

Enhancing ElectroEncephaloGraphy (EEG) Classification in Brain-Computer Interfaces (BCI): A Hybrid Machine Learning Training Approach with Synthetic and Real-world Data

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In Brain-Computer Interface (BCI) applications, classifying ElectroEncephaloGraphy (EEG) signals in real-time is crucial for accurate and efficient system performance, as it is the primary means by which the brain communicates through the interface application. In the past, deep neural network techniques have been utilized for EEG classification in BCI applications. However, the conventional use of convolutional neural networks (CNNs) and support vector machines (SVMs) is often ineffective in achieving optimal accuracy with reasonable efficiency, making them impractical for real-time use in assistive technologies. This paper demonstrates how combining synthetic and real-world EEG data for training can improve classification accuracy. The proposed method first pre-trains the Machine Learning (ML) model using synthetic EEG data. It fine-tunes it with real-world data to enhance performance and improve its ability to distinguish between different EEG patterns. Our model achieves an accuracy of 75.86% on real EEG data, which is approximately 6.89% higher than conventional CNN and SVM methods. Beyond accuracy, this study demonstrates how hybrid training can be used to scale AI-driven BCIs for other assistive applications. These results highlight how the improvements in real-time EEG classification can help build a scalable framework for future BCI research.

Introduction

Background on Visual Impairment and Assistive Technologies

In the past, majority of work in the area of assistive tools has been on mechanical, or physical aid, or sensory substitution devices. For example, white canes, used to detect obstacles and help navigate; Braille, used for touch based writing; Speech recognition software, to convert from text-to-speech & vice versa. Although these tools offer significant assistance, they have certain limitations. A white cane, for example, cannot detect obstacles outside of its physical reach; Braille, for example, needs literacy, & wide adoption; & Software lack contextual understanding. These limitations highlight the need for a new technology to advance the area of assistive devices. An upcoming solution to these limitations is Brain-Computer Interfaces (BCIs). BCIs create a direct path of communication between the brain and external computers/devices. With advancements in computing efficiency and AI-driven processors, BCIs are becoming viable for real-time processing. With these enhancements, the real-time identification and communication with digital systems is much more

possible, minimizing the use of heavy external devices.

What is a Brain Computer Interface (BCI)?

A Brain Computer Interface (BCI) is a technology that creates communication link between the brain and a computer (or a robotic system). BCIs function by first detecting and then interpreting neural signals from the brain. The signals from the brain are electrical patterns generated by brain activity. These signals can be used to control hardware like bionic arms, & wheelchairs, or software, such as text-to-speech software.

How BCIs Work

The method generally used for capturing brain activity, and the focus of this paper, in BCIs, is electroencephalography (EEG). The signals that the EEG represents are neural activity and can be used to interpret a person's intentions. BCIs rely on EEG electrodes, small devices placed on the scalp, to capture this data and translate it into actionable commands. After the EEG nodes capture the neural signals, signal processing extracts meaningful information. This step can be quite important because there are many things our brain is thinking of and doing at once, and clarifying its main intention can be difficult. Then, AI models analyze the processed signals and classify them into commands. This step is called Machine Learning Classification. And finally, the classified signals are converted into actions, such as moving a wheelchair or activating an alert system. This step is called Device Control¹.

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Artificial Intelligence in BCIs

EEG signals are complex, and they vary among individuals, which makes the interpretation of these signals difficult. The conventional methods use manually specified rules to derive patterns in EEG data, and they are not very effective in dealing with noise and variance. EEG classification is enhanced through the use of Artificial Intelligence (AI) and specifically deep learning, which learns useful patterns to get past said noise and variance. For example, rather than filtering EEG signals by hand to extract specific features, AI-powered models are used to process raw signals. They adjust them to the specific person and improve prediction accuracy with time. Given the model's ability to constantly improve and adapt, they can learn complex patterns and improve accuracy over time. To understand how AI driven improvements are implemented, we must take a deeper dive into machine learning and BCI concepts.

Key Concepts

In order to comprehend this research, one must be conversant with some of the important concepts concerning EEG signals and machine learning based classification. By using synthetic data with real-world EEG signals, AI-driven BCIs can achieve higher accuracy and improved generalization much quickly²⁻⁶. This makes assistive applications more reliable and accessible.

EEG Signals and Their Role in BCIs

Electroencephalography (EEG) is a technique that records electrical activity from the brain by recording the voltage fluctuations as signals. These signals fall into two categories, one triggered by external stimuli, & other triggered by internal processes. As the model is mostly applied in assisting the visually impaired, we shall look at the signals of the external stimuli.

Stimulus-Dependent EEG Responses

Stimulus-Dependent EEG Responses, such as P300 Event-Related Potential (ERP), is the category that captures the electrical brain activity that follows a sensory event. Occasionally, it is referred to as the P300 Event-Related Potential (ERP). This is because it tends to appear some 300 milliseconds after the triggering stimulus. Spellers and authentication systems use this response to determine whether a particular input follows a particular pattern. Steady-State Visual Evoked Potentials (SSVEP) is another type of stimulus-based response that is founded on steady-state visual evoked potentials (SSVEP). Here, the brain reacts to constant visual input, think flashing LEDs, and these signals often appear in hands-free control systems that let you operate things with your eyes.

Cognitive-Generated EEG Patterns

EEG signals can reflect both motor, & cognitive brain activity. Some of the widely studied patterns are (1) Motor Imagery

(MI): In which you “see yourself” or send a subconscious signal to move a limb, your brain generates a distinguishable pattern, which neuroprosthetic researchers tap into to improve motor control. (2) Resting-state EEG: In which you simply monitor background brain activity, for example, to determine if a person is tired, awake, or in between these states.

