EEG2Image: Image Reconstruction from EEG Brain Signals

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Problem Statement

[1] https://beta.dreamstudio.ai/generate

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Uncle Jerry

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Our chef is watching pizza ad on a TV

Uncle Jerry

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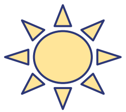

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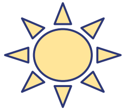

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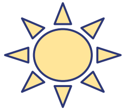

I want to bake a pizza similar to the one I saw on the TV last night.

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Problem Statement

I want to bake a pizza similar to the one I saw on the TV last night.

Is it possible to reconstruct an image just from our thoughts?

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Background

How can we record our thoughts?

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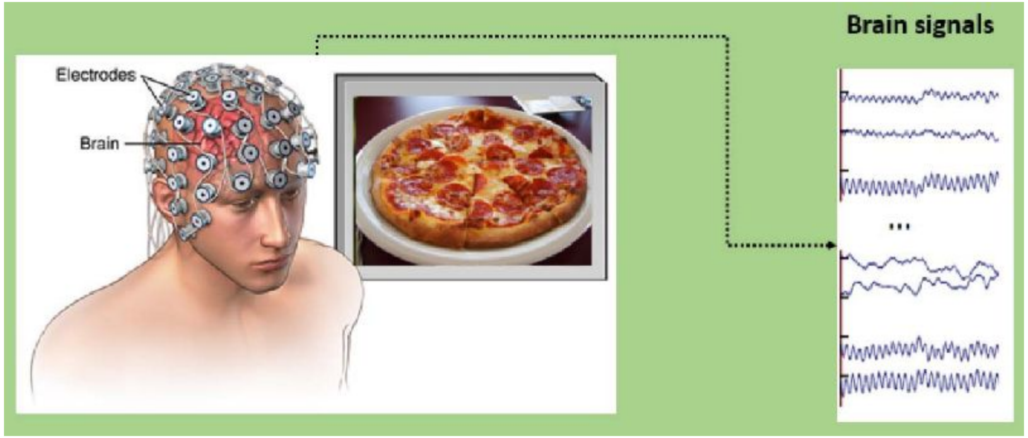
Through **EEG** (Electroencephalography) we can record the brain activity.



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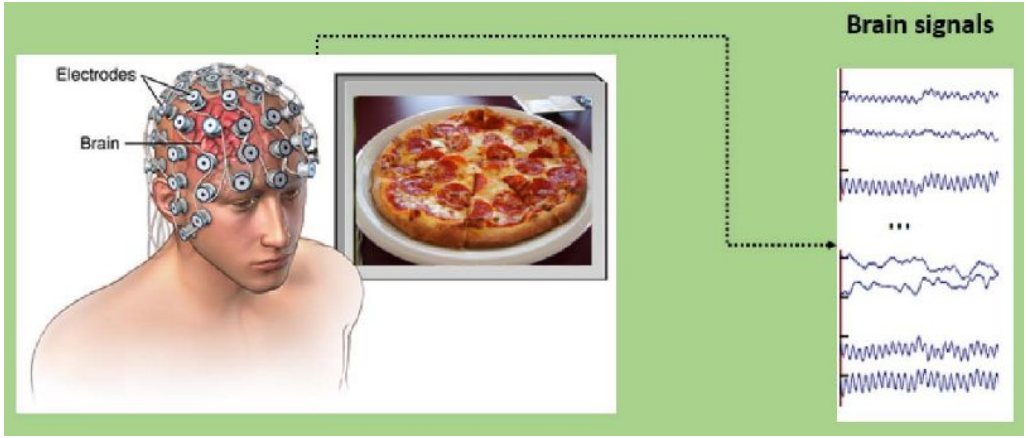
Background

How we are going to extract the image information from EEG?

Through **EEG** (Electroencephalography) we can record the brain activity.



