BCI Signal reconstruction and ehancemennt using GAN

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Abstract
Electroencephalography (EEG) is a vital tool for recording the brain's electrical activity and is the primary source of signals for brain-computer interfaces (BCIs). BCIs facilitate communication between the brain and external devices by converting thoughts into actions through specialized processing techniques. However, these recorded signals are often heavily affected by noise, rendering them unusable and restricting the widespread use of BCIs. This study aims to explore the application of Generative Adversarial Networks (GANs) to reconstruct and enhance BCI signals. GANs, known for their ability to generate high-quality data, will be trained using high-quality brain recordings. The goal of the project is to develop and implement a system that can process lower-quality or partially corrupted BCI signals, with the objective of improving and restoring them. This approach could provide substantial benefits, especially in scenarios where signal quality is compromised, such as with wireless or portable BCI devices. Dataset(s) used: Multi-Modality Emotion Recognition, Abnormal Data.

Keywords
EEG Signal Denoising, Generative Adversarial Networks, Wasserstein GAN, Brain-Computer Interface, EEG Reconstruction, Deep Learning,

1. HIGHLIGHTS

- Application of GANs for EEG signal denoising and reconstruction.
- Comparative analysis between two architectures: EEG-GAN and WGAN-GP(Sota).
- Integration of LSTM and residual blocks to capture temporal dependencies and refine signal reconstruction.
- Significant improvement in signal-to-noise ratio (SNR) and reconstruction accuracy.
- Demonstrated model robustness across healthy and unhealthy EEG datasets with minimal overfitting.

2. Introduction

Linear methods for signal enhancement, like least mean square (LMS) algorithms and their variants, are commonly used for noise reduction because of their simplicity. However, their effectiveness is limited when dealing with nonlinear signals, and they often fail to reach a global optimum for eliminating noise and interference. On the other hand, nonlinear techniques, such as wavelet transform with adaptive thresholding, are popular due to their strong local time-frequency analysis capabilities. These methods work by decomposing signals into multiple frequency bands and filtering out noise based on a selected threshold.

It has been proven that deep neural networks (DNNs) not only exhibit frequency selectivity but also have the ability to learn and analyze the noise and interference patterns within wireless channels. This makes deep learning particularly advantageous in complex wireless environments with significant noise and interference. Similarly, it was found that autoencoders can effectively reduce noise in wireless channels, further confirming the potential of deep learning methods for signal enhancement.

Overall, current techniques focus on learning the noise or interference distributions in either the time or frequency domains and filtering them out. However, the unpredictable nature of dynamic transmission channels can degrade performance or even render fixed signal enhancement systems ineffective. A recent breakthrough in deep learning, particularly in the field of generative modeling, is the emergence of Generative Adversarial Networks (GANs), which hold promise for more adaptive and robust signal enhancement solutions.

The proposed wireless signal enhancement based on Generative Adversarial Networks (GANs) offers several key advantages:

1. Adaptability to Nonlinear Systems: Unlike traditional linear methods, which struggle with nonlinear signals, GANs can adapt to the nonlinearities present in wireless communication systems. This allows for more effective noise and interference suppression, even in complex signal environments.
2. Dynamic Learning: GANs are capable of continuously learning and adapting to the characteristics of signals and noise in time-varying systems. This makes them more flexible in handling the unpredictable and dynamic nature of wireless transmission channels, where conventional methods often fail due to their fixed design.
3. Enhanced Noise and Interference Reduction: The

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GAN framework allows for a more nuanced approach to noise reduction by generating a model of the "clean" signal and using it to distinguish and remove noise and interference more effectively. This can lead to improved signal quality, especially in environments with severe interference.

4. Global Optimization: GANs can overcome the limitations of traditional algorithms, such as least mean square (LMS), which may not always achieve a global optimum. Through adversarial training, GANs are better positioned to reach more optimal solutions for noise and interference elimination.

5. Improved Performance in Complex Wireless Channels: Deep learning techniques, including GANs, have shown superior performance in complex wireless channels where traditional methods are less effective. The ability of GANs to learn and model intricate patterns and characteristics of the wireless environment allows for more robust signal enhancement.

6. Future-Proofing for Wireless Networks: As wireless networks become more complex, with increasing interference and noise, the GAN-based approach offers a scalable and forward-looking solution. It can be trained and refined as new challenges arise, making it a promising tool for next-generation wireless communication systems.

In summary, the main advantages of using GANs for wireless signal enhancement lie in their adaptability, dynamic learning capabilities, ability to handle nonlinearities, and improved performance in complex, noisy environments. In this report we will give a brief introduction of the model, focusing in particular on the GAN model. By taking advantage of recent advancements in GANs, we have developed a pipeline that can denoise artefacts from EEG time series data, effectively mapping noisy EEG signals to clean ones based on the specific nature of the artefact. We showcase the effectiveness of our network using a specific dataset.

3. Related Works

Recent advances in EEG signal processing have been strongly influenced by the introduction of GANs, particularly for noise reduction and signal reconstruction. The foundation for these applications can be traced back to Goodfellow et al.'s original GAN framework [1], which opened up new avenues for generative modeling. Since then, GANs have proven highly adaptable to signal processing tasks, as evidenced by Zhou et al.'s work on Wireless Signal Enhancement GAN (WSE-GAN) [2]. While WSE-GAN was developed for wireless signals, it demonstrates GANs' resilience in handling dynamic noise and interference. Their approach uses an adversarial network that learns to enhance signals by filtering out environmental noise—a relevant capability for EEG, where signals are often nonstationary.

