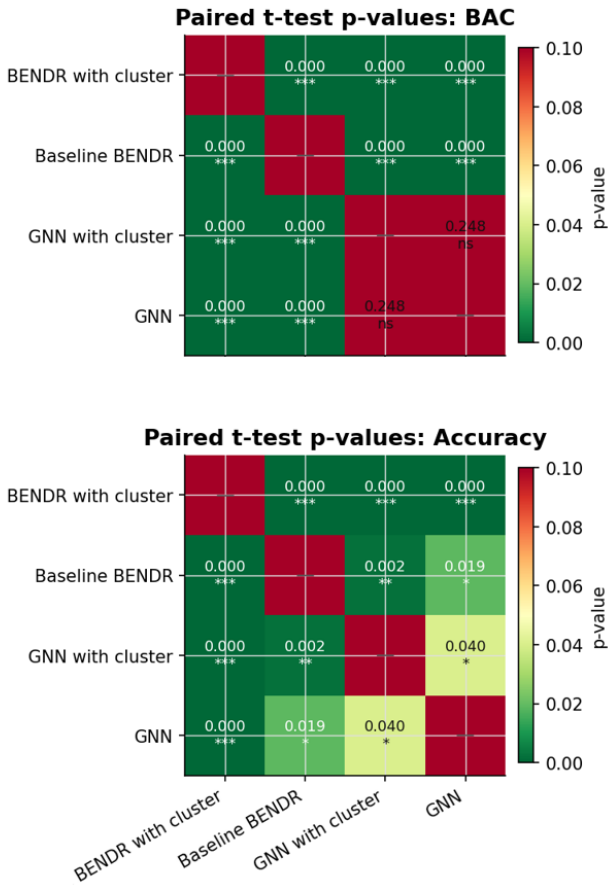

Fig. 8. Pairwise statistical testing over each model's performance in both BAC and accuracy

BAC (p = 0.208) and a marginal decrease in accuracy (p = 0.040).

IV. DISCUSSION

Broadly, we have shown that adding our cluster-based task-switching loss directly improves on the InfoNCE loss in the full BENDR architecture, and we show that our GNN based spatial encoder allows a compromise of somewhat reduced performance in order to extend to previously unusable layouts.

Our approach has demonstrated that incorporating task-switching priors to the loss utilized in pre-training for EEG models improves generalizability and performance. Adding the cluster labels both improved balanced accuracy and raw accuracy for the baseline BENDR model. This is a meaningful result as the cluster loss operates entirely at the pre-training stage, where the downstream architecture and fine-tuning are identical across conditions, reflecting an improved latent space learned during pre-training. Moreover, the violin plot for the BENDR model trained with the cluster loss not only achieves the highest mean BAC (0.5887), but also shows a relatively tight distribution compared to plain BENDR, suggesting the cluster loss reduces variance in performance across subjects in addition to improving average performance. A model that is consistently good across individuals is more deployable than one that performs well on average but fails on a subset of users. This subject-level variance is a known bottleneck in EEG systems, and any pre-training strategy that reduces it without access to subject-specific labels is worth noting [25].

These performance and consistency gains have significant implications in novel applications of EEG, and improve on the existing approach by expanding the ability to learn on limited downstream data. This translates directly to clinical and BCI contexts where large amounts of labelled data may be inaccessible or impractical to work with. A model that has organized its latent space around cognitive state boundaries requires fewer labelled examples to learn a new downstream task, as the relevant structure is already implicit in the representation. This opens the door to more few-shot applications for the diagnosis of rare neurological conditions or BCI calibration. This pre-training advantage is likely to compound over time, as the model is not just starting from better weights, it is starting from a representation space where the target signal is partially separated. In theory, a neurologist would be able to use any BCI configuration regardless of electrode channel layout, and gain further insight into prominent frequencies of the patient to improve diagnosis.

