

Synthetic EEG Data Generation for Bias Reduction in Motor Imagery Classification

There are currently more than 1 billion disabled people in the world. According to the World Health Organization (WHO) a disabled person is anyone who has “a problem in body function or structure, an activity limitation, has a difficulty in executing a task or action; with a participation restriction”. [WHO.Int](#)

• Problem

Our goal is to assist individuals with motor disabilities. We initiated a study to demonstrate that an EEG headset can identify when a person imagines moving right or left, without any physical arm or leg movements. We successfully showed that advanced AI techniques can accurately identify these mental states. Fig. 1 illustrates the system architecture.

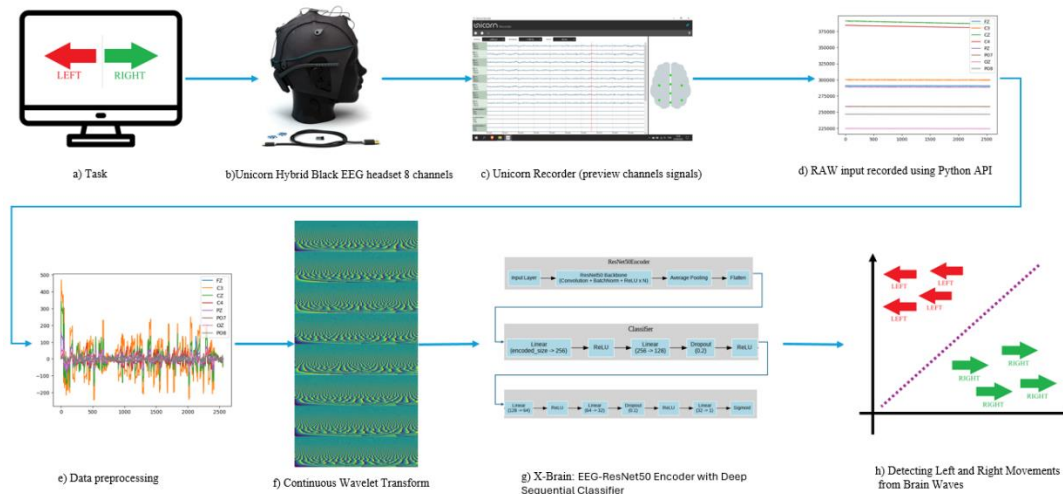


Fig. 1: X-BrainNet System with Unicorn Hybrid Black

• First Stage

In our initial study, data was collected from a single volunteer. We gathered 30 distinct samples for the left-pointing arrow stimuli and an equivalent 30 samples for the right-pointing arrow stimuli. Each sample represents 10 seconds recording of the volunteer imagining left or right movement. Although the dataset is limited, we aim to demonstrate that an innovative AI approach can effectively train a system for accurate classifications. We used the Unicorn Hybrid Black, an 8-channel wearable EEG headset.

Even if we successfully demonstrate that a model can be trained to identify binary motor imagery with high accuracy for one patient (88% accuracy on training and 76% on validation), the problem arises when using the same model on another patient. Individual differences in brain waves represent a challenge. We need a model general enough to be used by different individuals with minimal calibration, avoiding the need for retraining from scratch.

- **Second Stage**

For the second stage of our experiment, we utilized public data obtained from a more advanced EEG headset, EMOTIV EPOC+, with a 14-channel electroencephalogram (see Fig. 2). This device features a sampling frequency of 128 Hz and a 16-bit analog-to-digital converter, with electrodes positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. During each acquisition cycle, participants were shown images representing different voluntary motor actions: a right arrow for motor action to the right, a left arrow for motor action to the left, and a circle indicating no motor action. Using three distinct classes, rather than just two, enhances our ability to learn more detailed representations of brain activity and improves the differentiation between left and right motor actions. The dataset includes recordings from 4 different patients. As illustrated in Fig. 3, during the second experiment, we employed three distinct EEG states—left, right, and relaxation—using the advanced EMOTIV EPOC+ headset.