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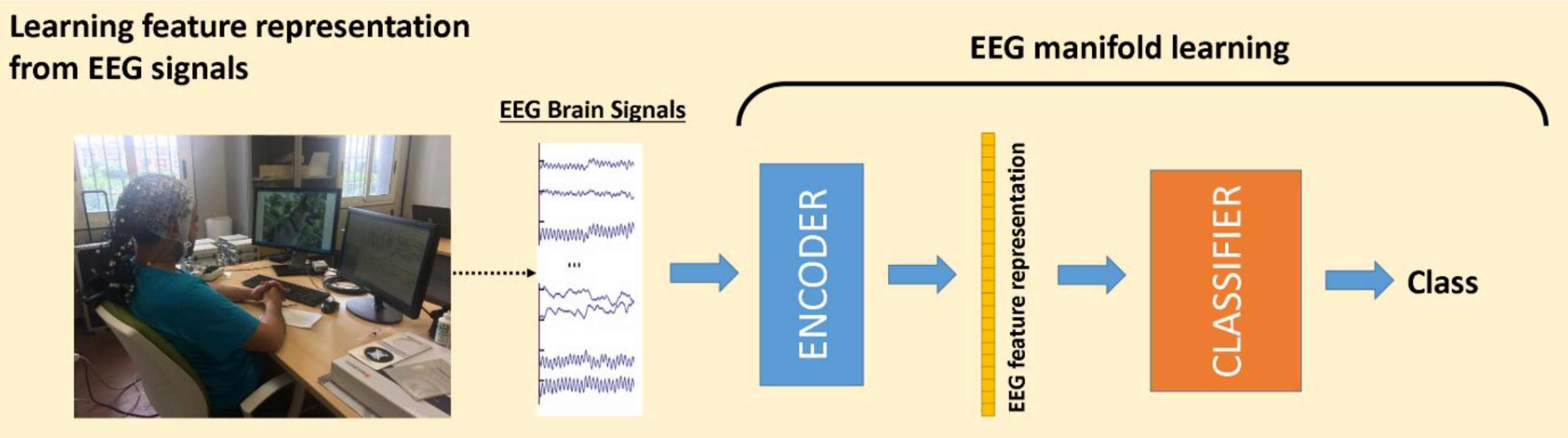
Related Works



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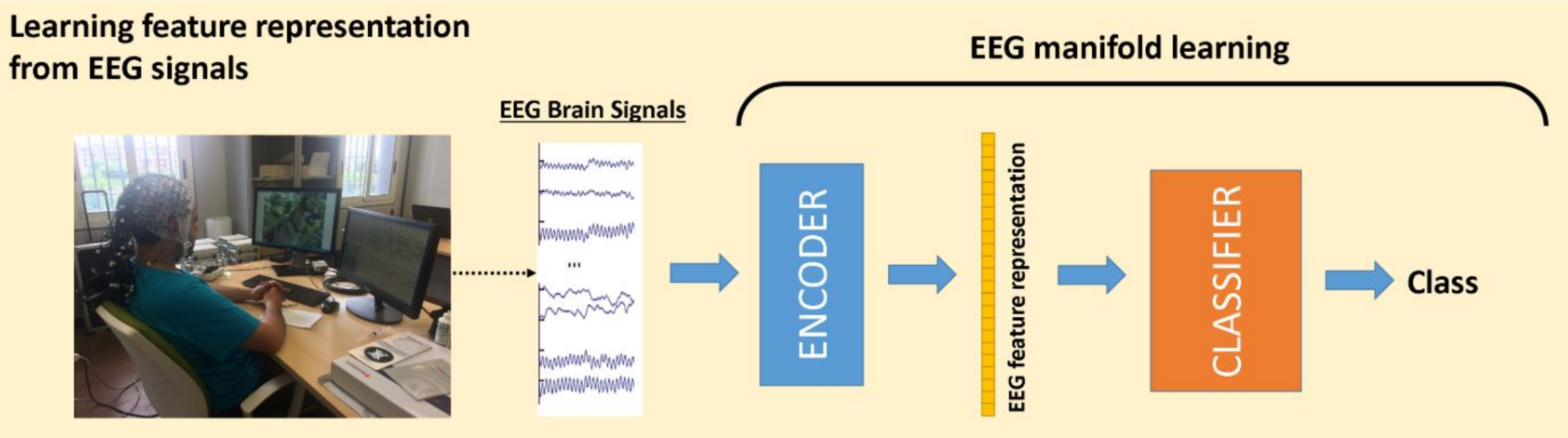