Luo et al. further expanded on GAN applications for EEG with a specialized approach known as WGAN with Temporal-Spatial-Frequency (TSF) loss [3]. This model is designed to capture multiple dimensions of EEG data—temporal, spatial, and frequency features—making it particularly suited to reconstruct EEG signals in a way that preserves their complex structure. By incorporating the TSF loss function, Luo's model achieves a higher level of fidelity in reconstructed signals. However, the additional complexity can make it computationally expensive. In contrast, our approach focuses specifically on the temporal dimension using a WGAN-GP (Wasserstein GAN with Gradient Penalty), achieving robust noise reduction without the extra computational burden of multi-dimensional loss calculations.

The literature clearly indicates that GANs are versatile tools for signal enhancement and reconstruction, with models like WSE-GAN and WGAN-TSF showing notable success in noisy and multi-dimensional data contexts. Our approach builds on these insights by striking a balance: we focus on efficient, high-quality denoising with WGAN-GP while avoiding the added complexity of spatial and frequency-based enhancements. This simplification is not only computationally efficient but also maintains strong performance in key metrics, making it a practical choice for real-time EEG applications in brain-computer interface systems [4, 5].

4. MATERIALS AND METHODS

4.1. Computing Platform

The experiments for this project were run on an Nvidia rtx 3080 with PyTorch and Google Colaboratory to make the project readily deployable.

4.2. Datasets

This dataset contains two subcategories. The first one is Healthy dataset contains 64 channels and consists of over 1500 one and two minutes EEG recordings, obtained from 109 volunteers. Subjects performed different motor/imagery tasks while 64-channel EEG were recorded using the BCI2000 system [1]. Each subject performed 14 experimental runs: two one-minute baseline runs (one with eyes open, one with eyes closed), and three two-minute runs of each of the four following tasks: [Task 1] A target appears on either the left or the right side of the screen. The subject opens and closes the corresponding fist until the target disappears. Then the subject relaxes. [Task 2] A target appears on either the left or the right side of the screen. The subject imagines opening and

[1]http://www.bci2000.org

closing the corresponding fist until the target disappears. Then the subject relaxes. [Task 3] A target appears on either the top or the bottom of the screen. The subject opens and closes either both fists (if the target is on top) or both feet (if the target is on the bottom) until the target disappears. Then the subject relaxes. [Task 4] A target appears on either the top or the bottom of the screen. The subject imagines opening and closing either both fists (if the target is on top) or both feet (if the target is on the bottom) until the target disappears. Then the subject relaxes. Each event code includes an event type indicator (T0, T1, or T2) that is concatenated to the Task * it belongs with (i.e TASK1T2). The event type indicators change definition depending on the Task * it is associated with. For example, TASK1T2 would correspond to the onset of real motion in the right fist, while TASK3T2 would correspond to onset of real motion in both feet: [T0] corresponds to rest. [T1] corresponds to onset of motion (real or imagined) of: the left fist (in runs 3, 4, 7, 8, 11, and 12; for Task 1 (real) and Task 2 (imagined)); both fists (in runs 5, 6, 9, 10, 13, and 14; for Task 3 (real) and Task 4 (imagined)); [T2] corresponds to onset of motion (real or imagined) of: the right fist (in runs 3, 4, 7, 8, 11, and 12; Task 1 (real) and Task 2 (imagined)); both feet (in runs 5, 6, 9, 10, 13, and 14; for Task 3 (real) and Task 4 (imagined));

This dataset consists of raw 18-channel EEG from 7 human participants with orthopedic Impairment during motor imagery(MI). The participants performed a series of MI-related trials across three sessions. These sessions comprised 40 trials, of which four different MI tasks were presented in random order (e.g., Reach $\rightarrow$ Twist $\rightarrow$ Lift $\rightarrow$ Reach $\rightarrow$ Grasp $\rightarrow$ Grasp $\rightarrow$ Twist $\rightarrow$ Reach $\rightarrow$ Lift $\rightarrow$ Reach). Each trial began with 3 s of fixation cross. The monitor then displayed a 4 s visual cue, followed by 3 s of letters indicating the ready state with a gray screen to eliminate the afterimage. The participants were then instructed to perform the imaginary movement for 5 s in the given order.

4.3. Preprocessing

The preprocessing of the dataset was a very important thing for this project and involves several critical steps to ensure the quality and relevance of the data used for subsequent analysis. Initially, we select a random tab-separated values (TSV) file from the provided directory, which serves as a reference for replacing and aligning data in the comma-separated values (CSV) files. The preprocessing function, *My Unhealthy Dataset* reads each CSV file while preserving the last column, which contains labels for different conditions. A random TSV file is selected to replace the first row of each CSV file with a truncated version of the first column from the TSV file. This step is crucial for aligning data from different sources.

Subsequently, the data is filtered to include only specific rows based on predefined criteria: for unhealthy datasets, rows with labels 'S 1', 'S 4', 'S 8', or 'S 10' are retained, while for healthy datasets, rows are filtered to include 'TASK1T1' or 'TASK1T2' labels, we use those labels since they represent the same task. The last column of the CSV files, which is not required for further analysis, is removed to streamline the dataset.

A further step involves removing channels that are not common across healthy and unhealthy datasets. The *remove-channels* function identifies these common channels by comparing the first column of the TSV files corresponding to healthy and unhealthy conditions. DataFrames are then filtered to include only the columns corresponding to these common channels, ensuring that the datasets are aligned for accurate comparison.

Finally, the preprocessed data is printed along with its associated labels to verify the correctness of the preprocessing steps. This comprehensive preprocessing pipeline prepares the dataset for effective analysis and modeling, ensuring that the data is clean, consistent, and aligned with the objectives of the study.