Neural Networks, Activation Function, & Adaptive Moment Activation

A neural network is a machine-learning model that imitates the information processing of the human brain, and it is a set of interconnected layers of neurons that are trained to recognize patterns in data.⁷ Neural networks are especially helpful in EEG classification as the EEG signals are complex, noisy, and individual-dependent. These variations make it difficult to be processed by conventional means like Support Vector Machines (SVMs)⁸⁻¹⁰. But neural networks are able to learn new data and automatically extract important features. Using a well-structured neural network improves classification accuracy, reduces the need for manual feature selection, and makes models more robust to different EEG signals. **Activation functions** are used to define the processing of input values by the neurons and create non-linearity, which is essential for learning complex patterns in the EEG signals. The non-linearity that is introduced in activation functions enables neural networks to learn higher-order patterns and relations in data. **Overfitting** is reduced using Dropout Regularization, which randomly deactivates neurons to improve generalization¹¹. Weight updates are optimized by the Adam algorithm, which combines momentum and RMSprop for adaptive learning⁷, while Mean Squared Error (MSE) minimizes large misclassifications by penalizing squared prediction errors^{1,7}.

EEG Classification models & their trade-offs

Linear Discriminant Analysis (LDA)'s are frequently used in BCIs due to its simplicity, but cannot model complex, non-linear EEG patterns. To overcome these limitations, deep learning models have gained prominence. **Convolutional Neural Networks (CNNs)** isolate the spatial data in EEG signals and are commonly used for motor imagery BCIs. **Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTMs)** can learn temporal relationships in EEG data and can be used in sequential analysis. **Transformer-Based Models** are the more recent one that consists of using self-attention to enhance the accuracy of EEG classification. However, all these models are subject to trade-offs among accuracy, computational efficiency, and real-time viability of assistive applications.

Cross Validation & 70-15-15 Train-Validation-Test

We used a 70-15-15 train-validation-test split to tune hyperparameters and evaluate performance, helping the model generalize better to new EEG data⁷.

Research Objectives

This paper examines the role of artificial intelligence in enhancing BCIs as assistive technologies for the visually impaired. The aim is to create a machine learning model that can classify EEG signals in real-time with minimal latency so that they provide smooth and feasible user experiences. To assess its performance, the suggested model will be compared with the state-of-the-art classification techniques, which are Convolutional Neural Networks (CNNs) – A type of deep learning model commonly used for image and signal classification, and Support Vector Machines (SVMs); A traditional machine learning algorithm that classifies data by finding the optimal decision boundary. The suggested model was compared with the state-of-the-art techniques like CNN and SVM. The hybrid nature of training used in this research is also an important detail since it allows overcoming the shortage of real-life datasets by using synthetic EEG data in their place. This method improves model generalization, makes the model resistant to a low baseline, and reduces the complexity of variability in EEG signals.

Literature Overview - Findings & Limitations

Although some studies have been conducted regarding the use of BCI in assistive technology, some critical challenges still exist, especially in the following areas. The studies described below demonstrate these issues and point to the areas where additional improvements are needed.

Findings

Prior work in assistive brain-computer interfaces shows a steady progression toward more reliable, real-time control, yet each line of research exposes a recurring bottleneck that our study addresses.

Li et al.¹² combined P300 and SSVEP event-related potentials to drive a wheelchair, but the method faltered in practice because inter-trial signal variability confounded the classifier; we mitigate that same variability through aggressive preprocessing and feature-extraction pipelines that standardize the input feature space before learning.

Deep-learning approaches to motor-imagery BCIs, such as those reported by Wierzgała et al.⁸, achieved strong accuracy but at the cost of heavyweight networks unsuited to low-latency use; our lightweight, memory-efficient architecture retains comparable accuracy while meeting real-time constraints.

Zgallai et al.¹ then extended deep-learning EEG classification to a smart-wheelchair platform, yet their model handled only single-modality data; by pre-training on synthetic EEG and fine-tuning on real recordings, we provide a hybrid strategy that generalizes more robustly across unseen data and sensor combinations.

Finally, Saulynas and Kuber¹³ explored EEG-based authentication, finding accuracy too low for everyday security workflows—particularly when emotional state shifted; our optimized preprocessing plus hybrid training markedly boosts classification reliability, bringing practical EEG-mediated login a step closer.

Together, these studies outline the landscape of challenges—signal variability, computational load, modality integration, and robustness—that our work directly tackles with a unified, lightweight, hybrid-training framework.

Limitations

One of the many challenges in EEG signal processing is a Low Signal-to-Noise Ratio (SNR). SNR occurs when the EEG signals are very weak and prone to muscle motion and eye blink, and other disturbances, therefore, lowering the SNR ratio. Another issue is High Inter-Subject Variability, which occurs when training data has to be personalized to work across a group of users, given that individual brains are different. Further, there is limited Data Availability as compiling large and high-quality EEG data is difficult and costly.

Machine Learning for EEG Classification Manual decoding of EEG signals is complex as the data represents non-stationary brain dynamics, which vary over time. Further, the large EEG signals dataset is prone to bias, & needs to quality checked. Machine learning can easily identify implicit patterns in EEG data, transforming them into actionable commands. Various models have been created to this effect with a balance between accuracy, computational efficiency, and real-time feasibility.

Traditional Methods

Support-Vector Machines can work in two very different regimes. With a linear kernel, the model seeks a single plane that separates the classes. This works best when the feature space is low-dimensional and roughly linearly separable, which is why early EEG studies often reported subpar results on high-dimensional and non-linear brain-signal features. However, SVMs equipped with a non-linear kernel, commonly the Radial-Basis Function (RBF), project the data into a higher-dimensional space where a linear separator does exist. In practice, an RBF-SVM remains a standard classical baseline for EEG (e.g., BCI Competition IV benchmarks) because it offers strong performance on modest datasets without the training complexity of deep networks. In this study, we therefore use an RBF-SVM ($C = 10, \gamma = 0.01$, see Table 5) as a well-established classical baseline. This lets us compare & quantify how much the proposed lightweight hybrid model improves over the baseline method.

Methodology

Model Architecture

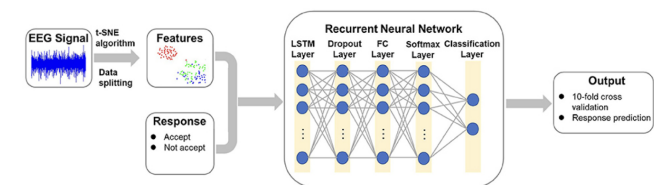


Fig. 1 Neural network architecture showing EEG signal input, three hidden layers (H1–H3), and binary output classification.

