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Brain and Artificial Intelligence Lab.

SEOULTECH
SEOUL NATIONAL UNIVERSITY OF SCIENCE & TECHNOLOGY

Domain-Incremental Learning Framework for Continual Motor Imagery EEG Classification Task (2024)

Dan Li, Hye-Bin Shin, Kang Yin, Seong-Whan Lee

Personalized Continual EEG Decoding: Retaining and Transferring Knowledge (2025)

Dan Li, Hye-Bin Shin, Kang Yin, Seong-Whan Lee

Prototype-Guided Non-Exemplar Continual Learning for Cross-subject EEG Decoding (2026)

Dan Li, Hye-Bin Shin, Yeon-Woo Choi

2026.02.09

BrainLAB Journal Club
인공지능응용학과 나영서

Overview

01 Author

BrAIn Lab.
Brain and Artificial Intelligence Lab.

Dan Li

Korea University
korea.ac.kr의 이메일 확인됨

팔로우

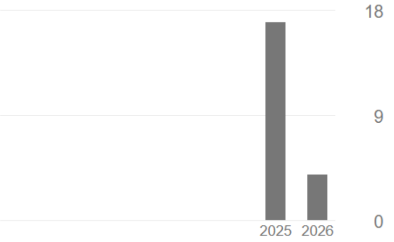
내 프로필 만들기

	제목	인용	연도
	EEG-based multimodal representation learning for emotion recognition K Yin, HB Shin, D Li, SW Lee 2025 13th International Conference on Brain-Computer Interface (BCI), 1-4	14	2025
Structure Expansion	Domain-Incremental Learning Framework for Continual Motor Imagery EEG Classification Task D Li, HB Shin, K Yin, SW Lee 2024 46th Annual International Conference of the IEEE Engineering in …	4	2024
Data Alignment	Personalized Continual EEG Decoding: Retaining and Transferring Knowledge D Li, HB Shin, K Yin 2025 13th International Conference on Brain-Computer Interface (BCI), 1-4	2	2025
	Personalized Continual EEG Decoding Framework for Knowledge Retention and Transfer D Li, HB Shin, K Yin arXiv e-prints, arXiv: 2411.11874	1	2024
Prototype & Privacy	Prototype-Guided Non-Exemplar Continual Learning for Cross-subject EEG Decoding D Li, HB Shin, YW Choi arXiv preprint arXiv:2511.20696		2025
	Toward Memory-Efficient Continual Adaptation for MI-EEG Decoding in BCIs D Li, HB Shin, SW Lee IEEE Transactions on Systems, Man, and Cybernetics: Systems 56 (1), 766-778		2025
	Toward Adaptive BCIs: Enhancing Decoding Stability via User State-Aware EEG Filtering YW Choi, HB Shin, D Li arXiv preprint arXiv:2511.07891		2025

학술자료 1–7 더보기

인용

	전체	2021년 이후
서지정보	21	21
h-index	2	2
i10-index	1	1



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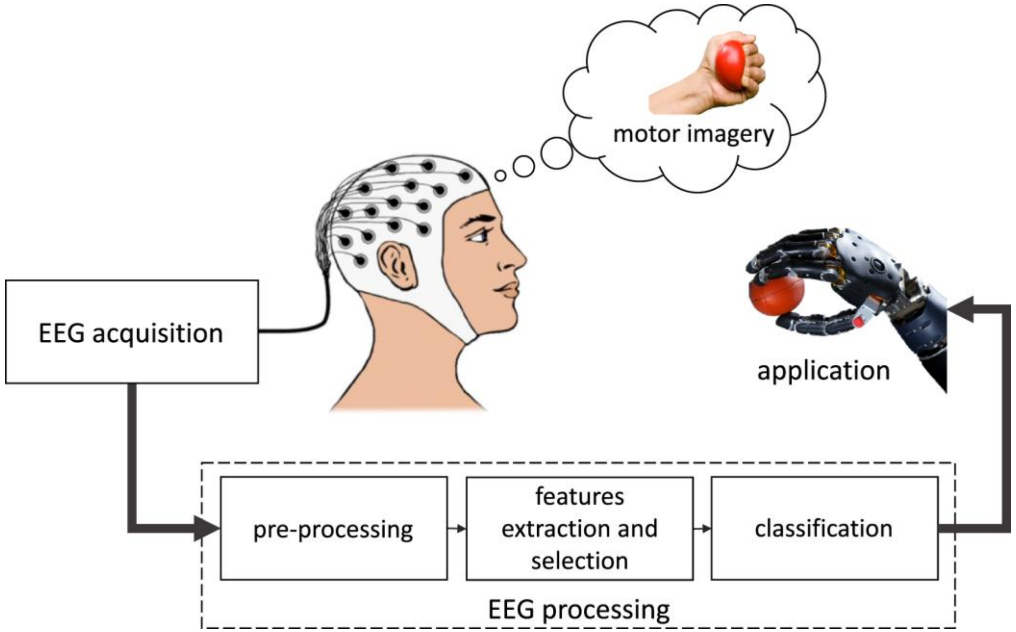
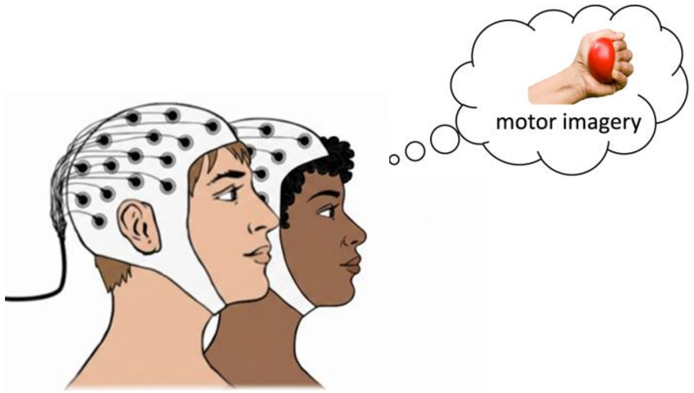
" Continual Motor Imagery EEG Classification "

새로운 피험자가 유입될 때마다 처음부터 재학습하는 비효율을 없애고,
과거의 지식을 온전히 보존하며 끊임없이 성장하는
'self-evolving BCI system'을 구축하자

Motor Imagery EEG



Continual



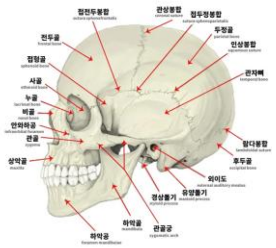
New Subject

02 Common Objectives : EEG classification의 3가지 난제

“ Continual Motor Imagery EEG Classification ”

1) Subject Variability

- 사람마다 뇌파 패턴이 다름 (Domain Shift)**
- 새로운 피험자가 오면 기존 모델이 잘 동작하지 않음



2) Catastrophic Forgetting

- 새로운 피험자(B)를 배우면, 이전 피험자(A)의 지식을 덮어써서 잊어버림

3) Real-world Constraints

- Privacy: 의료 데이터(EEG)를 서버에 영구 저장해도 되는가?
- Memory: 제한된 메모리*안에서 어떻게 효율적으로 학습할 것인가?

* Replay buffer size 혹은 model parameter size

** 학습 데이터와 테스트 데이터의 분포가 서로 다른 현상. EEG 기반 BCI 시스템의 성능 저하의 원인

03 Method

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Common Object: Subject Variability(SV), Catastrophic Forgetting(CF), Privacy & Memory(P, M)

연도	2024	2025	2026
Common Object	Subject Variability, Catastrophic Forgetting	Subject Variability, Catastrophic Forgetting, Memory	Subject Variability, Catastrophic Forgetting, Privacy & Memory
핵심 기술	**SV**: Subject-Invariant Extractor, Subject-Specific Encoder **CF**: Memory Replay	**SV**: Euclidean Alignment (EA) **CF & M**: Reservoir Sampling	**SV**: Dual Function Loss(L_{pro}, L_{align}) **CF**: Prototypes and EMA update **P & M**: Non-Exemplar
요약	피험자 개별 특징과, 피험자 공통 특징을 분리하여 학습	EA로 뇌파 공분산 행렬을 단위 행렬로 정렬해 도메인 차이를 줄임	Raw data 사용 X, feature들의 평균 사용