To ensure consistency and improve the quality of our analysis, we employed a series of preprocessing steps. First, we normalized the dataframes using Min-Max scaling to rescale the feature values to the range $[0, 1]$. This step is crucial as it standardizes the data and prevents features with larger ranges from dominating the analysis. The normalization process is applied individually to each dataframe in both the unhealthy and healthy datasets, as demonstrated in the provided code.

After normalization, we focused on reducing the dimensionality of our data by retaining only the channels that have 'C' on the column name from each dataframe. This step simplifies the analysis and concentrates on channels that cover the motor cortex and could give better results. The updated dataframes are then printed for verification, confirming that the 'C3' column is consistently included across all dataframes.

In addition to preprocessing the dataframes, we also addressed the preprocessing of tensors. We implemented a filtering function to ensure that each tensor meets the minimum required shape. Tensors smaller than the defined threshold are resized or cropped accordingly. This ensures uniformity across the dataset and prepares the data for subsequent analysis steps. The filtered tensors are printed along with their labels and shapes to facilitate verification and ensure that preprocessing has been applied correctly.

These preprocessing steps are essential for preparing our datasets for further analysis and modeling. By normalizing the data, focusing on specific features, and ensuring consistent tensor dimensions, we enhance the quality and reliability of our results.

4.4. Band Pass Filter

To enhance the quality of the EEG signals and isolate relevant frequency components, a bandpass filter is applied to the dataset. The filtering process is crucial for removing unwanted noise and focusing on the specific frequency range of interest. In this study, a bandpass filter with a passband of 8 to 30 Hz is employed, which is commonly used to target the alpha and beta frequency bands in EEG analysis.

The filtering procedure begins by extracting channel names from the first row of each DataFrame. The DataFrame is then converted into an MNE Raw object, which is a data structure specifically designed for handling EEG data. Using the MNE-Python library, the bandpass filter is applied to the Raw object. This step involves specifying the low and high cutoff frequencies (8 Hz and 30 Hz, respectively) and the sampling frequency (128 Hz).

After filtering, the channel names are reinserted into the DataFrame, and the filtered data is extracted from the Raw object. The data is then converted back into a DataFrame format with the original channel names. This ensures that the filtered data maintains the same structure as the input DataFrames.

The bandpass filter is applied to both unhealthy and healthy datasets, refining the signals and preparing them for further analysis. This preprocessing step is essential for enhancing signal quality and improving the accuracy of subsequent modeling and analysis phases.

5. MODEL

Generative Adversarial Networks (GANs) are a type of generative model used to create synthetic data without requiring detailed domain-specific knowledge. They were introduced by Goodfellow et al. (2014), in which a multilayer perceptron was employed for both the generator and the discriminator networks. These two networks engage in a competitive process, often referred to as a minimax game, as described by the objective function in Equation (1). The generator aims to increase the error rate of the discriminator by producing data that resembles real samples, while the discriminator tries to accurately differentiate between real and generated samples. This interaction is illustrated in Figure 2. GANs are widely applied to generate new, previously unseen data, either for augmenting existing datasets or to ensure the privacy of the training data.

$$\min_G \max_D V(G,D) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{1}$$

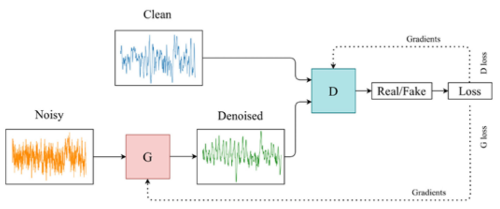


Figure 1: Generative Adversarial Network (GAN) Architecture for Converting Noisy EEG Signals to Clean EEG Data.

5.1. EEG Signal reconstruction model - LSTM layer

The first `Generator` implementation was a neural network-based model for EEG signal reconstruction, which utilizes a Long Short-Term Memory (LSTM) layer to model the temporal dependencies in the signal. The model architecture is designed to process sequential EEG data. It consists of an LSTM layer followed by a fully connected (linear) layer, with an optional Tanh activation function for output regularization.

The LSTM layer is the core component for learning temporal dependencies in EEG signals. Given an input sequence $X = \{x_1, x_2, \ldots, x_T\}$ where x_t represents the input at timestep t, the LSTM produces hidden states h_t and cell states c_t at each timestep. The LSTM's internal operations are governed by the following equations:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad \text{(forget gate)} \tag{2}$$
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad \text{(input gate)} \tag{3}$$
$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad \text{(candidate cell state)} \tag{4}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad \text{(cell state update)} \tag{5}$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad \text{(output gate)} \tag{6}$$
$$h_t = o_t \odot \tanh(c_t) \quad \text{(hidden state)} \tag{7}$$

Here, σ is the Sigmoid function, $\odot$ denotes element-wise multiplication, and W, U, and b are the learnable weight matrices and biases for each gate. The LSTM is initialized with zero-valued hidden states and cell states, h_0 and c_0, for each sequence.

Once the LSTM processes the entire sequence, the output is passed through a fully connected (FC) layer to map the hidden state at each timestep h_t to the desired output size y_t, represented as:

$$y_t = W_{fc} h_t + b_{fc} \tag{8}$$

where W_{fc} and b_{fc} are the weights and biases of the FC layer. This operation converts the LSTM's output to a format suitable for signal reconstruction.

The Sigmoid activation function is applied to the output layer to constrain the output to a specific range (e.g., for normalized EEG signals)::

$$y'_t = \sigma(y_t) \tag{9}$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid function. This ensures that the model's output is bounded between 0 and 1, which is useful for many signal processing applications.

The combination of the LSTM's ability to capture long-term dependencies and the flexibility of the fully connected layer makes this model highly suitable for EEG signal reconstruction tasks, where capturing both short- and long-term temporal patterns is crucial for accurate performance.