We identify three candidate explanations for the GNN's lower downstream accuracy relative to BENDR under equivalent training conditions. Firstly, given that we had to limit our pre-train to a smaller set, we only trained on the standard 10-20 layout. As such, while the raw BENDR removed channels in order to train on a familiar layout, the GNN had to generate new parameters dedicated to collapsing the spatial dimensions of this specific sensor layout. This means that the spatial part of the encoder has to be retrained for every new sensor configuration. In this case, since the downstream dataset was in an unseen layout, it did not have access to pre-trained weights, and was initialized randomly for the supervised learning. Furthermore, given how our novel approach does not reject any channels, it is attempting to learn from a more complicated signal than the BENDR, which may make it more prone to underfitting. Finally, GNNs are quite sensitive to hyperparameters, and we used the same learning rate and dropout for all models [26]. Excessively high dropout and low learning rate could be contributing to the observed underfitting. While performance is lower, it remains capable of mapping a constant contextualizer head to novel dimensionalities, which may be a worthwhile tradeoff

in applications where training data for the desired sensor configuration is highly limited. Our GNN model remains capable of mapping the pre-trained contextualizer to BCI devices with sensor layouts beyond the 10-20 format such as headband or earpiece wearable devices. This represents an expansion of the scope of applications, even if there is a performance tradeoff.

During training, we also note that the baseline BENDR architecture very quickly converges to a training accuracy of around 99%, whereas all the other models have training accuracy more in line with testing. We believe that this suggests a higher level of overfitting, which may correspond to less room to grow when the network size and training set is scaled up in future work.

Adding the cluster loss to the GNN produced no statistically significant change in BAC ($p = 0.208$), but a statistically significant decrease in accuracy ($p = 0.040$). The insignificant effect is likely due to the spatial GNN encoder not benefiting from the pre-training, given that the cluster loss only operates at that stage. BAC accounts for class imbalance by averaging sensitivity and specificity across classes, so an unchanged BAC and decreased accuracy suggests that the model became worse at classifying the majority class. The fact that the cluster loss decreases accuracy in the GNN architecture may suggest that the contextualizer is more specialized to expect informative input from the encoder block, which may cause vulnerability to performance disruptions from reinitializing the encoder. This can be further tested by training on a downstream dataset that allows for spatial parameters to be reused from training.

In future work, we intend to increase the pre-train size and open the downstream testing across many more modalities and sensor configurations. This would allow for significantly more robust models, and a more thorough validation. We would also thoroughly validate all three potential reasons for GNN accuracy being lower, by comparing to results when a pre-trained encoder can be reused, training on a sensor configuration with the same number of channels as the baseline BENDR reads, and running hyperparameter optimization.

Directly training a few-shot personalized model would allow for detailed discussion of the generalizability in the few shot context and how this can be applied in a clinical setting. Training a model for data on highly limited sensor configurations would likewise allow for a more detailed discussion of the adaptive implications of our approach.

V. Conclusion

Altogether, this paper investigated whether incorporating neuroscience-grounded priors into the pre-training objective of an EEG foundation model improves downstream performance. We extended the BENDR framework in two directions: a graph-based encoder that accepts arbitrary electrode configurations without discarding channels, and a cluster contrastive loss that uses automatically detected cognitive state boundaries as pseudo-labels during pre-training. Our results on the Motor Imagery benchmark show that the cluster loss produces a statistically significant improvement in both accuracy and BAC for the baseline BENDR architecture, while the GNN encoder demonstrates a proof of concept for hardware-agnostic pre-training that BENDR cannot support by design.

The practical implications of these findings extend beyond the benchmarks. EEG-based systems face a recurring problem: every new device configuration, clinical context, or user population requires new labelled data, which is expensive and time-consuming to collect. A foundation model that learns better-structured representations during pre-training reduces how much of that labelled data is needed downstream. In clinical settings, this could lower the barrier to deploying EEG diagnostic tools for rare neurological conditions. In adaptive BCI, it could enable wearable devices with non-standard electrode layouts to benefit from pre-training on large clinical datasets they would otherwise be incompatible with.

It is worth comparing these contributions in the broader context of foundation models for biomedical signals. Large language models derive much of their power from the fact that language has strong statistical regularities that a pre-training objective can exploit without labels such as grammar and semantic coherence implicit in raw text. EEG lacks an equivalent universal structure; the signal is task-dependent, hardware-dependent, and individual. Our choice of prior, that EEG segments belonging to the same cognitive state should have similar representations, improved downstream performance, suggesting that the path forward for EEG foundation models is not just collecting more data, but being deliberate about what domain knowledge gets built into the training process itself. This work advances that direction, and we hope it encourages future models to more deliberately integrate neuroscience priors directly into training objectives.

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