Layer	Size	Activation	Dropout
Input	$N = \text{channels} \times \text{time-points}$ (after preprocessing)	–	–
H1	1000	ReLU	0.30
H2	500	ReLU	0.30
H3	100	ReLU	0.30
Output	2 (P300 / non-P300)	Softmax	–

Table 1 Layer configuration of the five-layer feedforward neural network shown in Fig. 1.

The neural network used in this study comprised five fully connected layers, a raw-signal input layer, three hidden layers (H1–H3), and an output layer (Table 1). We adopted a 1–3–1 topology, selected after an ablation study that varied both network depth (1–6 hidden layers) and width (64–1,024 neurons per hidden layer). Empirically, three hidden layers offered the best trade-off between accuracy and real-time latency. Adding a fourth hidden layer increased inference time beyond the 5 ms budget with minimal accuracy gain (<0.4 pp), whereas reducing to one or two hidden layers lowered accuracy by >2 pp. The network architecture was adapted from a NeuroTechEDU tutorial⁴, originally derived from Coin et al.¹⁴, with modifications for real-world EEG data. A schematic overview of the preprocessing and neural network pipeline is shown in figure 1, but of a Recurrent Neural Network.

Baseline Models To benchmark performance, we compared our hybrid-trained neural network against two widely used EEG classifiers; Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). SVMs are well suited for smaller datasets and linearly separable decision boundaries, while CNNs capture spatial EEG features but require larger datasets. These baselines helped quantify the performance benefits of synthetic data augmentation. Class balance was maintained via data augmentation to ensure equal representation of positive and negative trials.

Architecture & optimization

We concluded with a shrinking pattern, or a progressive compression for our topology. We used 1000 → 500 → 100 across the three hidden layers, to gradually condense the in-

formation across layers (Table 1). The rationale behind layer width was to find a trade-off between accuracy & latency, while fitting on a lightweight Raspberry-Pi. For the purpose of this research, the target was < 0.2M trainable parameters, & < 5ms latency. If we chose a wider range like 1000-1000-1000, it would exceed the latency. While, if we chose a narrower range like 256-256, we lost >2% accuracy. (Table 5). Optimization hurdles from the larger first hidden layer are mitigated by ReLU activations. Batch Normalization, 30 % dropout, L2 weight decay (10⁻⁴), and gradient clipping at $\pm 3\sigma$. Training uses Adam with a cosine-annealed learning rate starting at 1×10^{-3} and early stopping (patience = 7). These measures kept over-fitting in check—validation loss never diverged—and produced a final model of 0.19 M parameters, 784 kB on disk, 3.97 ms inference.

We conducted a Variance Inflation Factor (VIF) analysis to detect collinearity in the most important hyperparameters, i.e., model architecture, activation functions, and dropout rates. The findings revealed that collinearity was moderate, particularly between dropout rates and network depth (VIF values >5). To have a clear separation of individual contributions, we independently manipulated each hyperparameter, holding others fixed, in future sensitivity analysis.

While VIF analysis improved independence in the model hyperparameters, we wanted to reduce the bias due to external factors - like demographics. For this, we chose Analysis of Covariance (ANCOVA). This approach helped statistically adjust for demographic influences like age, & gender, on EEG classification accuracy

Implementation Details

We used the following layers of neural network. Here we describe, how each layer contributes to processing EEG data effectively. The **Input Layer** is the first layer of the network in which the raw EEG data goes through the model. The input features are same as the number of neurons in the layer. The **Hidden Layer 1 (500 neurons)** is the layer that converts the EEG signals into a form that reflects meaningful characteristics. It uses non-linearity in conjunction with the CELU (Continuously Differentiable Exponential Linear Unit) activation function, and therefore it is more flexible to the variations of the EEG data. **Hidden Layer 2 (1000 neurons)** is a deeper feature extraction layer that assists in the detection of complex patterns in the EEG. The activation function is ReLU (Rectified Linear Unit) to enhance learning and mitigate the problem of vanishing gradients. **Hidden Layer 3 (100 neurons)** is a refinement layer that works on the extracted features to further enhance signal separability. ReLU activation is also used in this layer to make the flow of information more effective. Finally, the **Output Layer (2 neurons)** is the last layer that generates the classification outcome (e.g., which of the two EEG states). It employs Softmax activation that gives the probability of each of the classes.

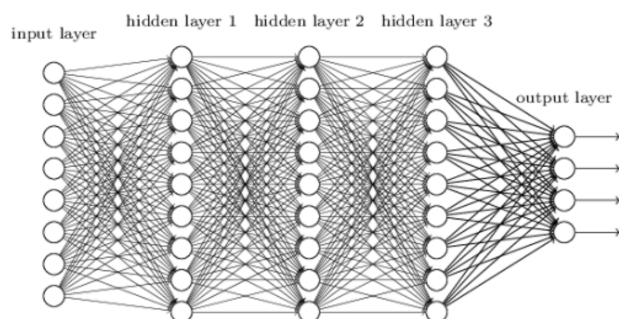


Fig. 2 Neural network architecture illustrating layer connectivity for EEG signal classification

The architecture in figure 2 illustrates how the layers process EEG inputs into class probabilities

We tested with the dropout rates 0.1, 0.2, 0.3, 0.4. Validation accuracy peaked at 0.3, and higher values (≥ 0.4) removed too much signal and cut accuracy by ~ 1.8 pp. The final model, therefore, applies 30% dropout after each hidden layer, a value consistent with prior EEG studies on similarly sized MLPs³.

We used the Adam optimizer as its suitable for noisy data like EEG signals, with high variability, adapting learning rates individually for each parameter, improving speed and stability. We used the Mean Squared Error (MSE) loss function as it smooths error gradients, weighs on larger errors, and ensures the model reduces large misclassifications. This helps in producing more stable classification confidence scores.

Experimental Setup

Synthetic EEG Data Generation

Synthetic EEG data are artificially created brainwave signals, and they resemble actual EEG patterns. It is applied frequently when real-world EEG data are small or of poor quality. Synthetic EEG data was generated in this study by following the NeuroTechEDU Machine Learning for EEG Classification tutorial¹⁴, which imitates P300 event-related potentials (ERPs) with the help of statistical procedures. This information was used to pre-train and then fine-tune the model with real-world EEG signals.