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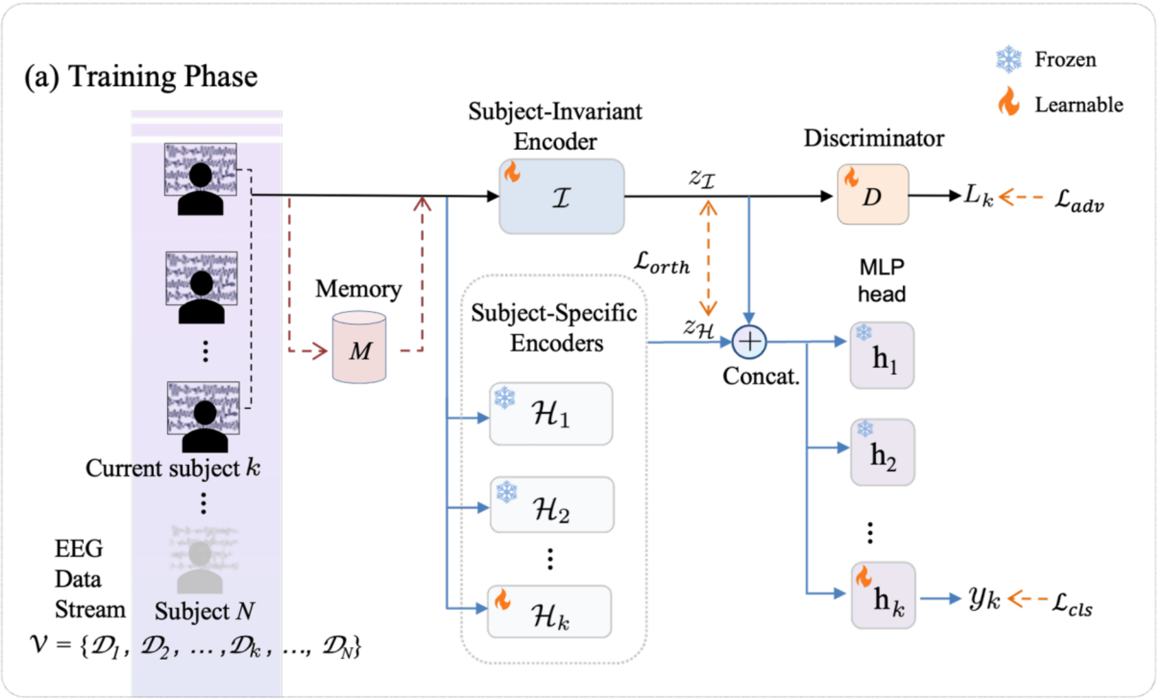
Common Object: Subject Variability(SV), Catastrophic Forgetting(CF), Privacy & Memory(P, M)

연도	2024
Common Object	Subject Variability, Catastrophic Forgetting
핵심 기술	**SV**: Subject-Invariant Extractor, Subject-Specific Encoder **CF**: Memory Replay
요약	피험자 개별 특징과, 피험자 공통 특징을 분리하여 학습

$$\mathcal{F}_k(x_k) = h_k([\mathcal{I}(x_k);\mathcal{H}(x_k)]). \quad (1)$$



$D_k = \{(X_k^i, Y_k^i, L_k^i)_{i=1}^{m_k}\}$, (input data, class label, subject label)

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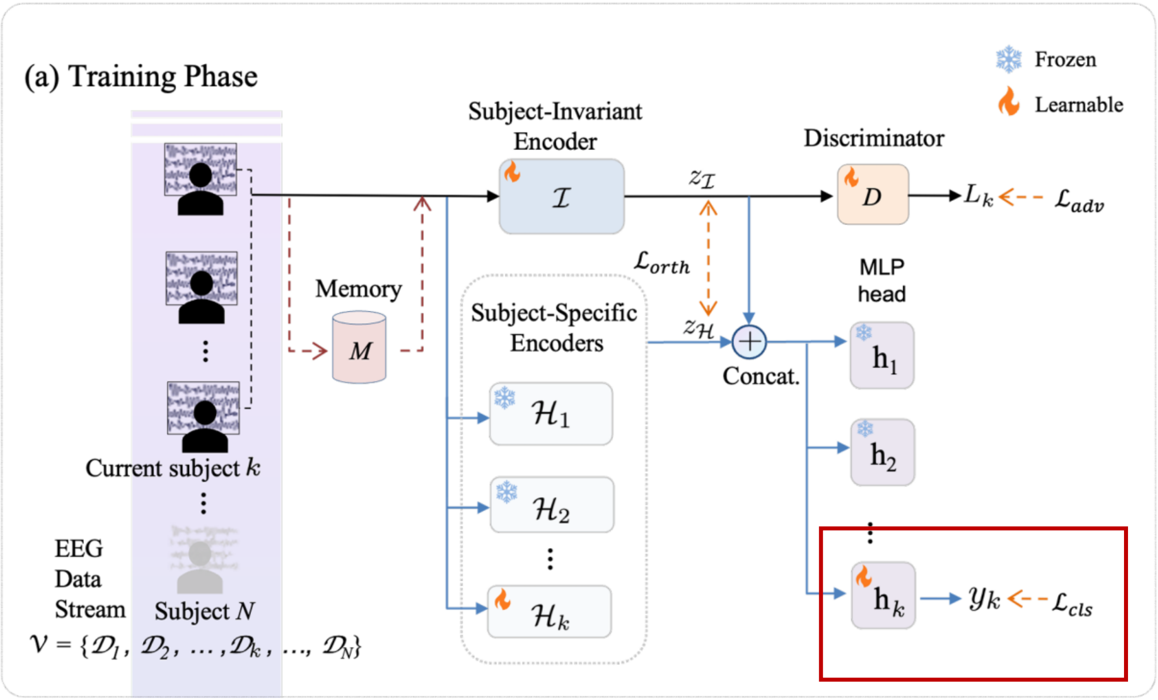
$$\mathcal{F}_k(x_k) = h_k([\mathcal{I}(x_k);\mathcal{H}(x_k)]). \quad (1)$$

$$\mathcal{L}_{\text{cls}} = -\mathbb{E}_{(x_k,y_k)\sim(X_k,Y_k)\cup M_k}\left[\sum_{c=1}^{C} \mathbb{1}_{[c=y_k]} \log\left(\sigma\left(\mathcal{F}_k\left(x_k\right)\right)\right)_c\right] \quad (2)$$



$D_k = \{(X_k^i, Y_k^i, L_k^i)_{i=1}^{m_k}\}$, (input data, class label, subject label)

$M_k \leftarrow \{x^i\}_{i=1}^{t} \sim \{D_j\}_{j=1}^{k-1}$

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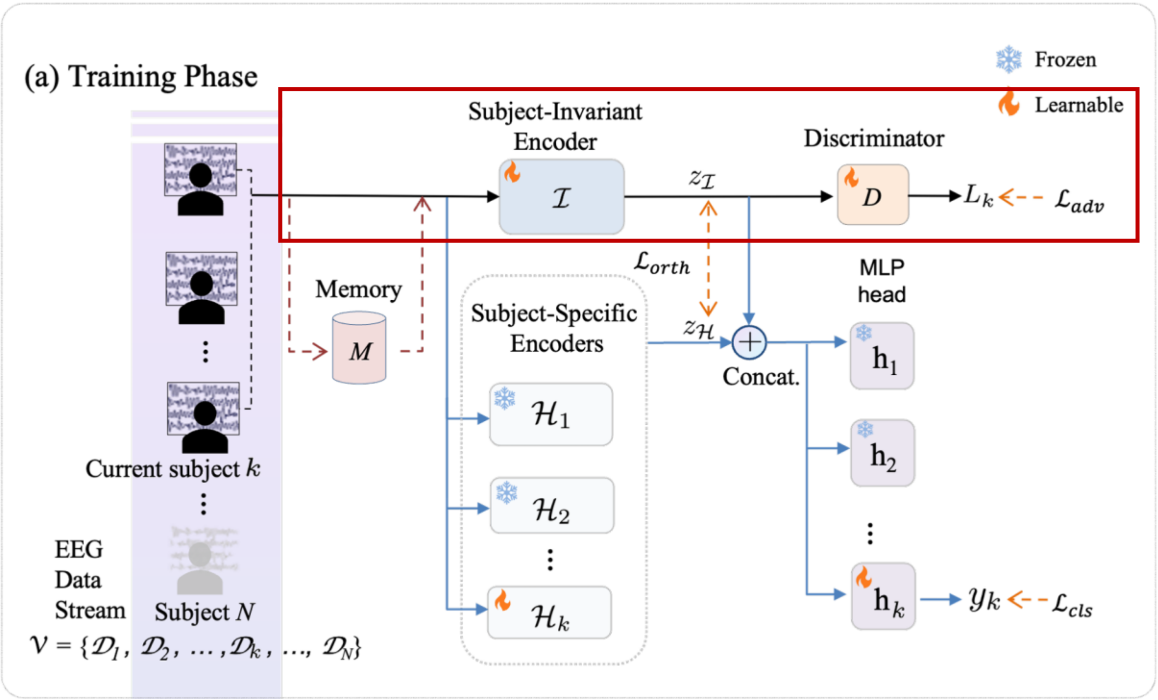
$$\mathcal{L}_{\text{adv}} = \min_{\mathcal{I}} \max_{D} \sum_{k=0} \mathbb{1}_{[k=L_k]} \log\left(D\left(\mathcal{I}\left(x_k\right)\right)\right), \quad (4)$$