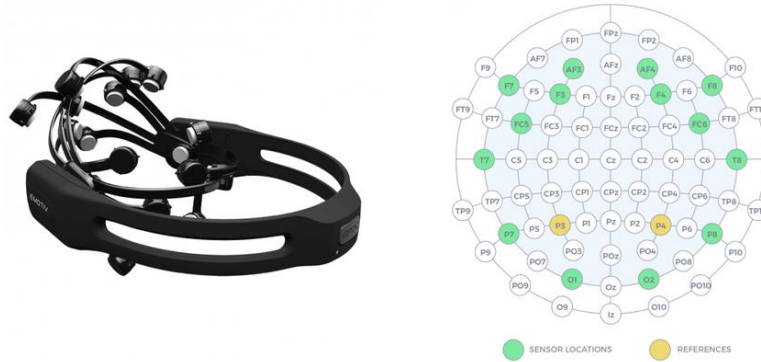


Fig. 2: Left: EMOTIV EPOC+ sensor; Right: its electrode arrangement on the 10-20 system (source: www.emotiv.com)

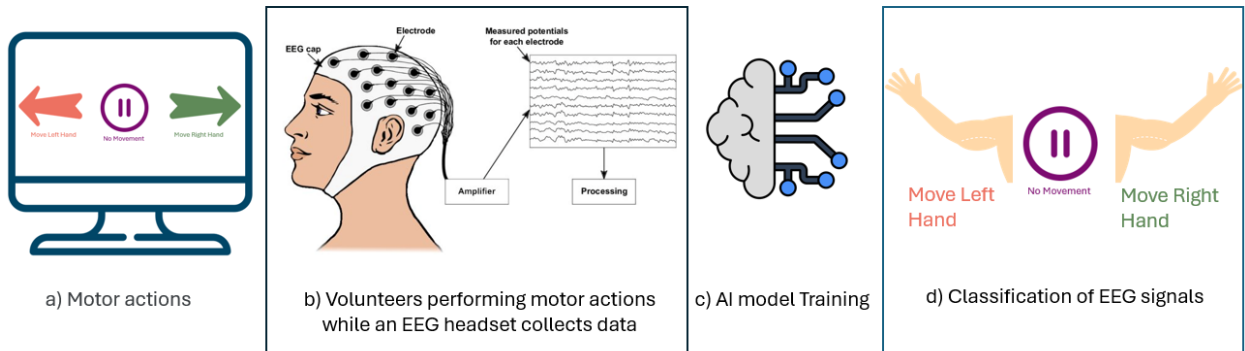


Fig. 3: Second Stage Experiment pipeline

Following our initial success with classifying brain waves using data from all 4 patients, with an 80%-20% training/validation split, the model is achieving an impressive accuracy of 98.41% on training and 96.69% on validation (see Fig. 4), we decided to refine our approach by training the model on only 3 patients and using the 4th patient exclusively for validation. While this setup performed admirably during training, with the same model achieving excellent results, the accuracy on the validation data from the 4th patient dropped significantly to 48-50% (see Fig. 5).