CVPR 2017 EEG-Imagenet40 Dataset

Number of classes	40
Number of images per class	50
Total number of images	2000

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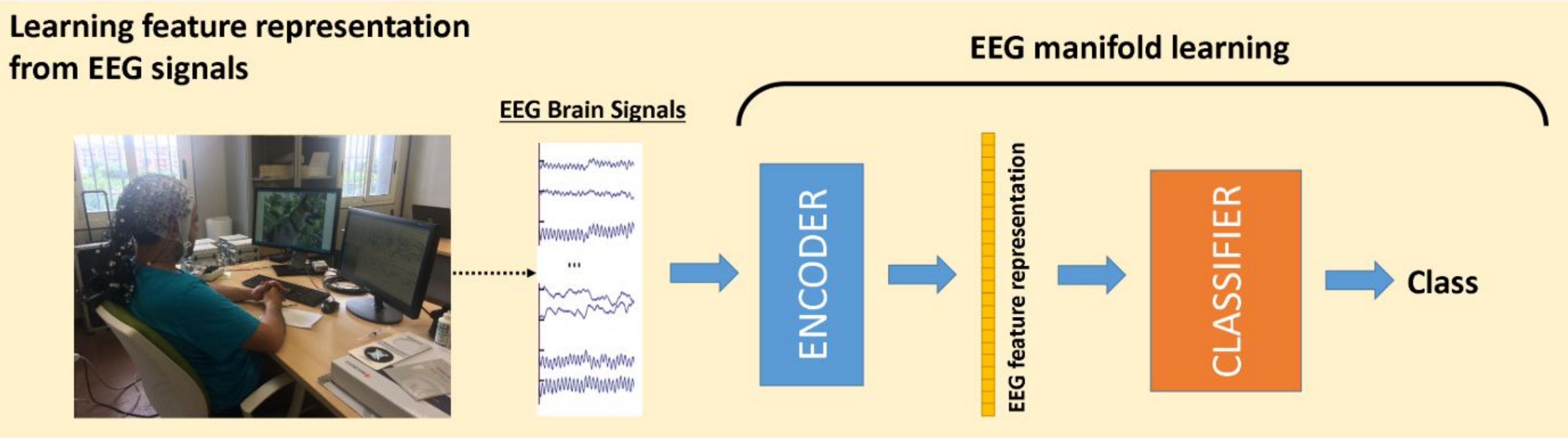

Total EEG Data ~ 12000 (6 Participants)

128 Channels
440 Timesteps

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EEG Classification

Model	Max VA	TA at max VA
LSTMs + nonlinear	86.1%	83.9%

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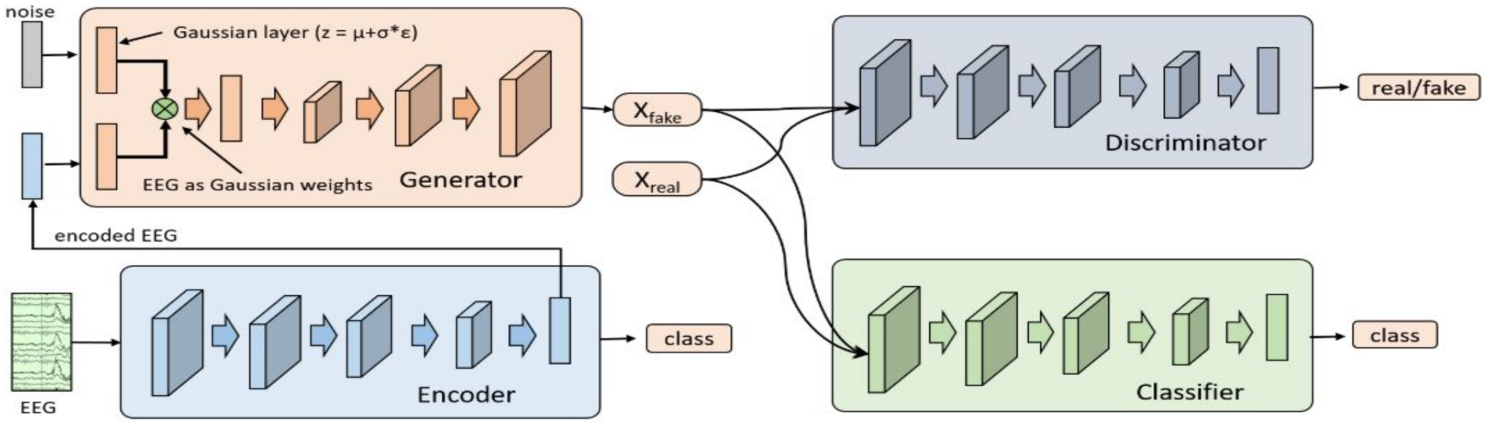

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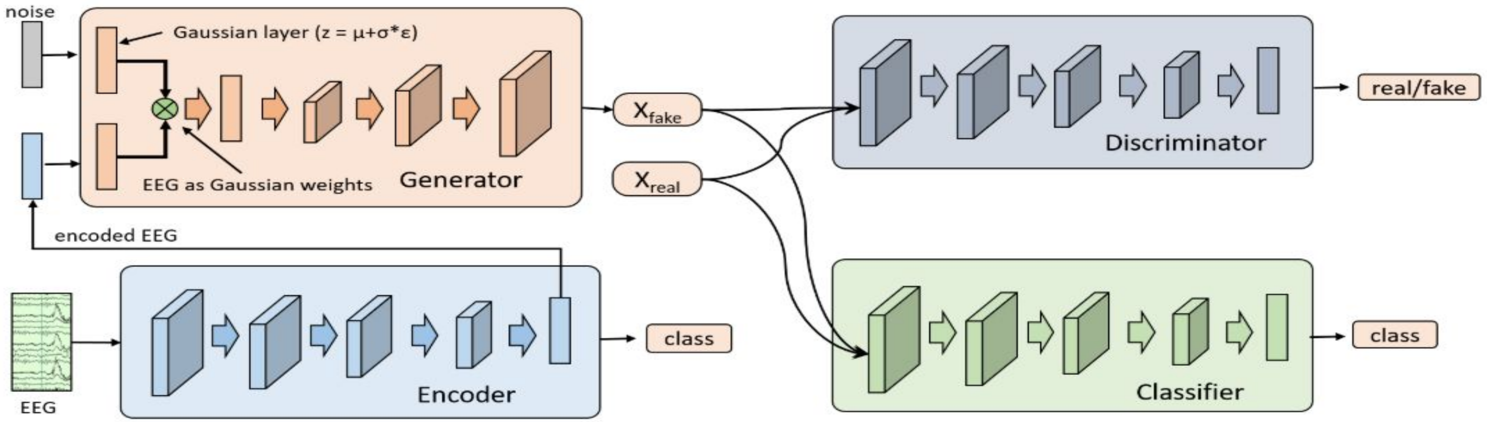