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04 Method : 2024

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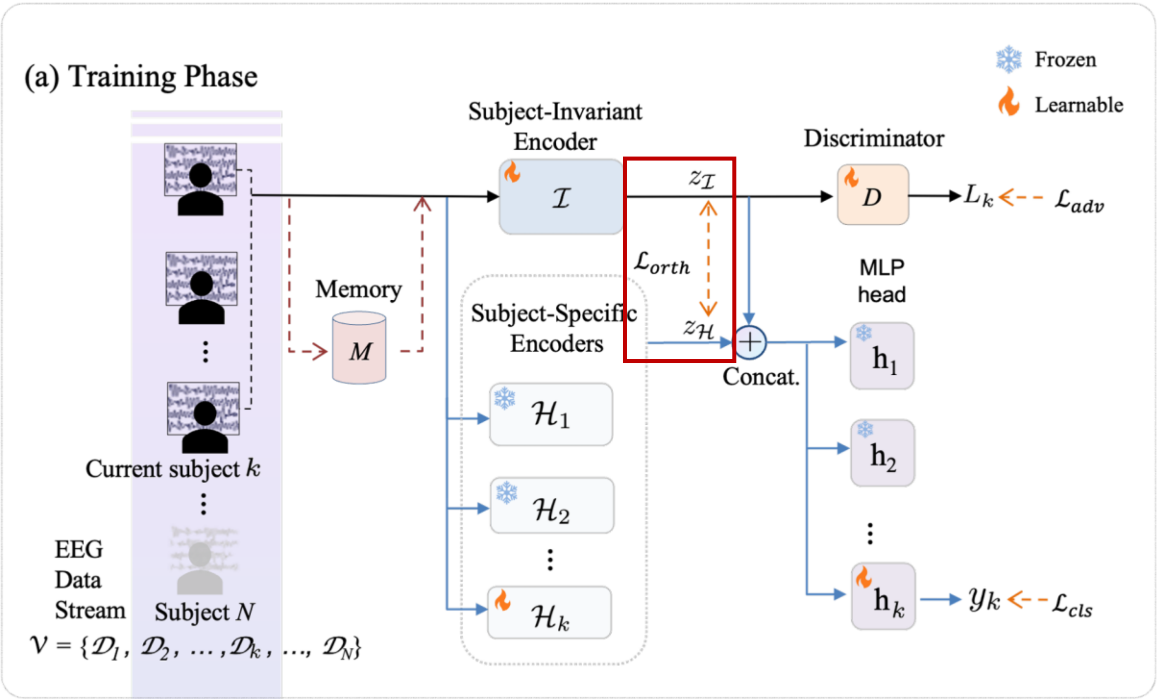
$$\mathcal{L}_{\text{orth}} = \sum_{k=1}^{N} \left\|\mathcal{I}\left(x_k\right)^{\mathrm{T}} \mathcal{H}_k\left(x_k\right)\right\|_F^2. \quad (5)$$



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04 Method : 2024

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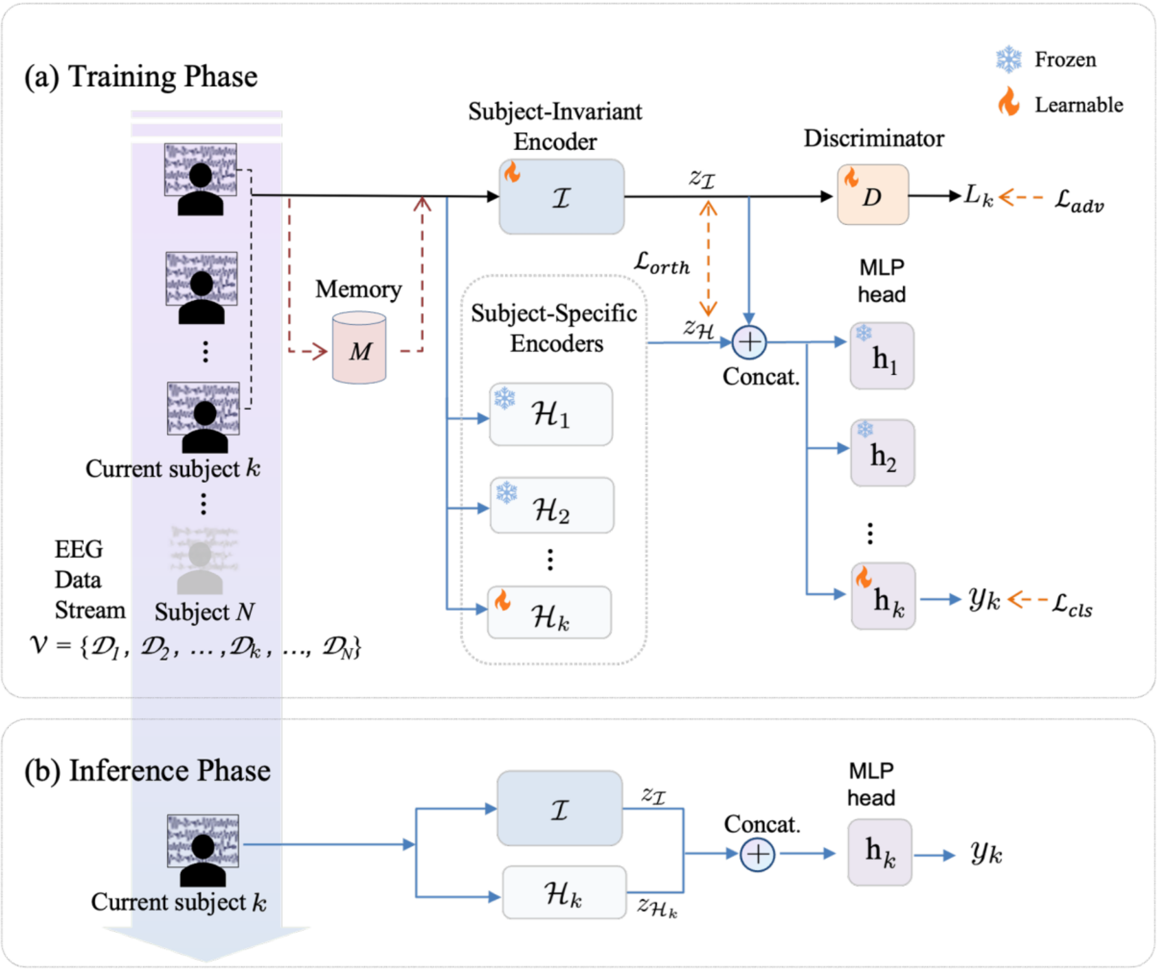
$$\mathcal{L}_{\text{adv}} = \min_{\mathcal{I}}\max_{D}\sum_{k=0}\mathbb{1}_{[k=L_k]}\log\left(D\left(\mathcal{I}\left(x_k\right)\right)\right), \quad (4)$$

$$\mathcal{L}_{\text{orth}} = \sum_{k=1}^{N}\left\|\mathcal{I}\left(x_k\right)^{\mathrm{T}}\mathcal{H}_k\left(x_k\right)\right\|_F^2. \quad (5)$$

$$\mathcal{L}_{\text{dis}} = \mathcal{L}_{\text{adv}} + \mathcal{L}_{\text{orth}}. \quad (3)$$

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{dis}} + \mathcal{L}_{\text{cls}}. \quad (6)$$

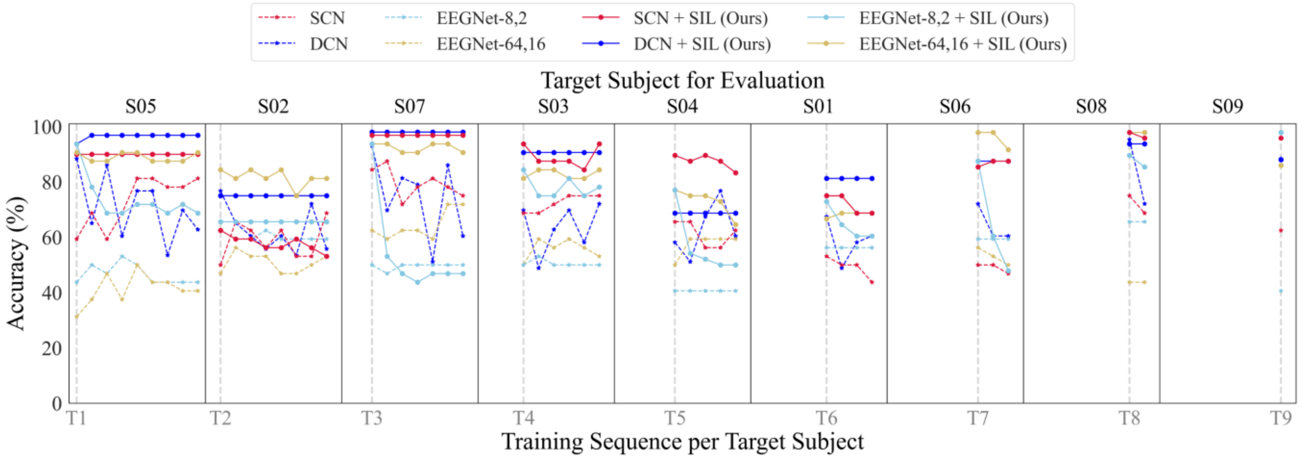


04 Result : 2024

TABLE I

PERFORMANCE OF THE BASELINE SUBJECT-SPECIFIC FINETUNING (SFT) APPROACH AND OUR SIL APPROACH IN TERMS OF AVERAGE BWT (%) AND ACC (%), COMPUTED AS SHOWN IN SECTION 7, AVERAGING ACROSS THREE RUNS, THE STANDARD DEVIATION IS NOTED IN PARENTHESES