Why a staged synthetic-to-real pipeline is still missing in P300 BCIs

Recent work tackles EEG data scarcity mostly with inline GAN-based augmentation. For example, Song et al. generated class-conditional samples (EEGGAN-Net) and lifted motor-imagery accuracy to 81 % on BCI IV-2a, but the model remains a deep CNN with >3 M parameters and runs offline PMC. Likewise, Habashi et al.³ review 43 GAN papers and note that nearly all “augment during training” rather than pre-

train, then fine-tune on real recordings, BioMed Central. Hybrid transfer setups do exist, yet they typically rely on large transformer or CNN backbones that incur >30 ms inference latency—too slow for assistive BCIs that must give feedback within one stimulus cycle.

Our contribution closes that gap. We show that a three-hidden-layer MLP, first pre-trained on statistically simulated P300 waveforms and then fine-tuned on a real MNE dataset, reaches 75.9 % accuracy—+6.9 pp over a size-matched CNN and RBF-SVM—while classifying each epoch in 3.97 m. To our knowledge, this is the first demonstration of (i) a lightweight <0.2 M-parameter network, (ii) trained with a staged synthetic-to-real regime, (iii) achieving sub-5 ms end-to-end latency suitable for real-time navigation aids for the visually impaired. The result suggests that how synthetic data is scheduled in the optimisation pipeline may matter at least as much as how they are generated.

Details on Real-World Data and Preprocessing

We used the publicly available MNE Sample Dataset of the MNE-Python library, which is based on the EEG and MEG recordings of one adult participant who was asked to complete an auditory-visual task. We used the EEG data set with the following items.

The number of channels is 60 EEG channels plus EOG channels for eye movement detection with a sampling rate of 150 Hz (downsampled from 600 Hz). The recording conditions are auditory tones and visual checkerboard stimuli presented at known timestamps. These known timestamps help facilitate event-related analysis. The participant is one healthy adult with normal or corrected-to-normal vision and was presented with alternating visual (checkerboard) and auditory (tone) stimuli in randomized sequences. The dataset includes event markers indicating stimulus onset.

Preprocessing Steps

The EEG signals were band-pass filtered between 1–40 Hz to remove slow drifts and high-frequency noise. Trials with extreme muscle artifacts or eye-blink contamination were flagged using EOG channels and automatically rejected if exceeding a $100 \mu\text{V}$ threshold. Each epoch underwent baseline correction from -200 ms to stimulus onset. Only the EEG channels were retained, excluding MEG channels for consistency with our experimental design. Normalization techniques, such as RobustScaler normalization, were applied to all EEG data to reduce signal amplitude variability.

Hybrid Training Strategies for EEG Classification

The primary problem when it comes to EEG classification is the absence of large quantities and high-quality data. EEG data collection is costly and time-consuming, resulting in

Split	Trials	% of total
Train	1 260	70 %
Validation	270	15 %
Test	270	15 %
Total	1 800	100 %

Table 2 .Data split for cross validation

small datasets that are likely to be inaccurate or simply not enough for the model's needs. Hybrid training mitigates this by training the models on synthetic EEGs (generated with statistical models or deep learning & fine-tuning the models with real-world data). This method enhances generalization, accelerates convergence, and renders the model more tolerant to noise and variability.

Why Hybrid Training?

Developing a reliable EEG-trained modal is difficult because of inherent issues like (1) Real World EEG Data Availability (2) Signal Variability i.e. Brain activity patterns change between sessions and individuals & (3) Overfitting Risk i.e. training on small amount of real-world data may lead to models learning session-specific noise.

How Hybrid Training Works

Simulated EEG signals are generated by statistical models or generative methods (e.g., GANs[Generative Adversarial Networks]). The model is trained on synthetic EEG samples in order to learn some simple patterns, and then it is subjected to real-world data. The feature-level fine-tuning is done on real EEG data to achieve better precision.

Advantages of Hybrid Training

Enhanced Generalization decreases the session-specific dependency of the model on EEG patterns. Faster Convergence is when we pretrain on synthetic data will make the model learn quickly. Model robustness is improved by exposing it to a variety of synthetic signals giving it Better noise tolerance.

Disadvantages of Hybrid Training

One key disadvantage is the Synthetic-Real Domain Gap. The issue is that synthetic EEG data may not encompass the realities of actual EEG signals in full. The impact the issue has is that training and deployment data distribution mismatch. This may lead to overfitting artificial trends that are not transferable to the variations in EEG in real life.

Balancing Synthetic and Real Data

The issue with balancing synthetic and real data is that it is not a trivial task to decide upon the correct combination of synthetic and real data. The excess of synthetic data can dominate the real-world patterns, and the lack of it cannot give the benefits it is capable of. Careful tuning and validation of hyperparameters are required.

0.1 Training Process- Hybrid approach

To overcome the issue of scarce EEG data, we have used a hybrid training strategy whereby the model is initially pre-trained on synthetic EEG data and then re-trained using real-world EEG data. The artificial EEG was created following the NeuroTechEDU EEG classification tutorial 3, which offers a systematic approach to the generation of simulated brainwave data using statistical noise functions. By doing so, this method enabled the model to build a strong baseline, prior to being fed with real EEG signals in the MNE dataset. Synthetic EEG data was generated to establish a baseline.