EEG-Object10 Dataset

Number of classes	10
Total number of Images	~850

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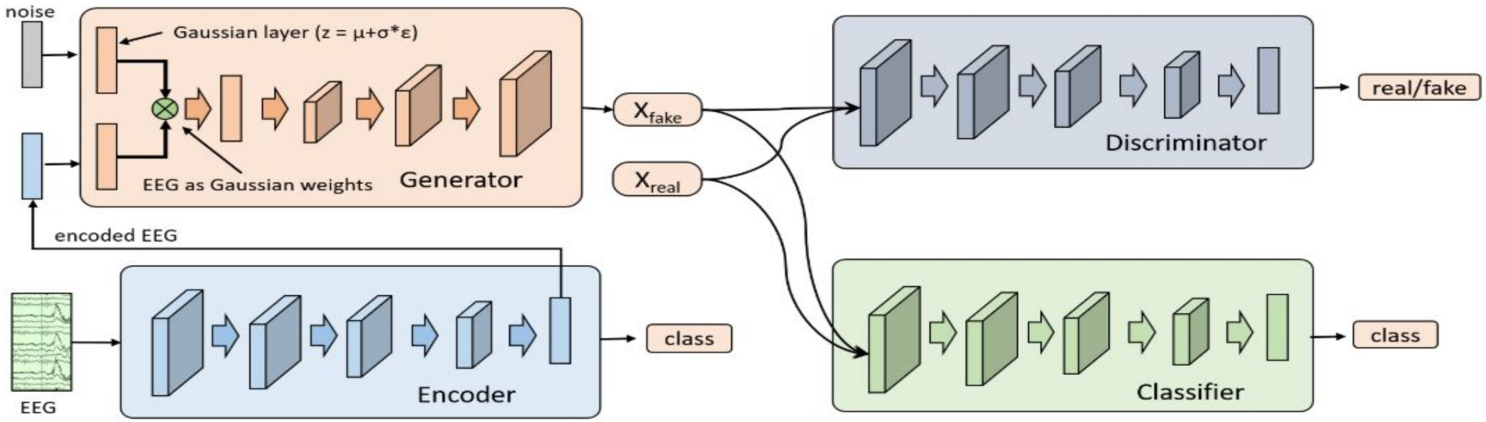

Total EEG Data ~ 230 (23 Participants)

14 Channels
32 Timesteps

EEG-Object10 Dataset

Number of classes	10
Total number of Images	~850

	Digits	Characters	Objects
Accuracy	72.88%	71.18%	72.95%

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Proposed Method

- How well contrastive loss works for EEG feature extraction?

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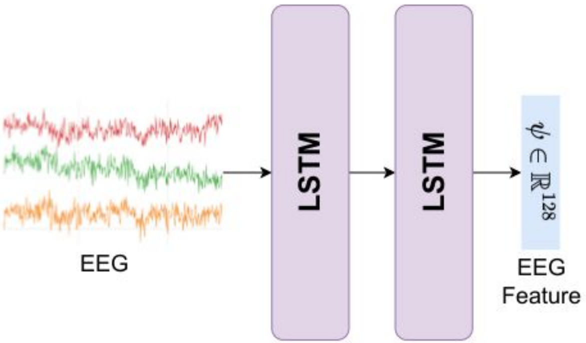

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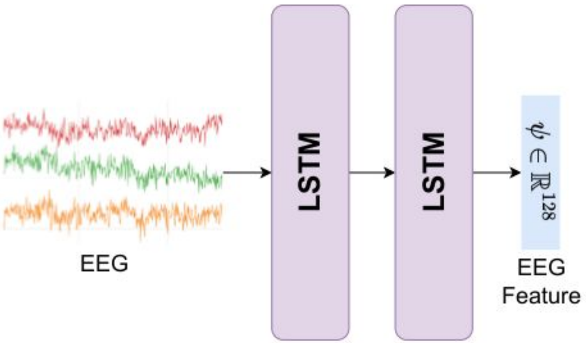