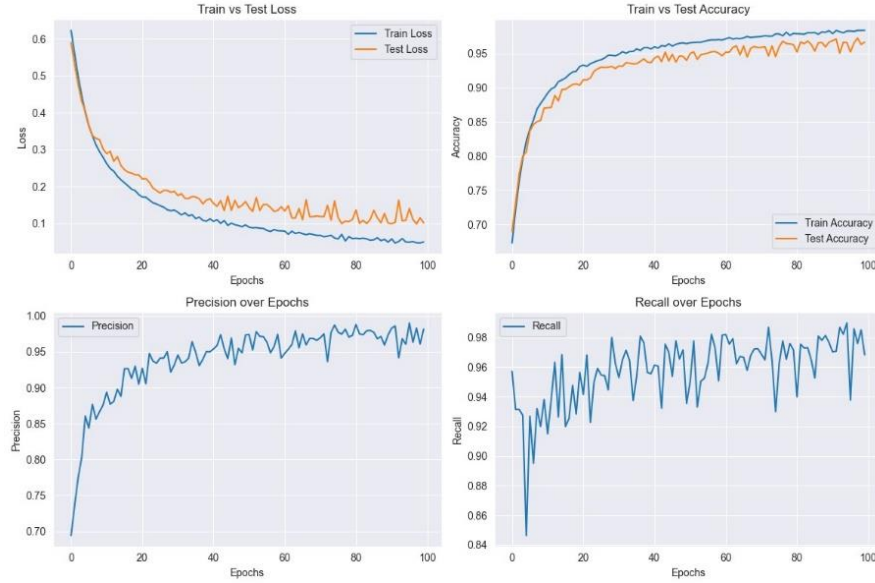


Fig. 4: Using all patients for training, and splitting 80-20% train/validation

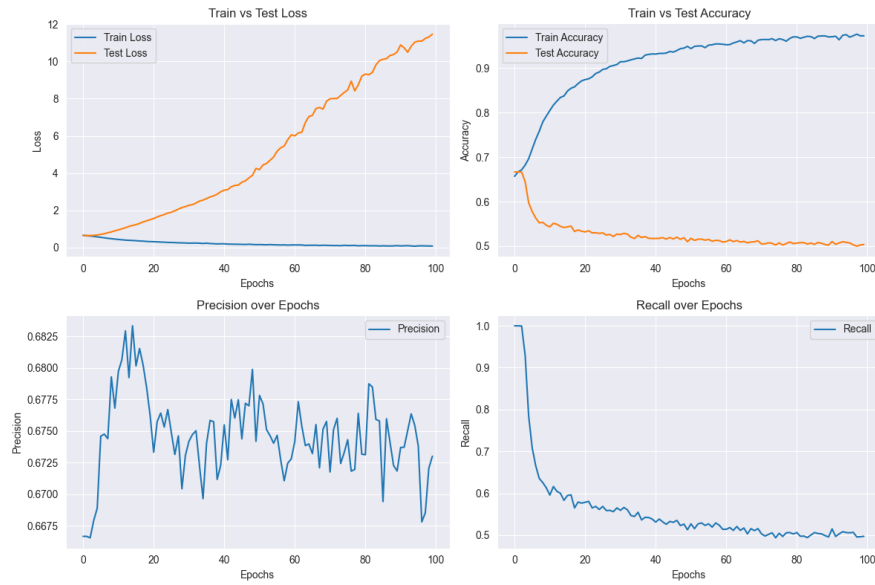


Fig. 5: Using 3 patients for training and the 4th for validation

This outcome aligns with our expectations, highlighting an issue: individual differences in brain activity. Each person's brain patterns are unique, and as a result, a model trained on a specific subset of individuals can struggle to generalize to new, unseen subjects. This variability raises significant concerns about the generalizability and potential biases of such systems. The challenges we observed underscore the importance of considering the demographic and health diversity of the training population. Systems trained on a specific group may exhibit biases that limit their effectiveness when applied to individuals outside this group. For instance, healthy individuals may perform poorly with older adults or those with neurological conditions. The results from our experiment emphasize the need for a broader and more representative training dataset to enhance the robustness and fairness of brain-computer interface technologies.

- **Synthetic EEG Data Generation**

A Variational Autoencoder (VAE) is a neural network model designed to encode input data into a compressed, probabilistic latent space and then decode this representation to reconstruct the original data. It consists of an encoder that outputs a distribution for the latent space and a decoder that reconstructs the data from samples in this latent space. The model is trained using a loss function that balances the accuracy of the reconstruction with the regularization of the latent space to approximate a standard normal distribution. After training, new synthetic data can be generated by sampling from the latent space distribution and passing these samples through the decoder. Refer to Fig. 6 for an overview of the X-Brain-VAE system and Fig. 7 for performance metrics using both real and synthetic data. Comparing Fig. 7 with Fig. 5 using synthetic data improved validation accuracy, reduced validation loss (from 12 to 3), and maintained stable precision.