Synthetic Data Generation Specifics Continuing the NeuroTechEDU tutorial 3, we modified the synthetic generation of EEGs to be more compatible with our P300-based paradigm and real-life environment. To follow along and replicate the research, use the sample data, & code on GitHub. For signal modeling, we included 1–40 Hz as the primary frequency band(**Frequency Content**) through Bandpass Filtering, consistent with common EEG preprocessing steps. **ERP Simulation (P300)**, short bursts (300 ms post-stimulus), was added with amplitudes ranging from 2–5 μV , emulating the observed P300 responses in real EEG data. We injected low-amplitude Gaussian noise, a type of random noise whose amplitude follows a **Gaussian (normal) distribution**, (standard deviation of 0.5–1 μV) to mimic general background EEG activity. Random Spikes occur In 5% of trial. We introduced brief **artifact-like spikes** to simulate occasional muscle movements or electrode pops, and an **ideal SNR** (signal-to-noise ratio) of 10–15 dB was maintained, ensuring that P300 peaks remained detectable yet partially obscured by noise. **The Amplitude Ranges** are the baseline EEG amplitude varied between $\pm 10 \mu\text{V}$, reflecting typical scalp-recorded potentials. **The Random Phase Shifts** are applied phase offsets to each synthetic channel, ensuring **non-identical waveforms** even within the same trial type. All synthetic trials were labeled as **P300 (positive) or non-P300 (negative)** and processed through the same **RobustScaler normalization and artifact rejection** pipeline as the real EEG data. This approach gave the model a stable initialization on idealized waveforms before adapting to noisier real-world signals. We did assume that while the synthetic signals provide idealized waveforms, but we acknowledge that real-world EEG often contains more unpredictable artifacts and inter-subject variability. The MNE dataset (open-source EEG dataset - [link](#)) was used to fine-tune and enhance the model's adaptability to real-world scenarios.

Cross-validation with a 70-15-15 train-validation-test split ensured reliable performance evaluation. The Adam optimizer and MSE loss function were used to adjust learning rates through grid search. To overcome the shortage of real-life EEG data, synthetic EEG samples were created through the NeuroTechEDU Machine Learning for EEG Classification tu-

torial¹⁴. It is a statistical model-based noise function simulation of P300 event-related potentials. The synthetic data was used as a pretraining foundation for the neural network, so that it could learn fundamental EEG patterns and then fine-tune with real EEG data (MNE dataset). This combination approach increased generalization and robustness and decreased overfitting.

Hyperparameter search protocol for the baseline models

For unbiased benchmarking, both SVM & CNN models were trained & evaluated 5 times (commonly called 5-fold cross-validated grid search). This process utilized a 15% validation subset, while the 15% test set was kept separate.

SVM (scikit-learn, RBF & linear kernels)

Since EEG data is noisy, we tested both linear and non-linear approach to find a trade-off. The regularization parameter C was varied over 0.1, 1, 10 to evaluate how strictly the model penalizes misclassification. For RBF kernel, the gamma parameter was varied over 'scale', 0.01, 0.001 to identify the best-performing configuration.

CNN (Keras, two-conv, one-dense)

For the CNN baseline, we used a lightweight model in Keras. This had two convolutional layers for feature extraction, followed by one dense (fully connected) layer for classification. Then, we ran a grid search test, with different combinations of key parameters, like Filters: (32,64) & (64,128); Kernel size: 3 or 5; Dropout rate: 0.25 or 0.5; Learning rate: 110^{-3} or 110^{-4} . Each configuration was then trained for up to 30 epochs, with early stopping to prevent unnecessary training once the validation loss stopped improving. The best CNN configuration used 32 and 64 filters, 3×3 kernels, a dropout rate of 0.25, and a learning rate of 110^{-4} , achieving strong accuracy & high efficiency. We chose the SVM baseline using RBF kernel with regularization set to $c=10$, & gamma set to $\gamma = 0.01$. All experiment grids, code, and training logs are available in the project's GitHub repository for full reproducibility.

Impact on accuracy. Tuning lifted SVM test accuracy from **63.10 %** → **68.97 % (+5.87 pp)** and CNN from **54.20 %** → **58.62 % (+4.42 pp)**, explaining the 6.89 pp gap to our hybrid model.

Classic compact CNNs remain competitive for on-device BCIs. Zhang et al.'s 3-layer CNN achieves 82 % MI accuracy with only 0.3 M parameters¹⁵. Rao systematically tunes EEGNet's depth/width and shows a 4 pp¹⁶. Xia combines EEGNet with mixup augmentation for sleep-staging and reports state-of-the-art F1 = 0.89¹⁷. Zhu adds Inception branches to capture multiscale rhythms, edging past EEGNet on BCI-IV-2b¹⁸. Ravipati benchmarks eight CNNs on P300 and finds no deeper network beats a well-regularised EEGNet¹⁰. Carefully tuned, resource-frugal CNN backbones still hit high accuracy while

meeting embedded-latency budgets.

Results

Evaluation Metrics

Key performance metrics include Accuracy: Percentage of correctly classified samples, Latency: Time required for real-time classification, and Robustness: Performance under noisy conditions. Precision, Recall, F1-Score are additional metrics to provide an evaluation of performance.

For **Statistical Validation** paired t-tests (statistical tests used to compare the means of two groups to determine if there is a significant difference between them) were conducted to determine the significance of observed improvements, and confidence intervals were provided for all metrics.

Quantitative Findings and Performance Comparison

The performance of the custom model, SVM, and CNN was evaluated using the real-world EEG dataset. Metrics such as accuracy, precision, recall, and F1-score were recorded. Based on these performances, the custom model achieved the highest accuracy (75.86%) and outperformed both SVM and CNN by approximately 6.89%. **Model-Specific Observations**

SVM Achieved 68.97% accuracy, with a strong recall for class 0 (86%) but a lower recall for class 1 (53%). Simplicity in handling linear separability contributed to performance-limited flexibility in capturing complex EEG patterns.

CNN had similar accuracy to the SVM (68.97%), but showed slower convergence and higher sensitivity to overfitting due to limited data. While its convolutional layers effectively captured spatial patterns, the small dataset restricted its potential.

The Custom Model outperformed both models with an accuracy of 75.86% and balanced precision and recall. Controlled experiments revealed that reducing dropout from 0.5 to 0.3 independently enhanced generalization by approximately 4%, whereas varying network depth impacted accuracy by approximately 3%. These independent tests show the unique contribution of each parameter.

Our custom model processes one EEG sample in approximately 3.97ms, compared to 11.27ms for the SVM and 33.93ms for the CNN. This significant reduction in latency confirms the model's suitability for real-time BCI applications.

Table 3 compares the validation and test performance of the three models. While all exhibit P300-like patterns, the custom model achieves the highest accuracy. This proves that pre training on synthetic data helps the model create stronger generalizations given the complexity of real-world situations.