Method	Backbone	BCI-C IV 2a+ (2-class)		BCI-C IV 2a (4-class)		BCI-C IV 2b (2-class)	
		ACC (std.)	BWT (std.)	ACC (std.)	BWT (std.)	ACC (std.)	BWT (std.)
SFT	EEGNet-8,2	51.0 (2.6)	-0.9 (0.5)	44.7 (4.0)	0.4 (5.6)	53.8 (2.6)	3.9 (1.8)
	EEGNet-64,16	57.7 (2.2)	4.17 (1.2)	43.8 (2.3)	-0.3 (2.4)	56.3 (0.5)	4.7 (1.1)
	ShallowConvNet	74.4 (3.0)	-4.7 (1.9)	48.0 (0.8)	-4.9 (2.5)	59.5 (1.7)	3.8 (1.2)
	DeepConvNet	63.3 (3.0)	-17.2 (2.7)	38.4 (0.8)	-14.9 (4.7)	72.1 (0.8)	-3.3 (2.7)
SIL (Ours)	EEGNet-8,2	71.5 (4.8)	-14.5 (5.3)	55.1 (3.5)	-21.7 (3.2)	73.3 (1.5)	-0.7 (1.0)
	EEGNet-64,16	80.7 (3.6)	-7.3 (5.6)	62.3 (2.0)	-13.9 (3.1)	**75.7 (1.1)**	-0.7 (1.0)
	ShallowConvNet	84.0 (2.5)	-0.9 (1.3)	69.5 (0.8)	**0.0 (0.0)**	61.2 (0.6)	**1.0 (2.4)**
	DeepConvNet	**85.8 (0.5)**	**0.1 (0.2)**	**72.2 (0.9)**	-2.4 (0.6)	75.3 (0.5)	0.1 (0.2)



* 왼손/오른손, 왼손/오른손/발/혀, 왼손/오른손 (9 subjects)

* EEGNet-8,2에서 BWT가 SFT에서 더 높은 이유는 ACC가 낮기 때문임

04 Limitation : 2024

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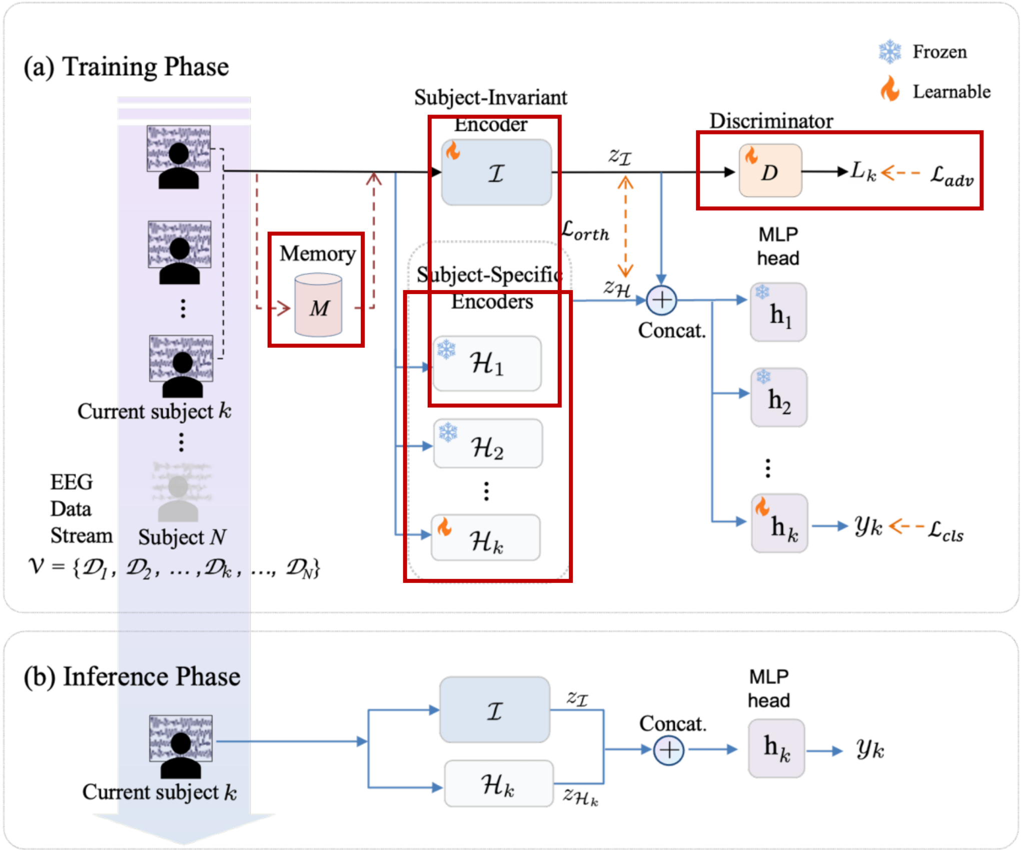

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- 소규모 subject: subject가 9명으로 매우 적음
- Baseline 부족: SFT 외에 다양한 최신 방법론과의 비교 X

- Scalability Issue: 피험자 수와 인코더 수가 비례함
- Privacy: Raw Data를 그대로 저장하므로 보안 문제
- Inefficient Architecture Design: 피험자 불변/특화 인코더 모두 동일하게 사용
- 단순 Random sampling: Hard example과 Representative Sample 선별 X
- Adversarial Training의 불안정성

04 Method

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연도	2024	2025	2026
Common Object	Subject Variability, Catastrophic Forgetting	Subject Variability, Catastrophic Forgetting, Memory	Subject Variability, Catastrophic Forgetting, Privacy & Memory
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요약	피험자 개별 특징과, 피험자 공통 특징을 분리하여 학습	EA로 뇌파 공분산 행렬을 단위 행렬로 정렬해 도메인 차이를 줄임	Raw data 사용 X, feature들의 평균 사용
한계점	Scalability Issue Privacy Inefficient Architecture Design 단순 Random sampling Adversarial Training의 불안정성 소규모 subject Baseline 부족		

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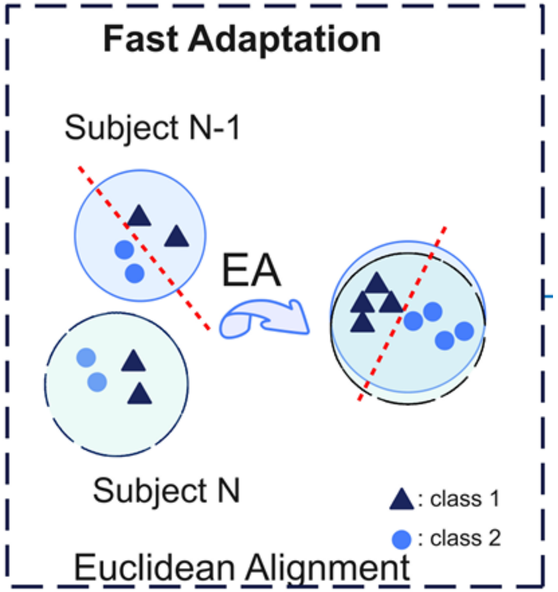
Common Object: Subject Variability(SV), Catastrophic Forgetting(CF), Privacy & Memory(P, M)

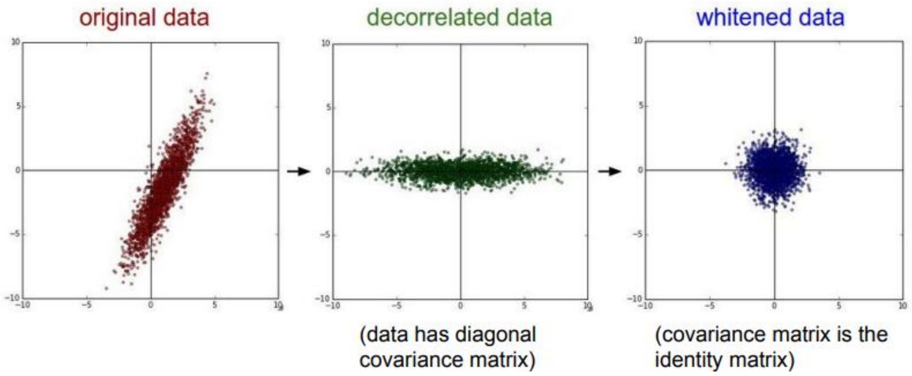
연도	2025
Common Object	Subject Variability, Catastrophic Forgetting, Memory
핵심 기술	**SV**: Euclidean Alignment (EA) **CF & M**: Reservoir Sampling
요약	EA로 뇌파 공분산 행렬을 단위 행렬로 정렬해 도메인 차이를 줄임