Triplet Loss

$$\min_{\theta} \mathbb{E}[||f_\theta(x^a) - f_\theta(x^p)||_2^2 - ||f_\theta(x^a) - f_\theta(x^n)||_2^2 + \beta]$$

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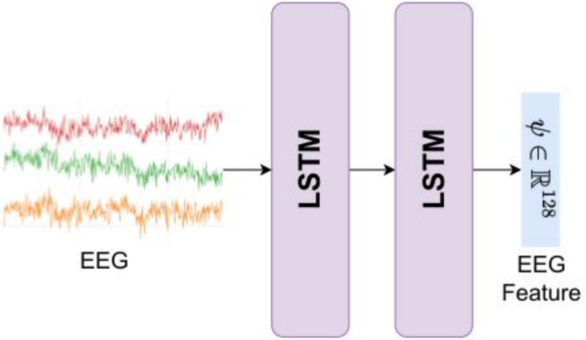

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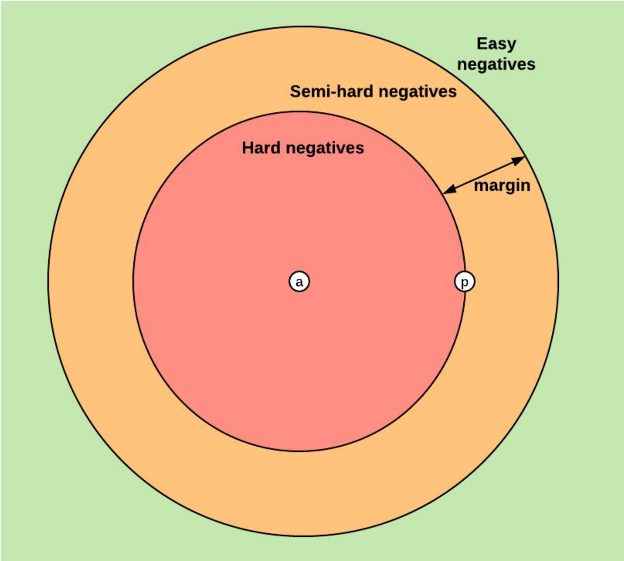
Semi-hard Triplets



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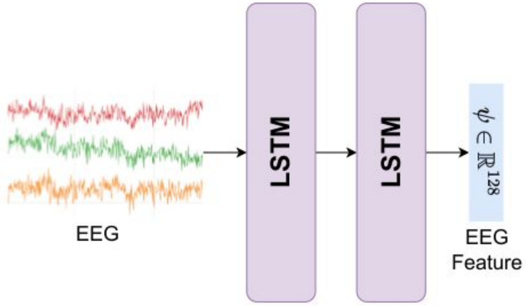

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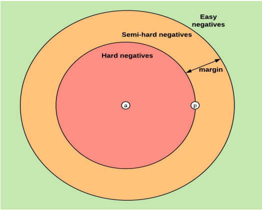

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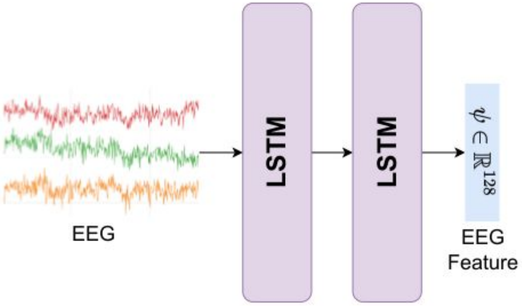

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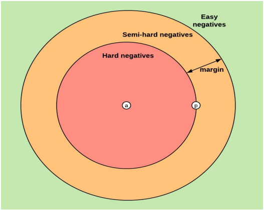

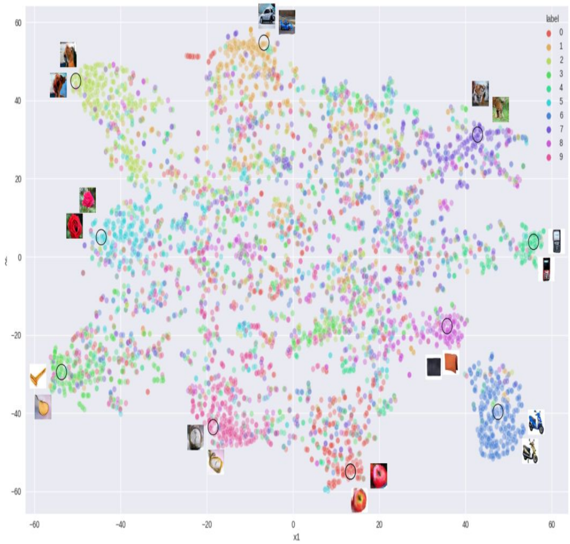

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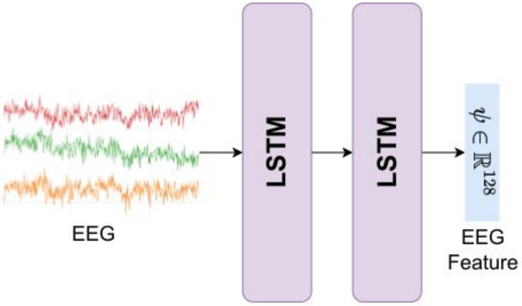