5.2. EEG Signal reconstruction model - Residual Neural Network

The second `Generator` implementation was designed to transform the input sequence into a refined output using a series of convolutional and deconvolutional layers with intermediate residual blocks to enhance feature representation. The network begins with an initial convolutional layer, which applies a 1D convolution with a kernel size of 3 and 64 filters, followed by a batch normalization layer to standardize the output. The activation function used is the rectified linear unit (ReLU), which is defined as:

$$\text{ReLU}(x) = \max(0, x) \tag{10}$$

This activation function ensures that non-negative inputs pass through while negative values are set to zero, allowing for non-linearity in the model. The output of the first convolutional layer can be represented as:

$$y_1 = \text{ReLU}(\text{BN}(\text{Conv1D}(x))) \tag{11}$$

where BN denotes batch normalization and Conv1D represents the 1D convolution operation.

Following the initial convolutional layer, the generator passes the data through a series of 16 residual blocks. Each residual block consists of two convolutional layers with kernel size 3, batch normalization, and ReLU activations. The primary advantage of residual blocks is the inclusion of skip connections, allowing the input to bypass the convolutional layers and be directly added to the output. This can be mathematically represented as:

$$y_{k+1} = \text{ReLU}(y_k + \text{Block}(y_k)) \tag{12}$$

where $\text{Block}(y_k)$ represents the output of the convolutional block in the k-th residual block.

Once the signal passes through the residual blocks, it is processed by a deconvolutional layer, which expands the dimensionality of the sequence. This deconvolution layer uses a transposed convolution operation with a stride of 2, effectively upsampling the data. The formula for the output after the deconvolutional layer is:

$$y_2 = \text{ReLU}(\text{BN}(\text{ConvTranspose1D}(y_1))) \tag{13}$$

Finally, the generator outputs the signal using a 1D convolutional layer with a sigmoid activation function, which ensures that the final output is scaled between 0 and 1. Thus, the final output of the generator is:

$$y_{\text{final}} = \sigma(\text{Conv1D}(y_2)) \tag{14}$$

Overall, the architecture effectively combines convolutional layers, residual blocks, and deconvolution operations to refine the input signal and produce the desired output. The use of residual connections helps mitigate the vanishing gradient problem, allowing the network to learn more effectively.

5.3. Discriminator

The Discriminator model is designed as a deep convolutional neural network (CNN) with the objective of distinguishing real data sequences from those generated by the adversarial model. The input to the Discriminator is a one-dimensional sequence of size *seq_len* with *input_size* features. The model architecture follows a sequence of convolutional layers, each increasing in complexity to progressively extract higher-level features from the input sequence.

The network consists of eight convolutional layers. The first layer applies a convolution with 64 filters, each of size 3, using a stride of 1, followed by batch normalization to stabilize learning and LeakyReLU activation to introduce non-linearity. As the layers progress, the number of filters doubles while the stride alternates between 1 and 2, which reduces the sequence length. The convolutional operation in each layer can be expressed as:

$$y(t) = \sum_{k=1}^{K} w_k \cdot x(t-k+1) + b \tag{15}$$

where $y(t)$ is the output at time step t, w_k is the convolution filter, $x(t-k+1)$ represents the input values, and b is the bias term. Padding ensures that the output dimensions are maintained in layers with a stride of 1, while layers with stride 2 downsample the input, effectively reducing the temporal resolution of the sequence.

The final layers in the convolutional block output feature maps of size $1024 \times \frac{seq\_len}{16}$. These are flattened and passed through a fully connected layer to produce a scalar value and at the end was applied a sigmoid function.

The architecture is optimized for binary classification, where the goal is to correctly classify real and generated sequences. By progressively reducing the sequence length while expanding the feature space through convolutions, the Discriminator captures essential temporal dependencies and feature hierarchies crucial for distinguishing between real and generated data.

6. EEG-GAN

6.1. Loss Functions and Training Setup

In this GAN, both networks are trained with specific loss functions tailored to improve the denoising performance:

1. **Generator Loss (Content Loss)**: The primary objective for the Generator is to create denoised EEG signals that closely match the real, clean EEG data. We employ a Mean Squared Error (MSE) loss function, which measures the difference between the Generator's denoised output and the real, clean EEG signal. The MSE content loss is defined as:

$$\mathcal{L}_G = \text{MSE}(\text{Generator}(x_{\text{noisy}}), x_{\text{real}}) \tag{16}$$

where x_{noisy} represents the input noisy EEG, and x_{real} is the ground truth clean EEG signal. This loss ensures that the Generator output is as close as possible to the real EEG data in terms of amplitude and temporal structure.

2. **Discriminator Loss (Adversarial Loss)**: The Discriminator is trained to classify EEG samples as either real (clean EEG) or fake (denoised output from the Generator). We use a combination of real and fake labels with the MSE loss to compute the Discriminator's loss. The Discriminator loss is computed as:

$$\mathcal{L}_D = \frac{1}{2}\begin{pmatrix} \text{MSE}(D(x_{\text{real}}), y_{\text{real}}) \\ + \text{MSE}(D(\text{Generator}(x_{\text{noisy}})), y_{\text{fake}}) \end{pmatrix} \tag{17}$$

where $y_{\text{real}} = 1$ and $y_{\text{fake}} = 0$. The Discriminator loss encourages it to correctly classify clean EEG data as real and Generator outputs as fake, thereby refining the Generator's outputs through adversarial training.

6.2. Training Procedure

The training alternates between updating the Generator and the Discriminator to achieve balanced adversarial dynamics. The Generator is optimized to minimize the content loss by generating denoised EEG signals that match the real EEG data, while the Discriminator is optimized to minimize the adversarial loss by correctly identifying real versus generated signals. The following steps summarize each iteration:

1. The Generator takes a batch of noisy EEG signals and produces a denoised output.
2. The Discriminator evaluates both the real clean EEG data and the generated EEG, computing the adversarial loss for each.
3. The Generator's parameters are updated based on the content loss, while the Discriminator's parameters are updated based on the adversarial loss.