$$X \in \mathbb{R}^{N \times C \times T}$$

$$R_i = \frac{1}{T-1}\sum_{t=1}^{T}(X_{it}-\mu_i)(X_{it}-\mu_i)^\top$$

$$X_i^{EA} = \left(\frac{1}{N}\sum_{i=1}^{N} R_i\right)^{-\frac{1}{2}} X_i$$





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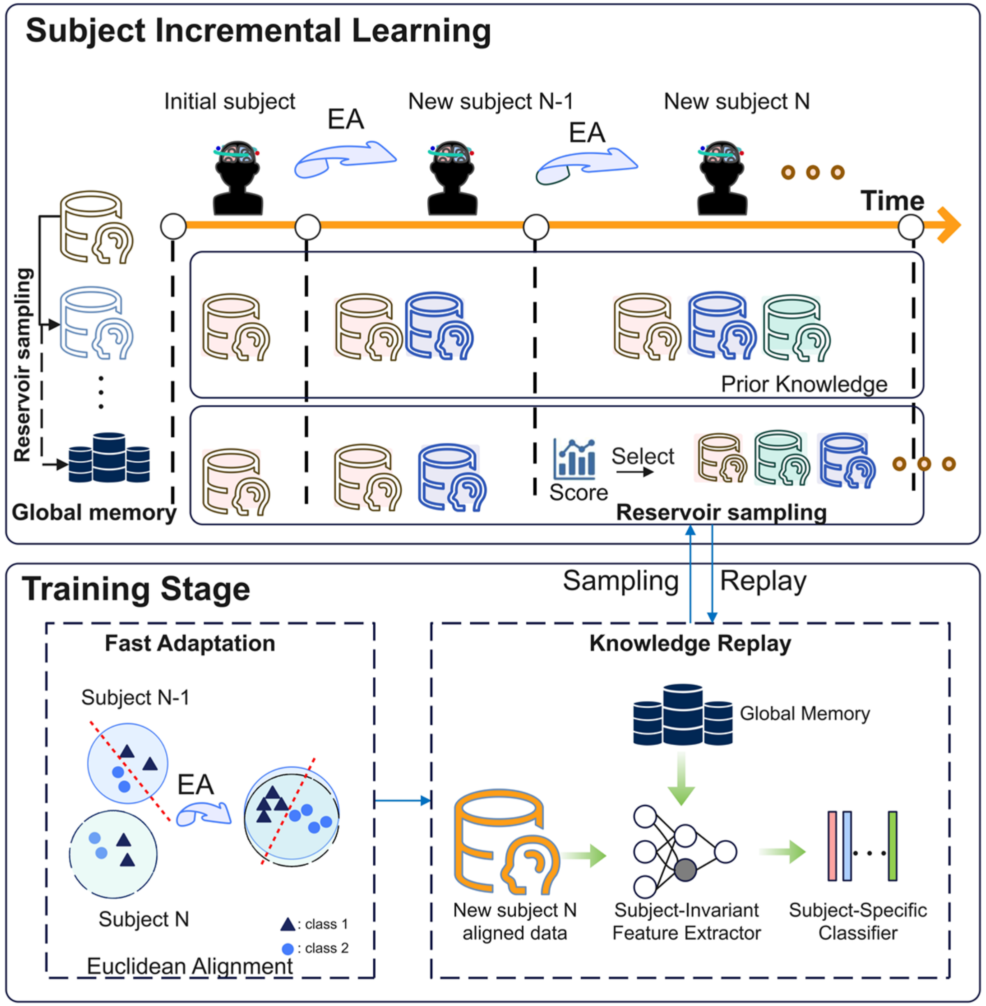
요약	EA로 뇌파 공분산 행렬을 단위 행렬로 정렬해 도메인 차이를 줄임

$$p = \frac{B}{B + |\mathcal{M}|}$$

$$\mathcal{M} \leftarrow \mathcal{M} \cup \{(x_i, y_i, t_i)\} \quad \text{if } |\mathcal{M}| < B,$$

$$\mathcal{M}_j \leftarrow (x_i, y_i, t_i) \quad \text{with prob. } p = \frac{B}{B + |\mathcal{M}|}$$



04 Result : 2025

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TABLE I
COMPARATIVE STUDY ON THE PERFORMANCE OF DIFFERENT MODELS AND BACKBONES FOR THE OPENBMI DATASET.

Method	Backbone	ACC (%)	BWT (%)
SFT	SCN [28]	50.37 ± 0.33	-14.93 ± 1.14
	DCN [28]	50.76 ± 0.44	-20.33 ± 0.26
	EEGNet-8,2 [29]	49.81 ± 0.67	-17.04 ± 0.18
	EEGNet-64,16 [29]	49.70 ± 0.69	-22.50 ± 0.29
EWC [25]	SCN [28]	66.31 ± 0.53	-4.01 ± 0.34
	DCN [28]	67.93 ± 0.13	-4.67 ± 0.90
	EEGNet-8,2 [29]	65.93 ± 0.93	-5.17 ± 0.89
	EEGNet-64,16 [29]	66.10 ± 0.21	-5.01 ± 0.93
ER [26]	SCN [28]	74.46 ± 0.91	-5.58 ± 0.67
	DCN [28]	74.20 ± 0.26	-2.98 ± 0.58
	EEGNet-8,2 [29]	74.49 ± 0.33	-1.49 ± 0.60
	EEGNet-64,16 [29]	74.11 ± 0.38	-2.24 ± 0.37
PCED (Ours)	SCN [28]	79.89 ± 0.63	-1.85 ± 1.03
	DCN [28]	**82.27 ± 0.43**	**0.22 ± 0.48**
	EEGNet-8,2 [29]	79.89 ± 0.59	-2.99 ± 0.56
	EEGNet-64,16 [29]	79.93 ± 0.23	-3.17 ± 0.38

*ACC: average accuracy, BWT: backward transfer, SFT: subject-specific finetuning.

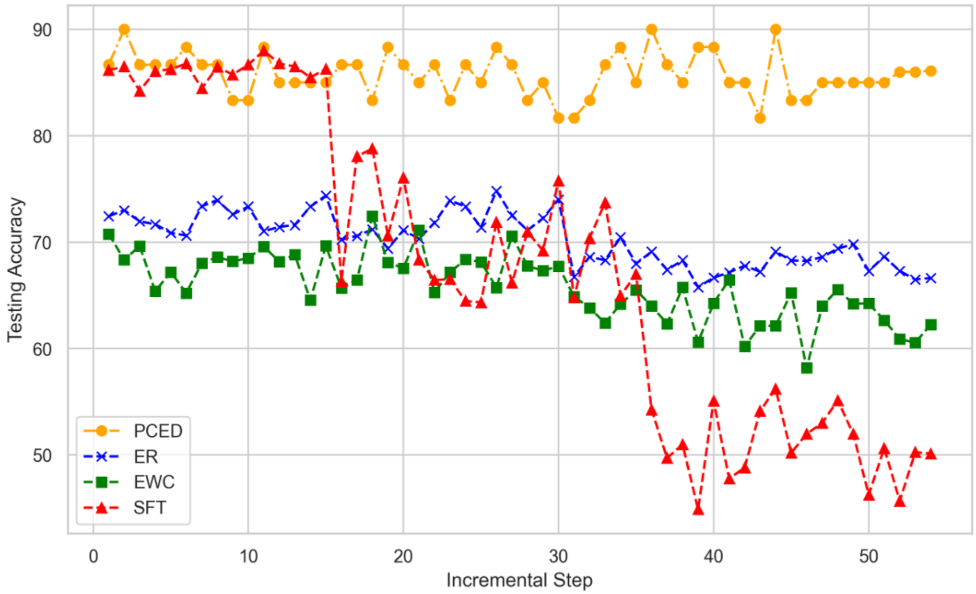
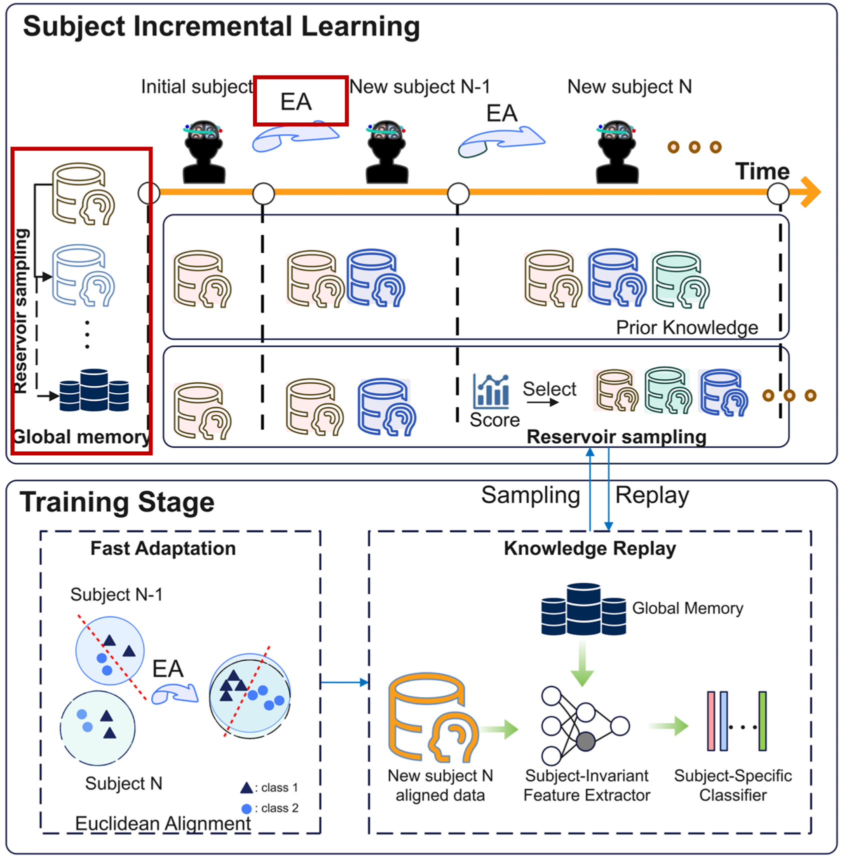


Fig. 2. Testing accuracy of different methods at each incremental learning stage for the initial subject in continual EEG decoding.