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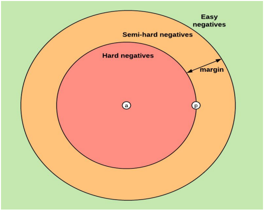

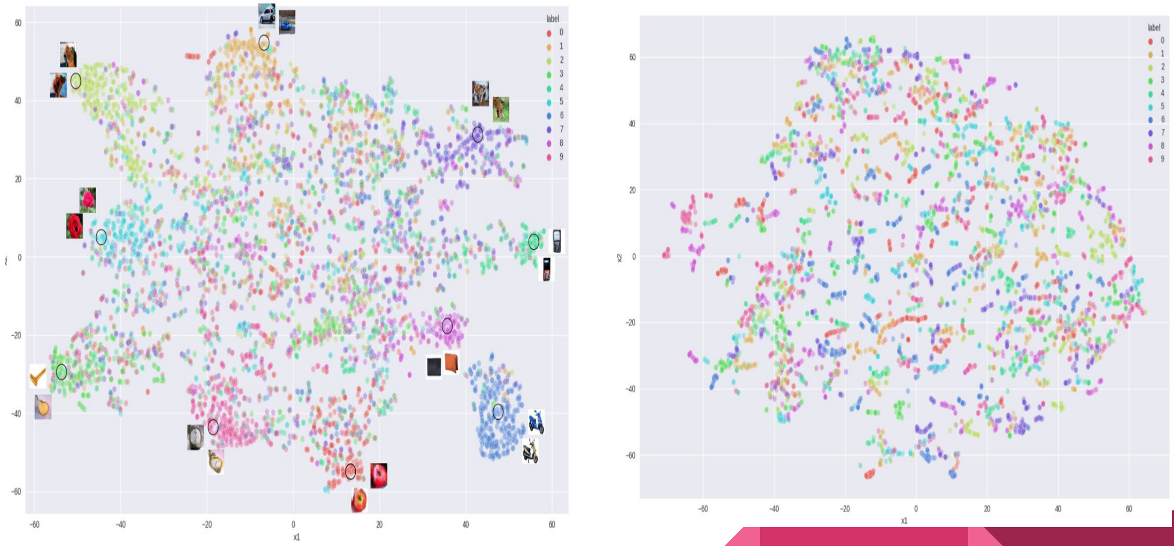

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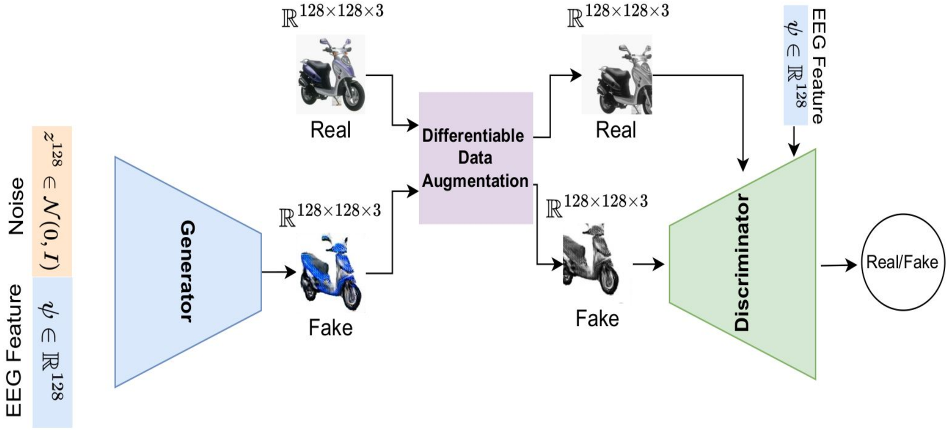