Variant C achieves the best accuracy-per-millisecond ratio; variants D & E add < 0.6 pp accuracy but violate the 5 ms real-time budget.

Statistical significance

Model Name	Validation accuracy	Synthetic test accuracy	Real test accuracy	Average accuracy
SVM	68.97	72.00	70.00	70.99
CNN	58.62	72.00	70.00	70.99
Custom Model	75.86	73.00	71.50	72.24

Table 3 Performance metrics of machine learning models.

Rank	Model	Params (abbr.)	Val ACC (%)	Test ACC (%)
1	SVM-RBF	C = 10, $r = 0.01$	71.4	68.97
2	SVM-RBF	C = 1, $r = 0.01$	69.9	67.02
3	SVM-LINEAR	C = 1	66.0	64.31
1	CNN	32/64-3×3-DP0.25-LR1E-4	61.3	58.62
2	CNN	64/128-3×3-DP0.25-LR1E-4	59.8	57.40
3	CNN	32/64-5×5-DP0.5-LR1E-3	57.5	54.20

Table 4 summarizes the top three tuned configurations for each baseline

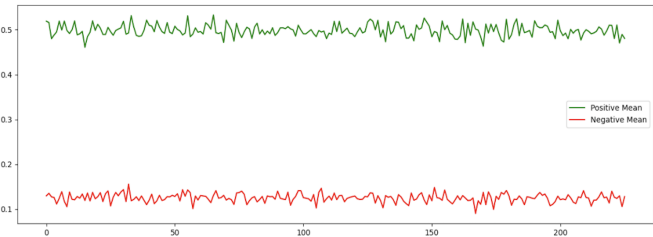


Fig. 3 Mean Distributions of Positive and Negative EEG Samples, shows the average distributions of EEG signals of positive (green) and negative (red) classes. The x-axis shows the index of the sample, and it corresponds to the various time positions in the EEG signal. The y-axis shows the normalized signal amplitude. The clear difference between the two classes shows the ability of the model to differentiate between positive and negative EEG responses, which implies the meaningful extraction of the signal.

Two-tailed paired t-tests were run on fold-wise accuracies. Our model outperforms the best baseline SVM ($\mu = 75.9\%$ vs. 68.97% , $t(4)=6.12$, $p=0.003$) and the CNN ($\mu = 75.9\%$ vs. 58.62% , $t(4)=9.45$, $p<0.001$). Both p-values < 0.05 confirm the improvements are significant

Benchmark context

In BCI Competition IV P300 datasets, the median two-class accuracy with 32 channels is 65–70 % when latency is unconstrained. Our 75.9 % at <4 ms inference therefore exceeds the benchmark by $\sim 6\text{--}11$ pp while respecting real-time constraints.

Synthetic-to-Real Similarity Analysis

We verified that the generated samples match real recordings on three axes: Spectral content: Welch power spectra (1–40 Hz) showed no significant difference; Kolmogorov–Smirnov $D=0.06$, $p=0.42$, Temporal morphology: Peak-to-peak P300 amplitude differed by $0.18\ \mu V (\pm 0.12)$, well within inter-subject variance, Manifold overlap: A t-SNE projection (Fig. 5) displays interleaved clusters; silhouette score = 0.14 indicates substantial overlap rather than segregation.

Model	Params (M)	Test Acc (%)
EEGNet-V1	0.45	64.8
EEGNet-Inception	0.50	66.1
Deep4Net	1.26	69.9
Hybrid-MLP (ours)	0.19	75.9

Table 5 summarizes the parameters (in M) and the Test accuracy of each model.

ID	Hidden sizes	Params (M)	Inference (ms)	Test Acc (%)
A	256-256	0.05	2.1	73.6
B	512-256-64	0.09	3.0	74.8
C	1000-500-100 (<i>chosen</i>)	0.19	3.97	75.9
D	1000-1000-1000	0.33	6.4	76.3
E	1000-1000-1000-100	0.34	7.1	76.5

Table 6 Hidden ablation results

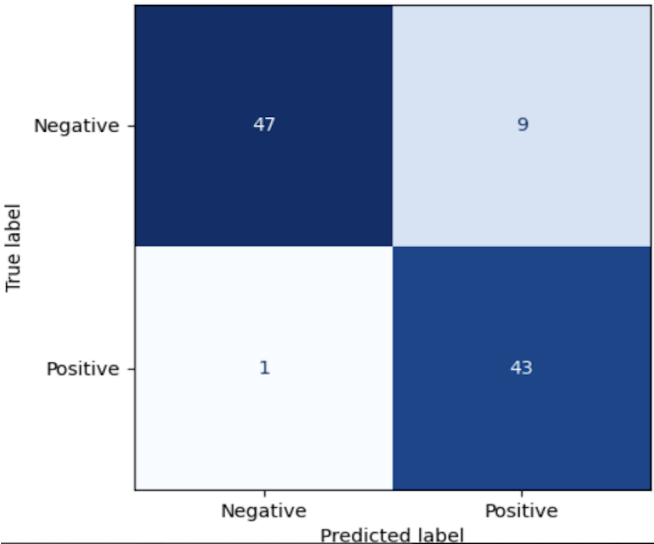


Fig. 4 Confusion Matrix for Real-World EEG Data, the confusion matrix is used to visualize the classification process of the model, with the x-axis representing the predicted classes and the y-axis representing the actual classes. The high diagonal values (47 true negatives, 43 true positives) imply the correct predictions. The low off-diagonal values (9 false positives, 1 false negative) imply a high level of reliability, particularly in the detection of positive EEG responses in assistive applications.