* 왼손/오른손 (54 subjects)



- Privacy: Raw Data를 그대로 저장하므로 보안 문제
- Hard example 삭제 위험
- Online 적용 어려움: 1개씩 데이터가 들어올 경우, EA의 공분산 계산 비용이 높음
- EA의 한계: 현재는 데이터 전체의 공분산을 보지만, 클래스 정보를 활용하지 않음. 최근에는 class-aware alignment를 사용하기도 함.
- 이상치 오염: 노이즈가 심하거나 패턴이 이상한 사람이 들어오면, EA는 평균적인 공분산을 기준으로 데이터를 반환하기에, Negative Transfer이 발생할 위험이 큼

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Common Object: Subject Variability(SV), Catastrophic Forgetting(CF), Privacy & Memory(P, M)

연도	2024	2025	2026
Common Object	Subject Variability, Catastrophic Forgetting	Subject Variability, Catastrophic Forgetting, Memory	Subject Variability, Catastrophic Forgetting, Privacy & Memory
핵심 기술	**SV**: Subject-Invariant Extractor, Subject-Specific Encoder **CF**: Memory Replay	**SV**: Euclidean Alignment (EA) **CF & M**: Reservoir Sampling	**SV**: Dual Function Loss(L_{pro}, L_{align}) **CF**: Prototypes and EMA update **P & M**: Non-Exemplar
요약	피험자 개별 특징과, 피험자 공통 특징을 분리하여 학습	EA로 뇌파 공분산 행렬을 단위 행렬로 정렬해 도메인 차이를 줄임	Raw data 사용 X, feature들의 평균 사용
한계점	~~Scalability Issue~~ ~~Privacy~~ Inefficient Architecture Design 단순 Random sampling Adversarial Training의 불안정성 ~~소규모 subject~~ ~~Baseline 부족~~	Privacy Hard example 삭제 위험 Online 적용 어려움 EA의 한계(class-Agnostic) 이상치 오염	

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연도	2026
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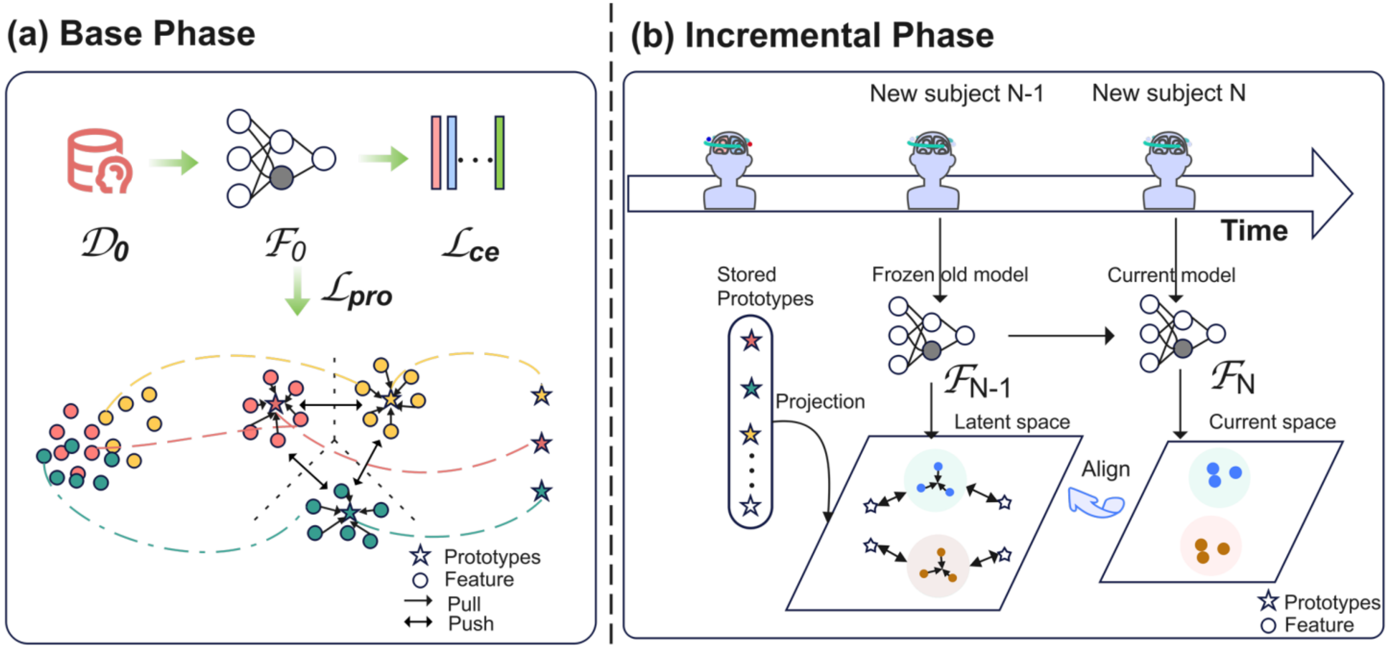
핵심 기술	**SV**: Dual Function Loss(L_{pro}, L_{align}) **CF**: Prototypes and EMA update **P & M**: Non-Exemplar
요약	Raw data 사용 X, feature들의 평균 사용

$$Z_k^i = E_\phi(X_k^i), \quad (1)$$

$$P_c^k = \frac{1}{|\mathcal{D}_c^k|} \sum_{(X_k^i, Y_k^i = c)} Z_k^i, \quad (2)$$

$$P_c \leftarrow \alpha P_c + (1-\alpha) P_c^k, \quad (3)$$



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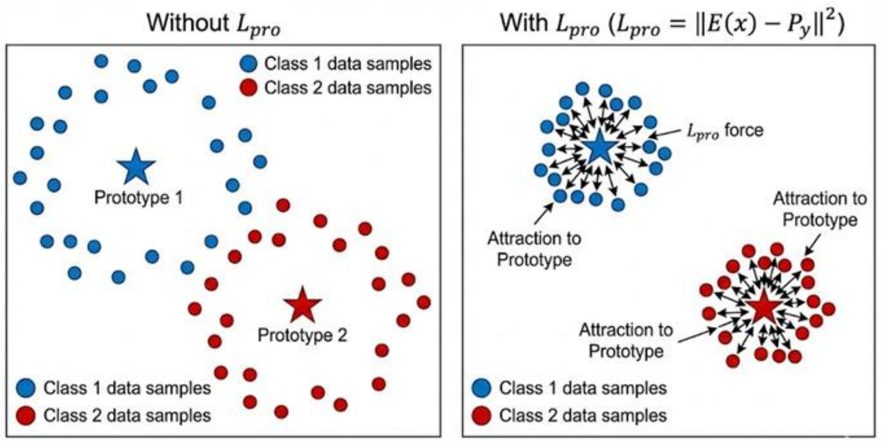
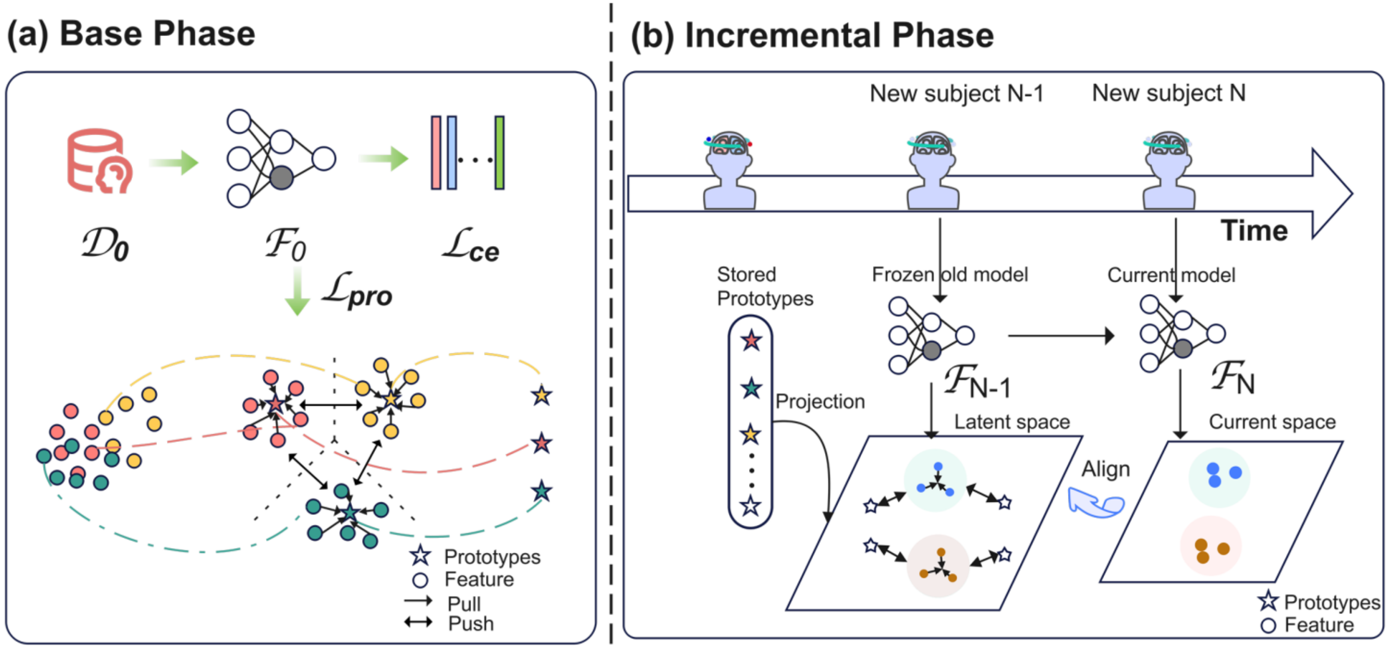
$$\mathcal{L}_{\text{pro}} = \mathbb{E}_{(x_k, y_k)\sim(X_k, Y_k)}\left[\|E_\phi(x_k) - P_{y_k}\|_2^2\right]. \quad (5)$$