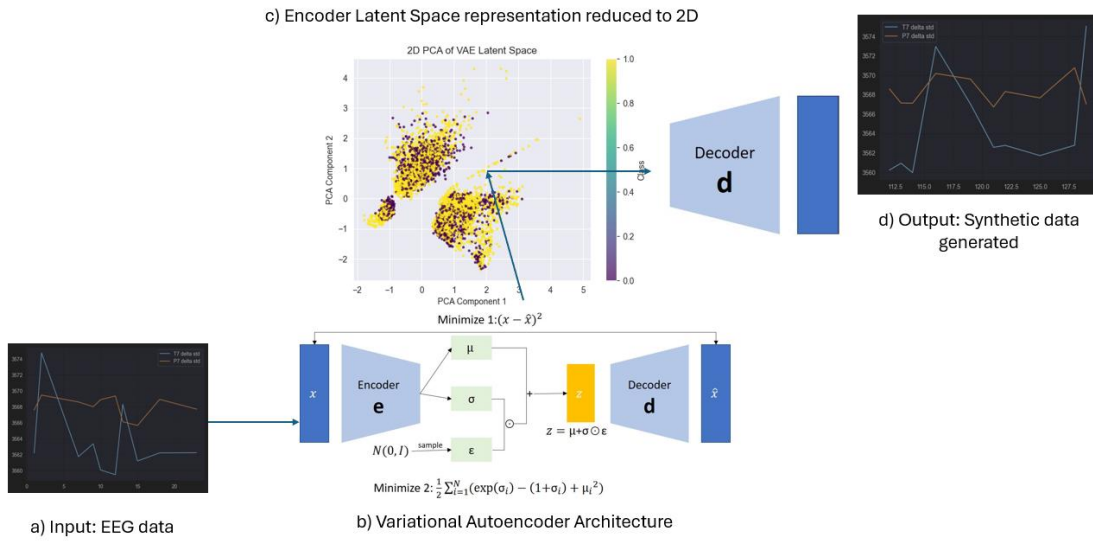


Fig. 6: X-Brain-VAE: **Synthetic EEG Data Generation using VAE**

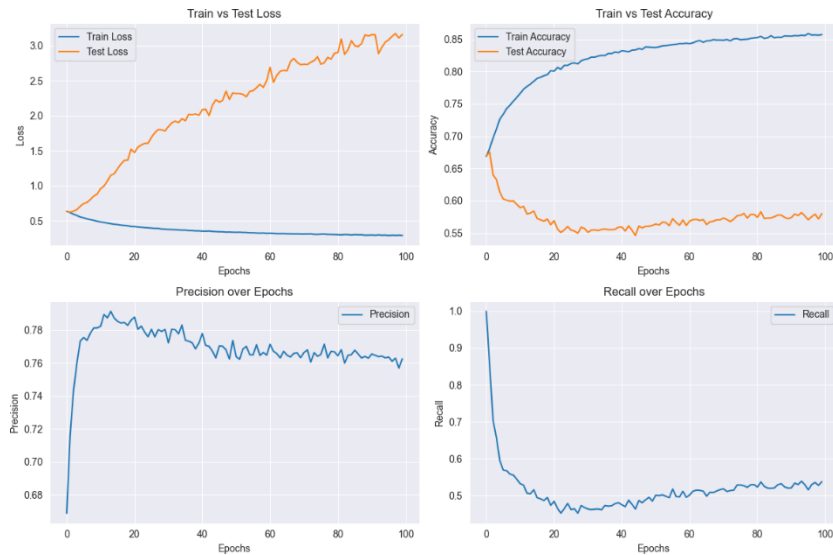


Fig. 7: Training with real and synthetic data and evaluation on real 4th patient

- **Potential Impact**

Generating synthetic EEG data plays an important role in addressing several key issues in neuroscience and healthcare technology. Here's a breakdown of its importance:

1. *Bias Reduction*

- Real-world EEG data may be limited in diversity, often reflecting the demographic and socio-economic characteristics of the populations from which it is collected. Synthetic EEG data can be generated to include a broader range of demographic variables, such as age, gender, ethnicity, and health status. This helps ensure that EEG-based technologies are more inclusive and effective across diverse populations.
- Machine learning algorithms trained on limited or non-representative data can develop biases, leading to less accurate or equitable outcomes. By incorporating synthetic data that better represents a variety of scenarios and populations, researchers and developers can train more robust algorithms that are less likely to be biased.

2. *Democratization of Technology*

- High-quality EEG data collection often requires expensive equipment and specialized expertise, which can be a barrier for many research groups and institutions, especially in lower-resource settings. Synthetic data can be generated at a lower cost and made widely available, allowing more researchers and organizations to develop and test EEG-based technologies.
- With synthetic data, researchers from different regions can collaborate more effectively. It can serve as a common ground for testing and validating EEG-based technologies, facilitating more inclusive research and innovation.

We identified several applications for the synthetic dataset generation framework:

1. Computer Mouse Control Using Brain Waves
2. Bionic Hands/ Legs Controlled Using Brain Waves
3. Brain Waves Signals Transformed into Speech