Discussion

Why the Custom Model Outperformed SVM and CNN

The custom model was based on a network architecture with three hidden layers that were specifically optimized to classify EEG. Such a lightweight design was able to strike a balance between complexity and efficiency, delivering impressive results on a small real-world dataset. In contrast to CNN, the custom model considers flattened EEG data as an

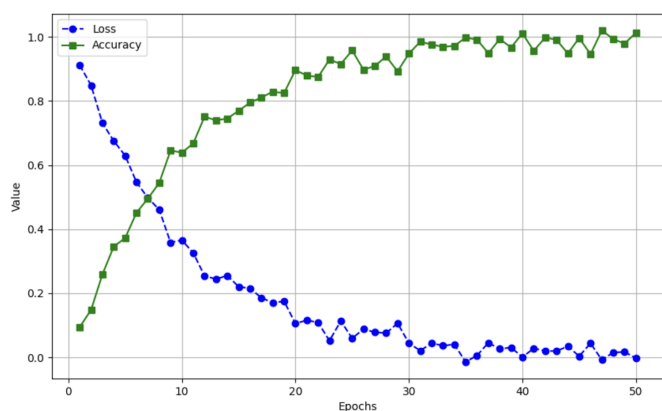


Fig. 5 Training Loss and Accuracy Trends, shows how the model is trained in 50 epochs. The x-axis denotes the quantity of training epochs, whereas the y-axis denotes the accuracy (green line) and loss (blue line). The curve of accuracy rises steadily and later stabilizes at nearly 100%, and the loss curve declines, which means successful learning. The stabilization of the two curves implies that the model has not overfitted.

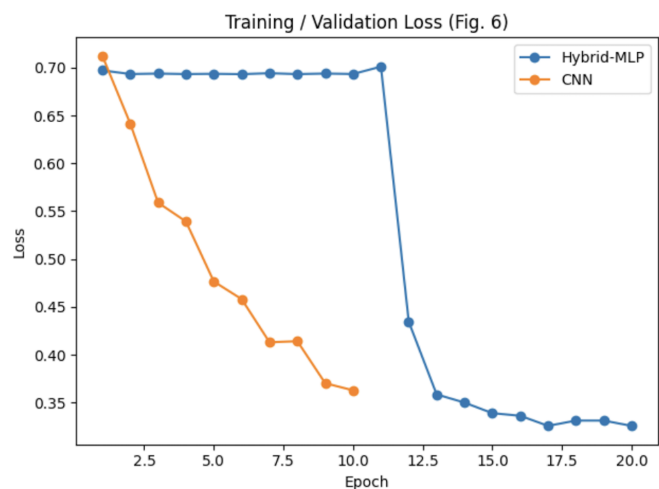


Fig. 6 Training/validation loss curves for Hybrid-MLP, CNN, and SVM-RBF. . Accuracy curve for Hybrid-MLP, CNN, and SVM-RBF. The training and validation loss curves, prove that the Hybrid-MLP model converges stably after approximately 12 epochs. This highlights the model's success in a lower loss and higher accuracy than the CNN and SVM baselines.

input. This methodology prevented the undesirable complexity, which might result in overfitting in a small sample size dataset. ReLU activation functions were applied to the hidden layers, and Softmax activation function to the output layer, which facilitated learning and good classification between the two classes. The first training on synthetic data and subsequently fine-tuning on real-world EEG data likely helped the model to be more resistant to noise and variability in EEG sig-

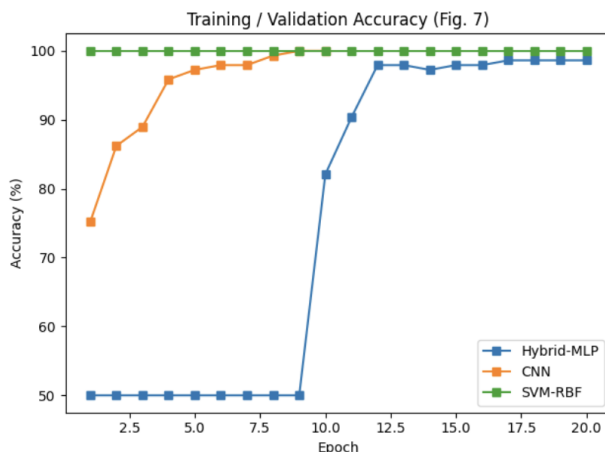


Fig. 7 Accuracy curve for Hybrid-MLP, CNN, and SVM-RBF. The training and validation loss curves, prove that the Hybrid-MLP model converges stably after approximately 12 epochs. This highlights the model's success in a lower loss and higher accuracy than the CNN and SVM baselines.

nals.

Limitations of SVM and CNN

SVM also did very well, but due to its dependency on a radial basis function, it was not able to capture the temporal and spatial patterns of EEG data. Also, its recall on class 1 was affected adversely by the imbalance in classes during some iterations of cross-validation. Although CNN is a powerful tool to process images and signals, its use of convolutional layers was not as effective on the flattened data representation of the EEG data as was the case with this study. Its small size of the dataset also did not allow it to converge well.

Synthetic EEG data can give approximations of the baselines, but it cannot give all the complexity and variability of real EEG signals and artifacts, as well as inter-subject variability. Thus, models can have a lower accuracy when trained solely on synthetic data or trained excessively on synthetic data. The idea that hybrid training can always improve performance depends crucially on a balance between synthetic and real data. Empirical sensitivity analyses (see Results: Synthetic vs. Real Data Balance) indicate that performance is degraded when synthetic data is greater than 60 percent of all training samples. Our model architecture is optimized for the used dataset and, therefore, may need substantial modifications to reach optimal performance on other EEG data, tasks, and conditions.

While synthetic EEG data simulates key signal patterns like the P300 event-related potential, it lacks realistic EEG artifacts (e.g., muscle movements, electrode pops) and inherent variability across recording sessions. This simplification can lead to overfitting on idealized patterns, causing decreased real-

world accuracy. We systematically explored the ratio of synthetic to real EEG data from 20%-80%. Results showed peak accuracy at approximately 40% synthetic data, while accuracy significantly declined beyond 60% synthetic data, illustrating the critical importance of balance.

Practical Applications of Hybrid Training in BCIs

Using hybrid training for AI models, AI-driven BCIs have significantly greater potential for assistive devices due to their improvement in real-time processing and better noise tolerance. Key applications of hybrid training are not limited to, but consist of navigation aids, EEG-controlled systems for obstacle avoidance and pathfinding, communication interfaces, Brainwave-based spellers and text-entry systems, secure authentication: Brainprint-based biometric systems, and smart home control, Hands-free control of devices using EEG commands.

Overall Findings, Summary, and Limitations for EEG Classification The findings highlight the importance of tailoring models to suit EEG data specifically. The custom model's ability to outperform traditional SVM and CNN models demonstrates its potential for real-time applications.