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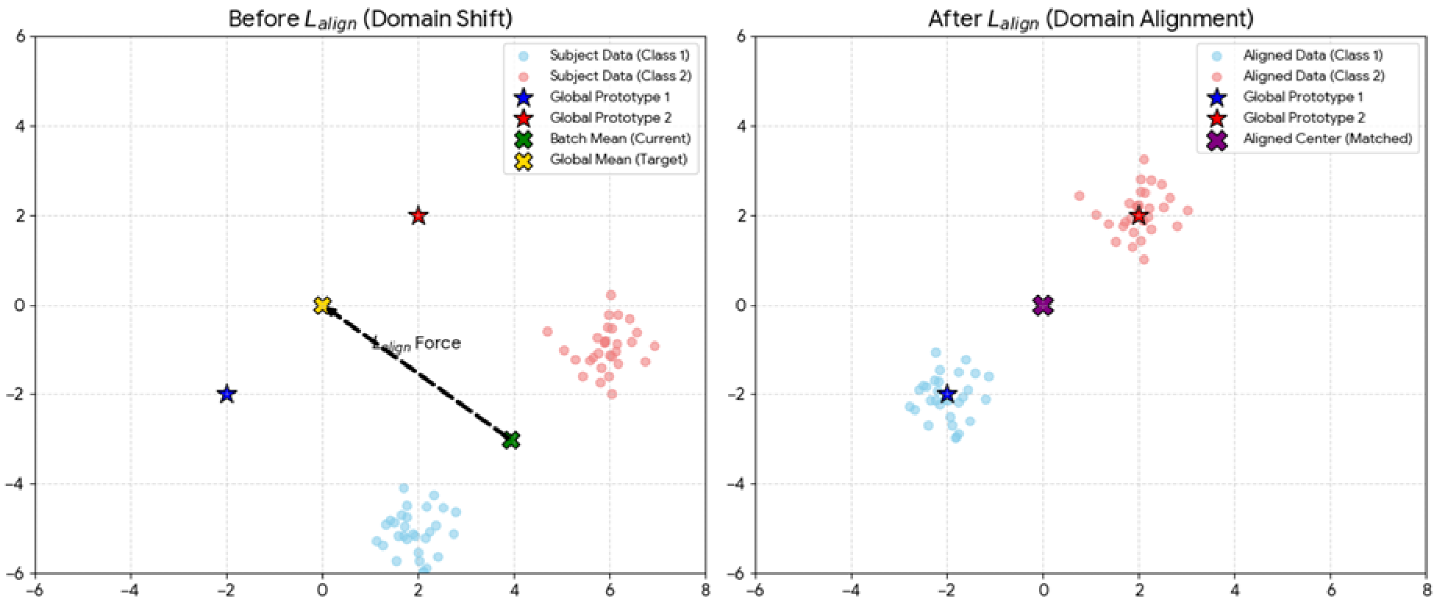
$$\mathcal{L}_{\text{align}} = \left\| \frac{1}{m_k} \sum_{i=1}^{m_k} E_\phi(X_k^i) - \frac{1}{C} \sum_{c=1}^{C} P_c \right\|_2^2, \tag{6}$$



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Common Object: Subject Variability(SV), Catastrophic Forgetting(CF), Privacy & Memory(P, M)

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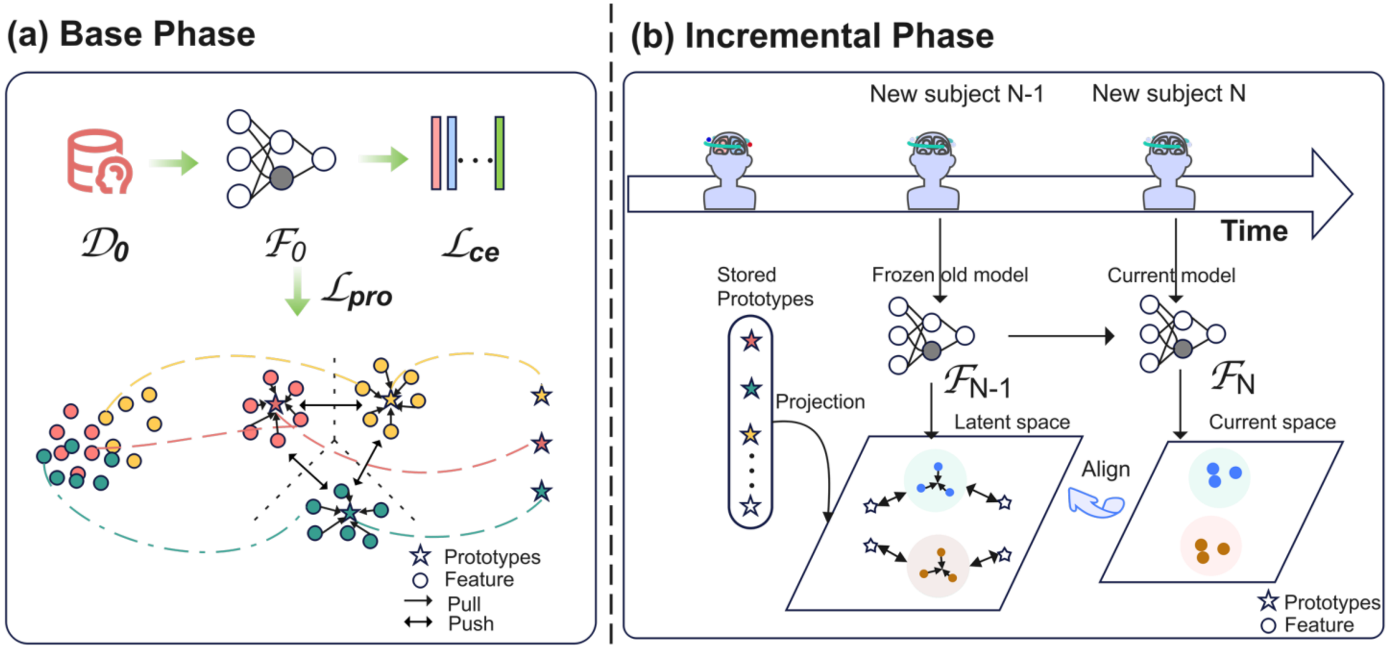
$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{ce}} + \lambda_{\text{p}} \mathcal{L}_{\text{pro}} + \lambda_{\text{a}} \mathcal{L}_{\text{align}}, \tag{7}$$



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06 **Result** : 2026

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TABLE I
PERFORMANCE COMPARISON OF PRONECL AND BASELINES ON TWO BCI BENCHMARKS, WITH RESULTS REPORTED AS AVERAGE ACCURACY (ACC, %) AND BACKWARD TRANSFER (BWT, %) WITH VALUES REPRESENTING THE MEAN AND STANDARD DEVIATION OVER FIVE RUNS, AND THE BEST PERFORMANCE IN BOLD.

Method	BCI-C IV 2a [29]		BCI-C IV 2b [30]	
	ACC (std.)	BWT (std.)	ACC (std.)	BWT (std.)
Finetuning	32.33 (4.19)***	-42.70 (6.96)	55.39 (3.47)***	-22.19 (3.88)
EWC [32]	44.67 (2.19)***	-34.11 (2.76)	60.08 (1.94)***	-21.65 (1.89)
MUDVI [33]	46.41 (1.03)***	-18.11 (1.27)	67.20 (5.41)***	-9.49 (5.60)
CGER [34]	49.84 (3.75)***	-21.38 (2.44)	67.43 (2.98)***	-9.05 (2.77)
ProNECL (Ours)	**77.18 (1.76)**	0.12 (1.53)	**81.15 (2.11)**	0.33 (0.79)

*ACC: average accuracy in %, BWT: backward transfer in %, std.: standard deviation. *Significance levels comparing each method to ProNECL (Ours):* $^{*}p < 0.05$, $^{***}p < 0.001$.

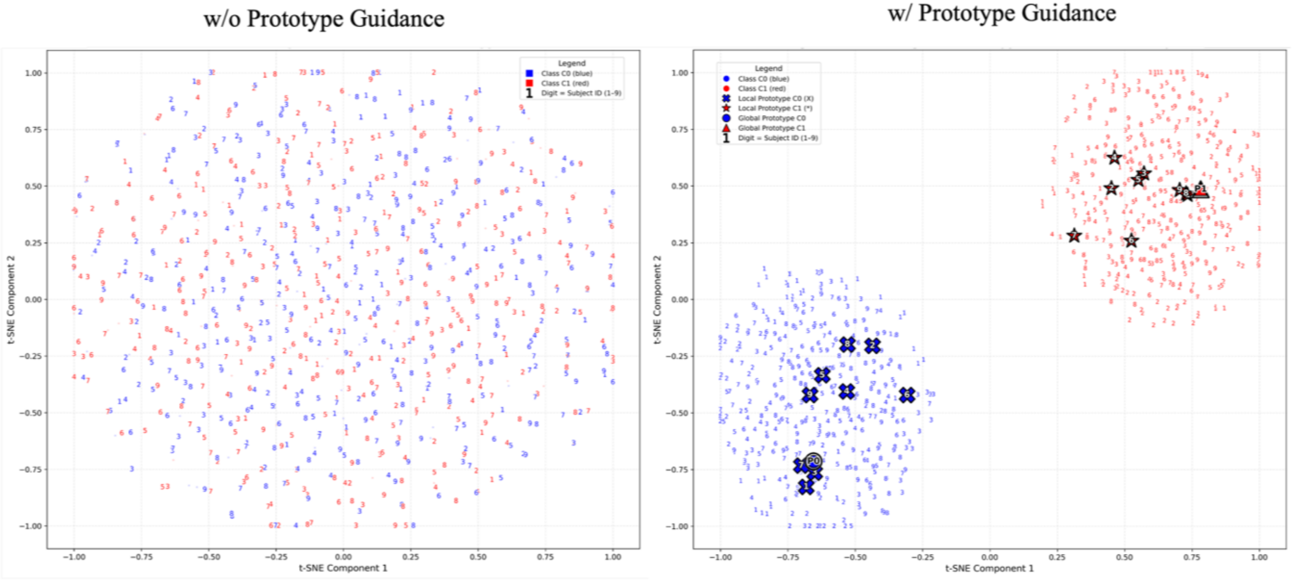

Fig. 2. t-SNE of subject-invariant features on the 2a dataset (S1–S9): comparison without/with prototype guidance. Digits (1–9) indicate subject IDs, while markers “X”, “☆”, and “P” denote local and global prototypes, respectively.