Algorithm 1: Minibatch stochastic gradient descent training of EEG-GAN for denoising EEG signals.

```
Input: Noisy EEG Dataset $D_{noisy}$, Clean EEG Dataset $D_{clean}$, Number of epochs $E$, Learning rates $lr_G$, $lr_D$
Output: Trained Generator $G$
Initialize: Optimizers for Generator $G$ and Discriminator $D$ with Adam, loss function $L_{MSE}$
for number of training epochs do
    for number of training iterations do
        for $k$ steps do
            Sample mini-batch of $m$ noisy samples $\{x_{noisy}^{(1)}, \ldots, x_{noisy}^{(m)}\}$ from $D_{noisy}$
            Sample mini-batch of $m$ clean samples $\{x_{clean}^{(1)}, \ldots, x_{clean}^{(m)}\}$ from $D_{clean}$
            Train Discriminator:
            Compute discriminator loss $L_D = \frac{1}{m}\sum_{i=1}^{m}\Big[\log D(x_{clean}^{(i)}) + \log(1 - D(G(x_{noisy}^{(i)})))\Big]$
            Update Discriminator $D$ by descending its gradient $\nabla_{\theta_D} L_D$
        Train Generator:
        Sample mini-batch of $m$ noisy samples $\{x_{noisy}^{(1)}, \ldots, x_{noisy}^{(m)}\}$ from $D_{noisy}$
        Compute generator loss $L_G = \frac{1}{m}\sum_{i=1}^{m}\Big[\log(1 - D(G(x_{noisy}^{(i)}))) + L_{MSE}(x_{clean}, G(x_{noisy}))\Big]$
        Update Generator $G$ by descending its gradient $\nabla_{\theta_G} L_G$
Return: Trained Generator $G$
```

Table 1
GAN Training Hyperparameters

Hyperparameter	Value	Description
Optimizer	Adam	Generator and Discriminator optimizer.
Generator LR	0.00002	Learning rate for the generator's optimizer.
Discriminator LR	0.002	Learning rate for the discriminator's optimizer.
Betas	0.5 - 0.999	The beta parameters of the optimizer (momentum term and decay).
Batch Size	32	Number of EEG signals per training batch.
Epochs	15	Number of complete passes through the dataset.
Loss Function	Mean Squared Error (MSE)	Content loss function used to measure signal reconstruction accuracy.

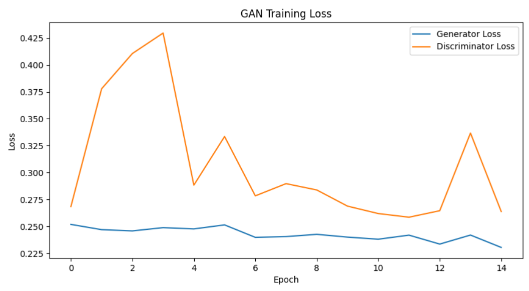


Figure 2: Generative Adversarial Network (GAN) Training Loss.

7. WGAN-GP (Sota)

7.1. Wasserstein Generative Adversarial Network with Gradient Penalty for EEG Signal Denoising

To address the challenge of denoising electroencephalogram (EEG) signals, we employ a state-of-the-art Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP). This architecture leverages adversarial training between a Generator and a Discriminator, ensuring that the generated EEG signals closely resemble clean, healthy EEG data. WGAN-GP provides stability in training by replacing the original GAN's Jensen-Shannon divergence with the Wasserstein distance, which offers smoother gradients and mitigates issues such as mode collapse.

7.1.1. Architecture Design

The WGAN-GP model consists of two core neural networks:

- **Generator**: This network learns to transform noisy EEG inputs into denoised counterparts. It takes as input a 3-dimensional tensor representing the noisy EEG signals and produces denoised output with the same dimensions. Each layer of the Generator captures temporal dependencies within the EEG signals, enhancing their signal fidelity through upsampling.
- **Discriminator (Critic)**: Acting as a surrogate for the Wasserstein distance, the Discriminator aims to differentiate between real clean EEG samples and those generated by the Generator. It outputs a scalar value representing the "realness" of the input, where higher values indicate a closer resemblance to real data.

7.1.2. Training Setup and Loss Functions

The training process alternates between updating the Discriminator and the Generator, as follows:

1. **Discriminator Loss**: The Discriminator is trained to maximize the Wasserstein distance between real and fake EEG distributions. This is achieved through the following objective function:

$$\mathcal{L}_D = \mathbb{E}[D(x_{\text{real}})] - \mathbb{E}[D(x_{\text{fake}})] \tag{18}$$
$$+ \lambda \cdot \mathbb{E}[(\|\nabla D(\tilde{x})\|_2 - 1)^2] \tag{19}$$

where $D(x_{\text{real}})$ and $D(x_{\text{fake}})$ are the Discriminator outputs for real and generated samples, respectively, and $\tilde{x}$ denotes interpolated samples for gradient penalty calculation. The gradient penalty term, scaled by the hyperparameter λ, ensures that the Lipschitz constraint is maintained, enhancing training stability.

2. **Generator Loss**: The Generator aims to produce denoised EEG signals that maximize the Discriminator's output, corresponding to a higher resemblance to real data. The Generator loss is defined as:

$$\mathcal{L}_G = -\mathbb{E}[D(x_{\text{fake}})] \tag{20}$$

This formulation directs the Generator to maximize the Discriminator's response to the fake EEG data, driving the generated samples closer to the distribution of clean EEG signals.