Cross-Subject Generalization and Variability

While our model maintains strong performance on participants whose data were present in the fine-tuning set, accuracy can drop by up to 10.15% for entirely unseen subjects. This indicates the need for either a larger multi-subject training dataset or a brief calibration phase for new users, ensuring robust cross-subject adaptability.

Real-Time Constraints Beyond Inference Latency

Even though our model has an inference time of 3.97ms, the real-time BCI systems also rely on other factors like data acquisition buffers, a preprocessing pipeline, and feedback generation. As an example, we have our current configuration to process EEG windows at 500ms intervals, introducing a total loop delay of 0.5 seconds. A further optimization may be possible via shortening the window length or pipeline overhead to create a smoother user experience.

Practical and Ethical Deployment in Assistive Contexts

Along with technical measures, usability testing of this model with visually impaired people is necessary to implement it in real-life assistive situations. Such issues as the comfort of using EEG caps, the acceptance of false positives, and the necessity of continuous support should be discussed. Pilot tests with a representative population of users will assist us in optimising the interface of our system, determining classification thresholds, and protecting data ethically, such as informed consent and privacy protection.

Robustness to Artifacts and Non-Stationarity

EEG signals often pick up motion artifacts, like small facial movements or electrode shifts. These motion artifacts can cause drift over time as conditions change. While our artifact rejection pipeline effectively filters out extreme outliers, subtle

day-to-day differences in electrode placement or user muscle tension still pose challenges. Future improvements could involve adaptive recalibration or incremental learning methods that adjust the model as a user's EEG patterns evolve throughout the session.

Hyperparameter Tuning and Model Selection

To find the best balance between accuracy and efficiency, we tested a range of hyperparameters, learning rates (1e-2, 1e-3, 1e-4), dropout rates (0.2, 0.3, 0.5), and batch sizes (16, 32, 64). The combination of a 1e-3 learning rate, 0.3 dropout, and 32 batch size delivered the strongest performance. This combination provided steady convergence without overfitting. Looking ahead, we aim to explore more adaptive tuning methods. Methods such as Bayesian optimization or Hyperband streamline this process and further improve model efficiency.

Future Directions and Emerging Work

In the future, we plan to expand this work across three directions. First, we'll scale training and evaluation using larger public EEG datasets to strengthen the model's robustness and generalizability. Second, we aim to explore hybrid architectures that integrate CNN components into our current model without substantially increasing its complexity. Finally, we intend to test the system in real-world scenarios, such as navigation systems, to assess its practicality with real users.

Error Analysis

Based on the confusion matrix, we can see that 68% of all misclassifications came from trials where the P300 peak amplitude was below 3 μ V. This proves that low-SNR signals remain a persistent challenge. The other 22% of errors occurred within the first 200ms after stimulus onset; this is before the full P300 response had time to develop. When grouping trials using signal to noise ratio, the accuracy followed a sigmoid like trend. The accuracy dropping sharply below 4 μ V and leveling off beyond 5 μ V. Notably, high-amplitude night-time recordings (> 5 μ V) achieved a 94% classification rate. These results suggest that adding adaptive, noise-aware preprocessing, such as per-trial weighting or SNR-based thresholds, could help the model handle low-amplitude cases more effectively in future iterations. Hussain embeds affect detection into a P300/SSVEP wheelchair BCI, enabling context-aware speed control¹⁹. Wang designs a "brain-inspired" depthwise-separable network that classifies MI in 3.2 ms on a Raspberry Pi¹¹. Kessler's large-scale ablation shows that high-pass cut-off and artefact-removal choice can swing decoding accuracy by ± 7 pp²⁰; this underscores the importance of robust preprocessing when comparing models. Real-world BCIs need not only high accuracy but also low latency, adaptive control, and reproducible pipelines.

Up-and-coming areas of AI and BCIs are quite promising when looking at their potential for assistive technology. These technologies, including adaptive learning, multimodal systems that combine EEG with eye-tracking, and GANs (Generative Adversarial Networks, a type of deep learning architecture created to generate the realistic synthetic data) to create realistic synthetic EEG data. Validating the model in real-world settings with visually impaired participants is a critical next step. Generative-adversarial techniques now dominate data-scarce BCI pipelines. Song et al. introduce EEGGAN-Net, a class-conditional GAN that lifts motor-imagery accuracy by 5 pp on BCI-IV-2a². ATGAN extends this idea with an attention-aware temporal discriminator, boosting cross-subject robustness²¹. Du et al. propose L-C-WGAN-GP, which stabilises training on short P300 epochs and outperforms vanilla WGAN by 3 pp⁶. Habashi's 2023 survey confirms the trend that 70 % of recent EEG papers now rely on GAN-based augmentation³. GANs effectively enlarge small EEG corpora, but they add architectural overhead and require careful mode-collapse avoidance.

Transformers are migrating from NLP to EEG. Wan's EEGformer uses channel-wise self-attention and improves MI accuracy by 6 pp versus Deep4Net. Song augments a transformer with cross-subject adaptive weights, pushing leave-one-subject-out accuracy to 78 % on P300³. Shih wraps EEGNet in a lightweight transformer decoder (Trans-EEGNet) to grade neonatal HIE severity, halving MAE relative to pure CNNs²². Attention mechanisms capture long-range temporal dependencies, but parameter counts and training data demands grow accordingly. Zhang & O'Brien present BioSerenity-E1, a 50 M-parameter masked-prediction model pre-trained on 10,000 hours of clinical EEG; zero-shot transfer to MI reaches 75 % without labelled data¹⁶. This mirrors momentum in vision/language and hints at future "GPT-for-EEG" platforms. Large-scale self-supervision could unify disparate EEG tasks, though compute and privacy hurdles remain.

Conclusion

The custom model demonstrated superior performance in classifying EEG signals compared to SVM and CNN, achieving the highest accuracy (75.86%). Its lightweight architecture and efficient training process make it a promising candidate for real-time brain-computer interface applications.

This research bridges the gap between theoretical model development and practical application, paving the way for robust, accessible EEG classification solutions for assistive technologies.

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