* Memory-Updated Domain-Variant Invariant (MUDVI)
* Centroid-Guided Episodic Replay (CGER)
* 왼손/오른손/발/혀, 왼손/오른손 (9 subjects)

06 Limitation : 2026

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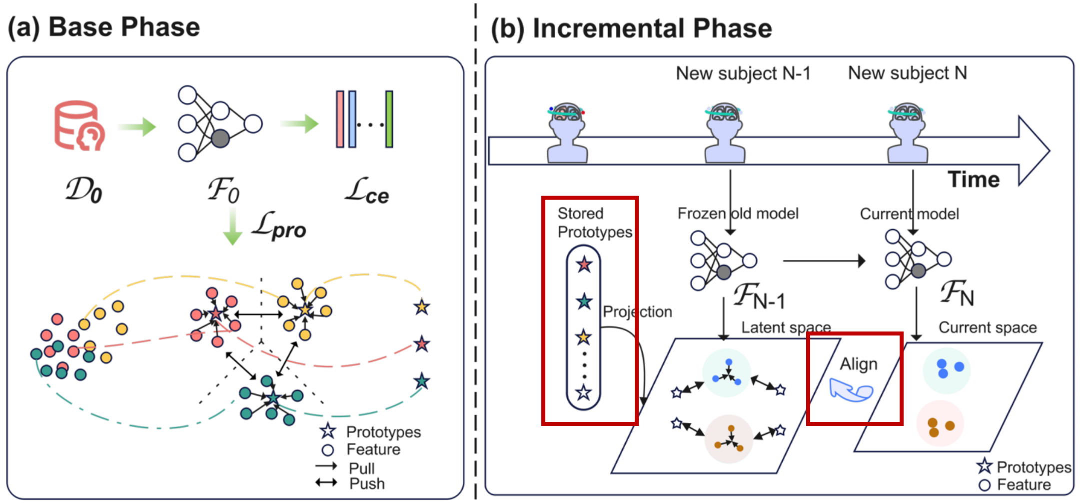

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*ACC: average accuracy in %, BWT: backward transfer in %, std.: standard deviation. *Significance levels comparing each method to ProNECL (Ours):* $^*p < 0.05$, $^{***}p < 0.001$.

- Single Gaussian Assumption: 복잡한 뇌파 분포를 하나의 점으로 표현하여 정보 손실 가능
- Online 어려움: L_{align}을 계산하려면 batch 단위의 평균 필요
- Class Imbalance 취약함
- Rigid Alignment: L_{align}은 단순하게 직선 거리로 당기거나 미는 역할만 함. 실제 도메인 변화는 회전 등을 포함할 수 있음

- Backbone Fairness: 비교 모델들의 원래 성능을 내기 어려운 DCN으로 백본 통일
- Regressed Validation Scale: 2025년에 54명으로 실험하고, 다시 9명으로 소규모 실험함

06 Method

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Common Object: Subject Variability(SV), Catastrophic Forgetting(CF), Privacy & Memory(P, M)

연도	2024	2025	2026
Common Object	Subject Variability, Catastrophic Forgetting	Subject Variability, Catastrophic Forgetting, Memory	Subject Variability, Catastrophic Forgetting, Privacy & Memory
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한계점	~~Scalability Issue~~ ~~Privacy~~ Inefficient Architecture Design 단순 Random sampling Adversarial Training의 불안정성 ~~소규모 subject~~ ~~Baseline 부족~~	~~Privacy~~ ~~Hard example 삭제 위험~~ Online 적용 어려움 ~~EA의 한계(class-Agnostic)~~ 이상치 오염	Single Gaussian Assumption Online 어려움 Class Imbalance 취약함 Rigid Alignment Backbone Fairness Regressed Validation Scale

Thank You

2026.02.09

BrainLAB Journal Club
인공지능응용학과 나영서

07 Proposed Idea

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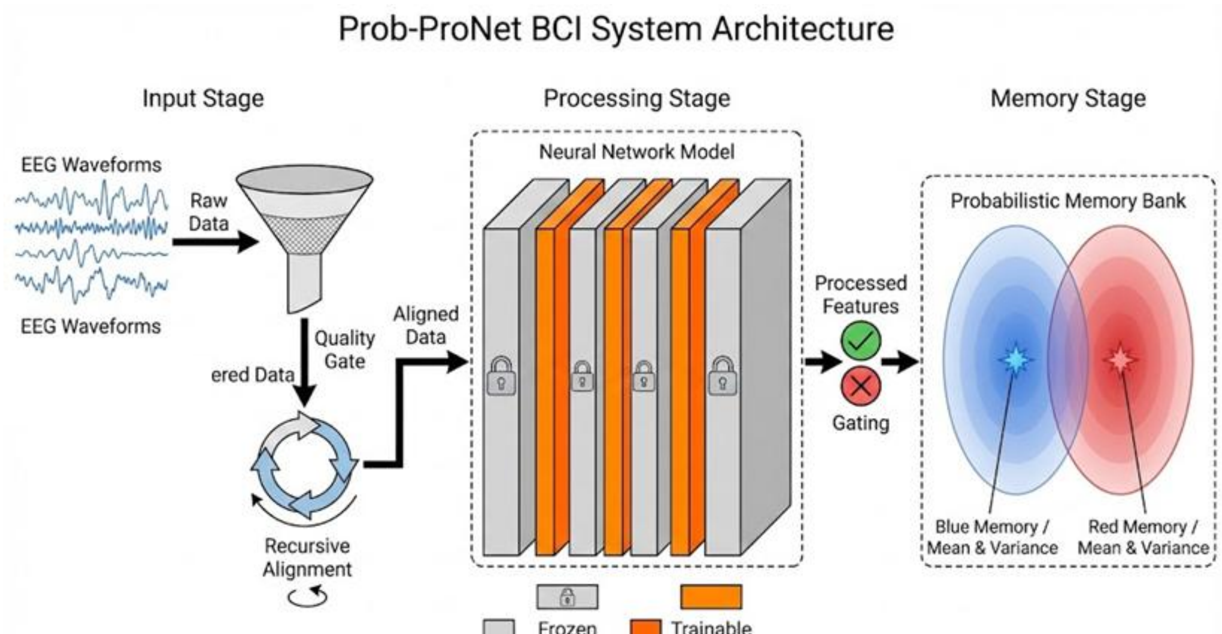
Prob-ProNe



$R_t = \alpha R_{t-1} + (1-\alpha) x_t x_t^T$

$\tilde{x}_t = R_t^{-1/2} x_t$

$L_{total} = L_{cls} + \lambda L_{proto}$

$$p(y=k|x) = \frac{\exp\left(-\frac{1}{2} d_{\mathcal{M}}(z, \mu_k, \Sigma_k)\right)}{\sum_{j=1}^{K} \exp\left(-\frac{1}{2} d_{\mathcal{M}}(z, \mu_j, \Sigma_j)\right)}$$

$$\mathcal{L}_{pro} = \frac{1}{2} \underbrace{(z-\mu_y)^\top \Sigma_y^{-1} (z-\mu_y)}_{\text{Mahalanobis Distance}} + \frac{1}{2} \underbrace{\ln|\Sigma_y|}_{\text{Volume Regularization}}$$

$$\mathcal{L}_{cls} = -\log p(y = y_{true}|x)$$

2026
Subject Variability, Catastrophic Forgetting, Privacy & Memory
SV: Dual Function Loss(L_{pro}, L_{align}) **CF**: Prototypes and EMA update **P & M**: Non-Exemplar
Raw data 사용 X, feature들의 평균 사용

Gaussian Prototypes (Mean+Covariance) ← Single Gaussian Assumption

Online 어려움 → Recursive Alignment (REA) + Incremental Update.

Mahalanobis Distance ← Class Imbalance 취약함

Rigid Alignment → REA + Adapter

Backbone Fairness

Regressed Validation Scale → 많은 subject 적용, 다양한 모델 사용

Mahalanobis Distance

$d(z, \mu_k) = \|z - \mu_k\|^2$

$d_{\mathcal{M}}(z, \mu_k, \Sigma_k) = (z-\mu_k)^\top \Sigma_k^{-1} (z-\mu_k)$