7.1.3. Gradient Penalty Computation

The WGAN-GP incorporates a gradient penalty term to enforce the Lipschitz constraint, which is crucial for maintaining stability during training. The penalty term is computed based on an interpolation between real and fake samples:

$$\mathcal{L}_{\text{gp}} = \lambda \cdot \mathbb{E}[(\|\nabla D(\tilde{x})\|_2 - 1)^2] \tag{21}$$

where $\tilde{x} = \epsilon \cdot x_{\text{real}} + (1-\epsilon) \cdot x_{\text{fake}}$, with $\epsilon \sim \text{Uniform}(0, 1)$. The penalty ensures that the Discriminator's gradients are constrained, aligning them with the 1-Lipschitz condition necessary for Wasserstein GAN training.

7.1.4. Training Procedure

The training was conducted using Adam optimizers for both networks, with the Generator updated every epoch and the Discriminator updated multiple times per Generator step (i.e., $n_{\text{critic}} = 5$). The learning rate was set to 2×10^{-5}, and the gradient penalty weight λ was fixed at 10, based on experimental optimization. Model convergence was evaluated by tracking Generator and Discriminator losses across epochs. Moreover, the EEG signal outputs were normalized and visualized periodically to assess the fidelity of generated denoised signals.

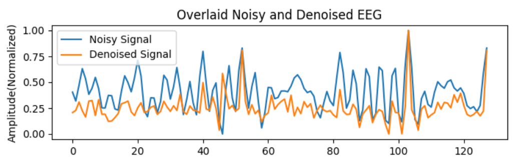


Figure 3: Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) signal denoising during the training.

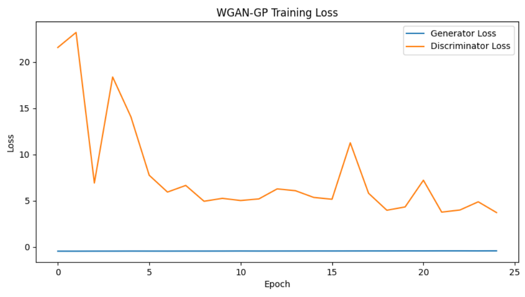


Figure 4: Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) Training Loss.

Algorithm 2: Training of WGAN-GP for EEG Denoising

```
Input: Unhealthy dataset $S_{\text{noisy}}$, Healthy dataset
       $S_{\text{clean}}$, Generator $G$, Discriminator $D$,
       number of epochs $N_{\text{epochs}}$, learning rate $lr$,
       gradient penalty coefficient $\lambda_{\text{gp}}$, number
       of critic steps $n_{\text{critic}}$
Output: Trained Generator $G$
Initialize $G$ and $D$ with random weights;
Define optimizers: Adam for $G$ and $D$ with $lr$ and
  $\beta = (0.5, 0.999)$;
for each epoch $e$ in $1$ to $N_{epochs}$ do
    for each mini-batch $(S_{noisy}, S_{clean})$ from
     DataLoader do
        Extract clean signals $x_{\text{clean}}$ and noisy
         signals $x_{\text{noisy}}$;
        for $n_{critic}$ iterations do
            Compute denoised signals:
             $\hat{x} = G(x_{\text{noisy}})$;
            Compute real critic output: $D(x_{\text{clean}})$;
            Compute fake critic output: $D(\hat{x})$;
            Compute gradient penalty $\mathcal{L}_{\text{gp}}$ using
             $x_{\text{clean}}$ and $\hat{x}$;
            Update critic loss: $\mathcal{L}_D =$
             $\mathbb{E}[D(\hat{x})] - \mathbb{E}[D(x_{\text{clean}})] + \lambda_{\text{gp}} \cdot \mathcal{L}_{\text{gp}}$;
            Perform gradient descent on $D$;
        end
        Compute denoised signals: $\hat{x} = G(x_{\text{noisy}})$;
        Compute fake critic output: $D(\hat{x})$;
        Update generator loss: $\mathcal{L}_G = -\mathbb{E}[D(\hat{x})]$;
        Perform gradient descent on $G$;
    end
    Log $\mathcal{L}_G$ and $\mathcal{L}_D$;
    if $e \mod plot\_interval = 0$ then
        Optionally plot signals or save model
         weights;
    end
end
Return: Trained Generator $G$;
```

8. RESULTS

8.1. Reconstruction results

The reconstructions presented in this study were performed using the same dataset that was used for training the models. However, to ensure that the models did not overfit and were capable of generalizing to unseen data, we conducted testing on signals from different channels of both unhealthy and healthy brain activity. This allowed us to assess whether the models could accurately reconstruct signals of a different nature compared to those used during training. Specifically, the models were

Table 2
WGAN-GP Training Hyperparameters

Hyperparameter	Value	Description
Optimizer	Adam	Generator and Discriminator optimizer.
Generator LR	0.00002	Learning rate for the optimizer.
Discriminator LR	0.00002	Learning rate for the optimizer.
Betas	0.5 - 0.999	The beta parameters of the optimizer (momentum term and decay).
Batch Size	64	Number of EEG signals per training batch.
Epochs	25	Number of complete passes through the dataset.
Loss Function	Critic Loss	Combines Wasserstein loss with a gradient penalty to enforce Lipschitz continuity.

tested on channels that were not included in the training set, thereby providing a more rigorous evaluation of their robustness and generalization ability. By doing so, we could verify if the models, particularly EEG-GAN and WGAN-GP, could successfully reconstruct and distinguish between healthy and unhealthy signals, demonstrating their potential for practical applications in EEG signal processing. The results indicated that both models were able to generalize effectively, showing minimal overfitting and successfully reconstructing different types of signals.