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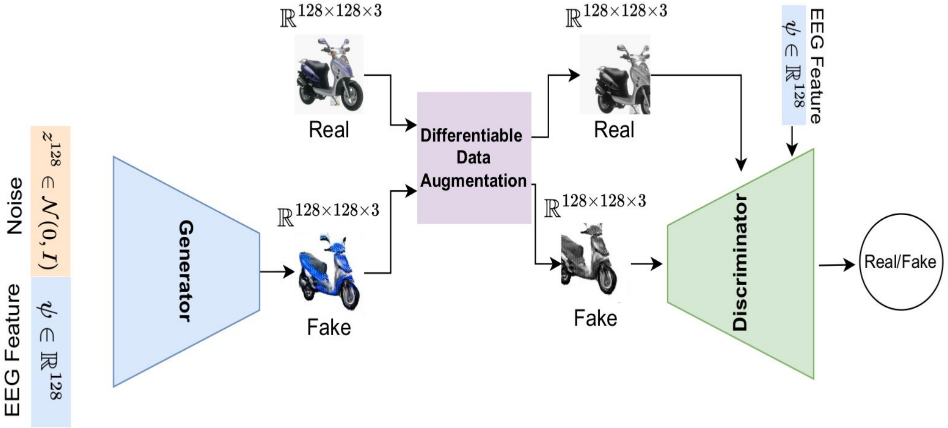


$$\mathcal{L}_D = \mathbb{E}_{(x,\psi)\sim p_{data}(x)}[max(0, 1 - D(T(x), \psi))] + \mathbb{E}_{x\sim p_{Z(z)}, \psi\sim p_{data}(x)}[max(0, 1 + D(T(G(z, \psi)), \psi))]$$

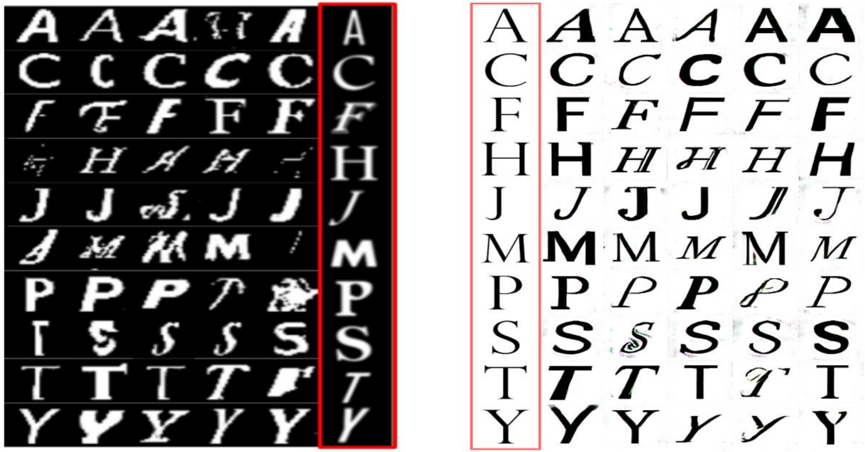
$$\mathcal{L}_{ms} = \min_G \left(\frac{d_I(G(\psi, z_1), G(\psi, z_2))}{d_z(z_1, z_2)} \right)^{-1}$$

$$\mathcal{L}_G = -\mathbb{E}_{x\sim p_{Z(z)}, \psi\sim p_{data}(x)}[D(T(G(z, \psi)), \psi)] + \alpha * \mathcal{L}_{ms}$$

[1] Zhao, S., Liu, Z., Lin, J., Zhu, J. Y., & Han, S. (2020). Differentiable augmentation for data-efficient gan training. Advances in Neural Information Processing Systems, 33, 7559-7570.
[2] Lim, J. H., & Ye, J. C. (2017). Geometric gan. arXiv preprint arXiv:1705.02894.
[3] Mao, Q., Lee, H. Y., Tseng, H. Y., Ma, S., & Yang, M. H. (2019). Mode seeking generative adversarial networks for diverse image synthesis. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 1429-1437).

Results: Qualitative

(a) ThoughtViz (b) EEG2Image (Ours)



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Results: Quantitative

Method	Inception Score
AC-GAN	4.93
ThoughtViz	5.43
EEG2Image (Ours)	**6.78**

Object Class	Apple (n07739125)	Car (n02958343)	Dog (n02084071)	Gold (n03445326)	Mobile (n02992529)	Rose (n12620196)	Scooter (n03791053)	Tiger (n02129604)	Wallet (n04548362)	Watch (n04555897)	All
Mean	6.09	6.15	6.99	6.98	7.33	5.44	5.81	5.67	6.48	6.67	6.78
SD	0.05	0.084	0.031	0.082	0.030	0.089	0.077	0.057	0.086	0.037	0.086

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[3] Odena, A., Olah, C., & Shlens, J. (2017, July). Conditional image synthesis with auxiliary classifier gans. In International conference on machine learning (pp. 2642-2651). PMLR.

Ablation Study

(a) no modeloss and dataaug, inception score 3.61.

(b) with modeloss and no dataaug, inception score 4.27.

(c) no modeloss and with dataaug, inception score 6.5.