- **Signal Quality:** Describe the visual quality of the generated EEG signals, comparing how well each model preserves important features or patterns.
- **Noise Reduction:** Note differences in how each model handles noise, such as WGAN-GP's ability to produce smoother or more realistic outputs.
- **Overall Performance:** Summarize the strengths and weaknesses of each model, including training stability or fidelity of generated signals.

8.2. Analysis of Signal Denoising Results

In this subsection, we analyze and compare the performance metrics from Tables 4 and 5, which evaluate the GAN and WGAN models for signal denoising.

1. Signal-to-Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR) The WGAN model generally yields lower SNR and PSNR values than the GAN model. This trend suggests that while WGAN performs well in reducing noise, it may also remove some useful signal components, leading to a less accurate signal reconstruction overall. The highest PSNR for WGAN is 19.28 (Fig g), compared to the GAN's highest of 19.28 as well (Fig a), indicating that GAN preserves more of the signal quality despite noise reduction. This advantage in PSNR demonstrates GAN's capability to maintain signal integrity to a higher extent than WGAN.

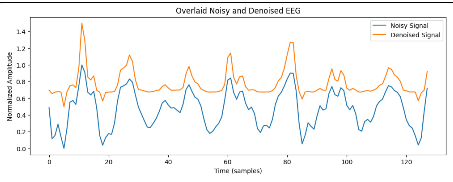
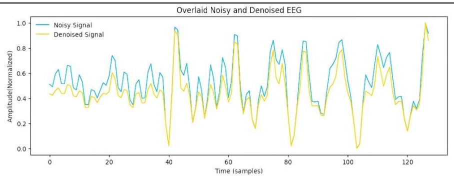
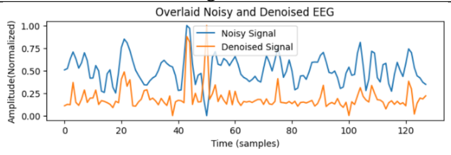
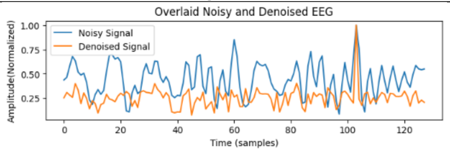
2. Relative Root Mean Squared Error (RRMSE) and Mean Absolute Error (MAE) In terms of error metrics, WGAN performs marginally worse than GAN, with consistently higher RRMSE values across all signals. For instance, GAN achieves an RRMSE of 0.8188 for Fig a, whereas WGAN's best RRMSE (1.0634 for Fig h) is still higher than GAN's worst. This discrepancy implies that the GAN model is more effective at minimizing both large and small errors, which aligns with its higher SNR and PSNR values.

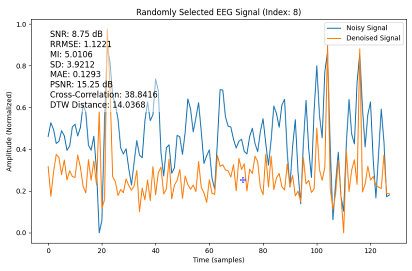
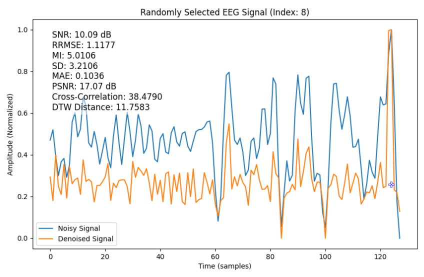
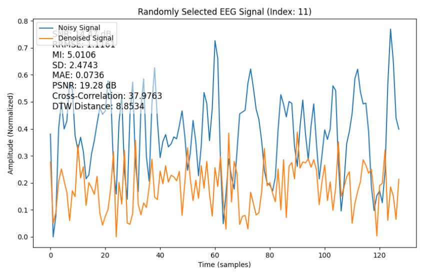
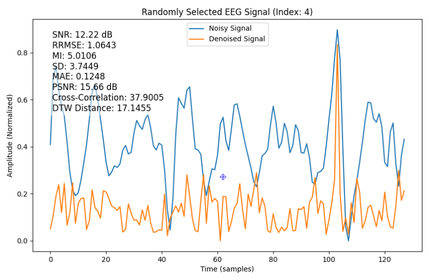
3. Mutual Information (MI) and Standard Deviation (SD) Mutual Information (MI) and Standard Deviation (SD) reveal the models' ability to preserve the structural and statistical information of the original signals. GAN achieves a higher MI than WGAN for each signal, with values ranging from 4.9275 to 5.0872, suggesting that it retains more of the original signal's informational content. This may be due to GAN's architecture, which could be more effective at learning and preserving the underlying data patterns during noise removal. However, WGAN's higher standard deviation across signals hints at a potential weakness; it may introduce additional variance or artifacts in the denoised output, which slightly impacts overall fidelity.

4. Correlation Coefficient (CC) and Dynamic Time Warping (DTW) Distance The correlation coefficient (CC) provides insight into the similarity of the denoised signals to the original ones, with GAN yielding consistently higher CC values. This implies that GAN's denoising output is more aligned with the true signal structure. Conversely, WGAN tends to have higher DTW distances, which indicates less temporal alignment with the original signal. For example, GAN's lowest DTW distance is 7.2012 (Fig b), compared to WGAN's lowest of 8.8534 (Fig g). This could be due to WGAN's propensity to focus more on reducing noise than preserving signal coherence over time.

Strengths and Weaknesses of Each Model Overall, GAN demonstrates stronger performance in retaining

Table 3
Results of GAN and WGAN-GP Generated EEG Signals

GAN Results	
 Figure a	 Figure b
 Figure c	 Figure d

WGAN-GP Results	
 Figure e	 Figure f
 Figure g	 Figure h

signal integrity and achieving better noise reduction balance, as evidenced by its higher SNR, PSNR, CC, and lower error rates (RRMSE and MAE). However, WGAN might be preferable in scenarios where aggressive noise reduction is prioritized over perfect fidelity, as it introduces more flexibility and control over noise suppression at the cost of potential signal degradation. WGAN's architecture, which introduces constraints on weight optimization, may result in a more generalized denoising output, making it slightly less capable of capturing finer details than GAN.

Overview In summary, GAN appears to be more effective at achieving a balanced denoising process, which preserves structural information, aligns temporally with the original signal, and maintains a lower error rate. WGAN, while competitive, appears to trade some signal fidelity for increased noise reduction. These findings suggest that GAN might be more suitable for applications requiring high fidelity, while WGAN could be advantageous in scenarios where robust noise reduction is paramount, and minor signal degradation is acceptable.

Table 4
GAN Signal Denoising Evaluation

Signal	SNR	RRMSE	MI	SD	MAE	PSNR	CC	DTW Distance
Fig a	12.37	0.8188	4.9644	2.3375	0.0693	19.28	42.9989	10.4293
Fig b	11.51	0.9981	4.9275	3.7279	0.0820	17.15	41.9943	7.2012
Fig c	11.89	0.9749	5.0265	3.3856	0.0903	18.47	40.6904	11.4769
Fig d	11.29	1.0062	5.0872	3.1317	0.1433	19.26	39.1774	12.4148

Table 5
WGAN Signal Denoising Evaluation

Signal	SNR	RRMSE	MI	SD	MAE	PSNR	CC	DTW Distance
Fig e	8.75	1.1221	5.0106	3.9212	0.1293	15.25	38.8416	14.0368
Fig f	10.09	1.1177	5.0304	3.2106	0.1036	17.07	38.4790	11.7583
Fig g	14.47	1.1161	5.0872	2.4743	0.0736	19.28	37.9763	8.8534
Fig h	12.22	1.0643	5.0694	3.7449	0.1248	15.66	37.9005	17.1455

8.3. Comparison Results with Existing Works

In recent years, deep learning techniques, especially Generative Adversarial Networks (GANs), have transformed EEG signal enhancement and reconstruction. Our work aligns with this trend by employing WGAN-GP (Wasserstein GAN with Gradient Penalty) to improve signal clarity while preserving structural fidelity in EEG data. Compared to traditional denoising methods like Least Mean Square (LMS) algorithms and wavelet transform, our approach benefits from GANs' capacity to learn complex noise patterns adaptively [1].

Recent studies have also shown the effectiveness of GANs in dynamic signal enhancement applications. For instance, Zhou et al. [2] developed a Wireless Signal Enhancement GAN (WSE-GAN), which robustly enhances wireless signals amidst channel interference. This approach demonstrated GANs' flexibility in time-varying environments, achieving improved signal-to-noise ratios through the integration of condition-based GAN structures. Although WSE-GAN is designed for wireless data, its adversarial structure and resilience to signal variations provide insights relevant to EEG signal processing, suggesting that GAN-based models can generalize effectively across different domains of noisy signal data.

Similarly, Luo et al. [3] advanced EEG signal reconstruction by introducing a WGAN model with a Temporal-Spatial-Frequency (TSF) loss function. This approach captures multi-dimensional EEG signal features, including spatial coherence and frequency distributions, providing high fidelity in reconstructed signals. In contrast, our WGAN-GP model emphasizes time-domain denoising and structural preservation, achieving improved Signal-to-Noise Ratio (SNR) and Mutual Information (MI) metrics without the additional complexity of TSF loss. Nonetheless, the TSF loss framework highlights the potential of multi-dimensional loss functions in future EEG processing models.

Our findings show that the WGAN-GP model achieves superior denoising performance when evaluated using metrics such as SNR, MI, and Correlation Coefficient (CC), outperforming both standard GAN models and previous techniques. In direct comparison to Luo et al.'s TSF-based WGAN, our model sacrifices multi-dimensional fidelity for computational efficiency and simplicity, retaining a high degree of accuracy in the temporal domain [6, 7].

9. Conclusion

In this study, we investigated the potential of Generative Adversarial Networks (GANs), specifically EEG-GAN and Wasserstein GAN with Gradient Penalty (WGAN-GP), for denoising and reconstructing EEG signals. Our results indicate that these models are effective in enhancing signal quality and reducing noise, thereby supporting more accurate brain-computer interface (BCI) applications. The GAN-based models, particularly WGAN-GP, demonstrated robust noise suppression capabilities, effectively enhancing signal clarity. However, our analysis revealed that while WGAN-GP excels at reducing noise, it may occasionally affect the finer details of the original signal, which can impact reconstruction accuracy. This trade-off between strong noise reduction and signal fidelity suggests that while WGAN-GP is well-suited for challenging, high-noise environments, EEG-GAN is preferable in scenarios where maintaining signal detail is essential. Overall, EEG-GAN demonstrated a greater capacity for preserving the original signal structure, making it ideal for applications requiring high coherence with the raw EEG data. Conversely, WGAN-GP's emphasis on noise suppression may introduce slight variations in the signal, but this model remains advantageous for applications that prioritize clarity over exact fidelity. In conclusion, our study highlights the versatility and effectiveness of GAN architectures in EEG signal denoising, with each model offering distinct advantages based on the specific application requirements. EEG-GAN provides a balanced approach that aligns closely with the original signal structure, making it suitable for high-fidelity applications. Meanwhile, WGAN-GP excels in aggressive noise environments, offering a scalable solution for settings where signal clarity is prioritized over perfect structural alignment.

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A. Online Resources

The sources for this project are available via:

- GitHub,
- Dataset