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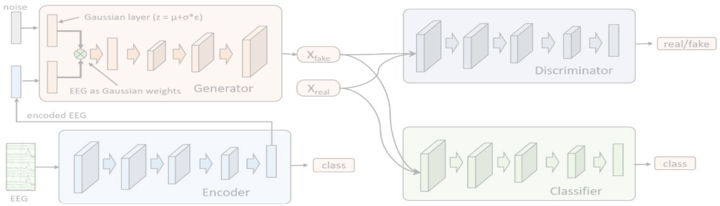
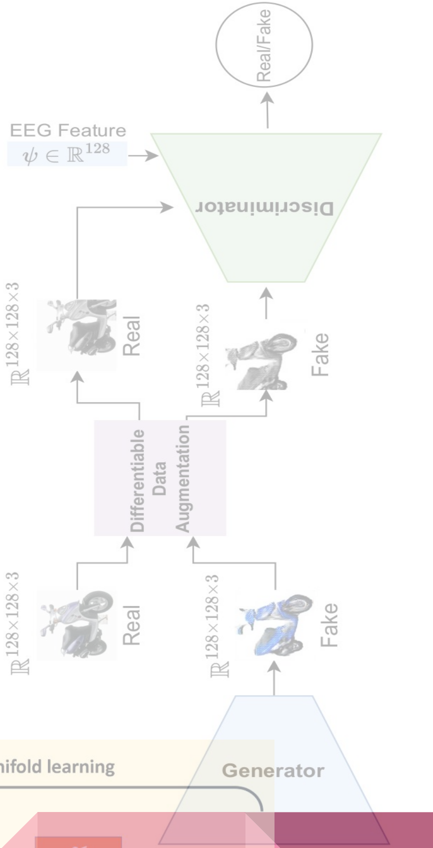
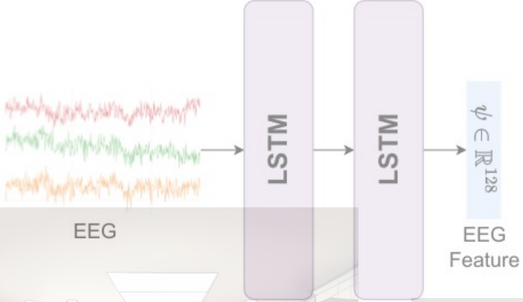
- We proposed a framework that uses a small-sized dataset for generating images from brain activity EEG signals.
- Our proposed framework has a better inception score than the previously proposed method for the small-sized EEG dataset and synthesized images of size 128×128.
- The framework consists of a contrastive learning approach to learn the good features of EEG data, which is empirically shown to perform better than the softmax-based supervised learning method.
- As future work, we plan to tackle large-size EEG datasets and approach for complete self/un-supervised learning for extracting features from EEG data and image synthesis.



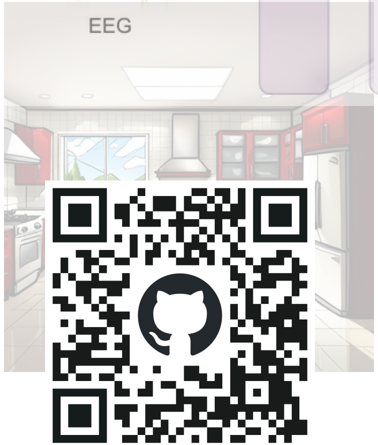
noise
Gaussian layer (z = μ+σ*ε)
EEG as Gaussian weights
Generator
encoded EEG
EEG
Encoder
class
Discriminator
real/fake
Classifier
class



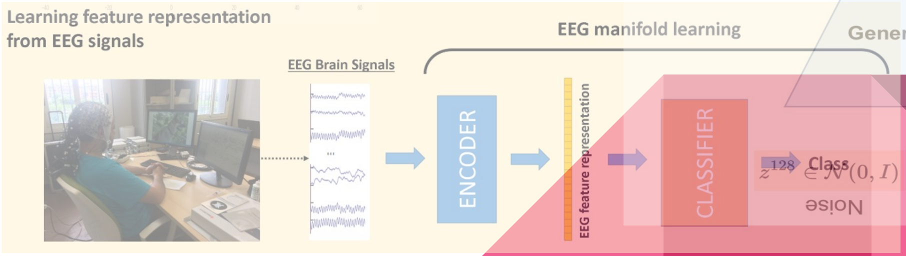
Real/Fake
EEG Feature
$\psi \in \mathbb{R}^{128}$
Discriminator
Real
Fake
Differentiable Data Augmentation
Real
Fake
Generator



EEG
LSTM
LSTM
$\psi \in \mathbb{R}^{128}$
EEG Feature



Thank You !



Learning feature representation from EEG signals
EEG Brain Signals
EEG manifold learning
ENCODER
EEG feature representation
CLASSIFIER
Class