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A Decision Science Approach Using Hybrid EEG Feature Extraction and GAN-Based Emotion Classification

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Abstract

Purpose: Emotions play an essential role in human life and they profoundly influence behavior, decision-making, and well-being. This approach aims to classify human emotions by using Generative Adversarial Networks (GAN) and hybrid Electroencephalography (EEG) features with the DEAP dataset.

Design/methodology/approach: The proposed system addresses the limitations of traditional classification techniques by generating synthetic hybrid features that capture additional information about emotional states. Informed by decision science principles, the system recognizes that emotions heavily influence human decision-making processes.

Findings: The process consists of data collection, pre-processing, feature extraction, GAN training, hybrid feature generation, and classification. The DEAP dataset is pre-processed by using Independent Component Analysis (ICA) and Wavelet Transform to remove artifacts. A GAN model is trained to generate synthetic features that mimic the distribution of real EEG signals. The hybrid features are generated by combining the real EEG features and synthetic features.

Originality/value: The performance of the classification system is evaluated using accuracy at 97.4%, precision at 97.22%, recall at 96.8%, and F1 score at 97.08%. By leveraging EEG signals, the proposed system shows promise in enhancing the accuracy of emotion classification, opening up exciting avenues for future research in this domain.

Keywords: EEG; Emotions; DEAP Data; GAN; Independent Component Analysis

JEL classification: I12; I14

1. Introduction

Emotions are complex mental states that have a fundamental responsibility in human behavior and experience. Emotion classification is the process of identifying and categorizing emotions based on physiological signals such as facial expressions, body language, and brain activity. Electroencephalography (EEG) measures brain activity and classifies emotional states. However, traditional EEG-based emotion classification techniques face several challenges, such as limited feature extraction and the difficulty of generalizing across different participants and contexts. Emotions are integral to human behavior and experience, influencing thoughts, behavior, feelings, and happiness. The capability to classify human emotions is essential for various applications, including human-computer interaction (HCI) and mental health diagnosis. However, judging human emotions can be challenging, as it requires experience and perception.

The two-dimensional (2D) model for emotion recognition classifies emotions based on valence and arousal. In contrast, the three-dimensional (3D) model incorporates domination, which refers to the degree of control a person feels over their emotional state. However, the 2D model is used in research, as it is more straightforward and more accessible to use. The utilization of EEG data in emotion recognition studies has been widespread owing to its exceptional temporal resolution, cost-effectiveness, and ease of portability. Decision science is an interdisciplinary field that combines elements of psychology, economics, statistics, and cognitive science to study how individuals make choices and decisions. It explores the underlying cognitive processes, biases, and heuristics that influence human decision-making. By incorporating decision science principles into emotion identification, researchers can leverage the understanding of decision processes to improve the accuracy and interpretability of emotion classification models.

The DEAP dataset contains EEG data from individuals experiencing a range of emotions. The dataset consists of recordings from 32 channels, and each channel records the electrical activity of a specific region of the brain. It also contains additional information such as the age, gender, and emotional state of the participants (Ashokkumar et al., 2022; Pandey et al., 2021).

This study introduces a novel approach utilizing a Generative Adversarial Network (GAN) to classify human emotions using EEG data sourced from the DEAP dataset. We aim to investigate and compare to other conventional classification techniques. We also explore the potential of hybrid features, which combine both time and frequency domain features, in improving emotion classification accuracy.

To overcome these challenges, we suggest a new method to classify human emotions using Generative Adversarial Networks (GAN) and hybrid EEG features with the DEAP dataset. The proposed system generates synthetic hybrid features that capture additional information about emotional states, resulting in improved classification accuracy. In this five-page write-up, its contributions to the emotion classification. Classifying human emotions is through electroencephalography (EEG) recordings, which measure the electrical activity of the brain. EEG data has high temporal resolution and can give important insights into the essential neural mechanisms of emotions. However, analyzing and interpreting EEG data is complex and requires advanced analytical techniques.

In Section 2, we present a comprehensive review of existing literature on emotion recognition employing EEG data. Section 3 elaborates on the methodology employed in this study, encompassing data preprocessing, feature extraction, and the GAN-based classification approach. The experimental results and analysis are outlined in Section 4. Ultimately, Section 5 summarizes the findings, underscores key insights, and outlines potential avenues for future research in this domain.

2. Materials and Methods

2.1 Dataset

The EEG DEAP Dataset is a publicly available dataset that contains EEG signals recorded from 109 subjects (Koelstra et al., 2012). The subjects were asked to perform various tasks, including motor imagery tasks, mental arithmetic tasks, and a resting state task while wearing a 64-channel EEG cap. The dataset includes over 44,000 EEG epochs, each labeled with the task being performed at the time of recording. The data were preprocessed to remove noise and artifacts, and each epoch was segmented into one-second intervals with a 50% overlap between adjacent epochs. In addition, the dataset includes precomputed features commonly used in EEG-based classification tasks, such as spectral power, connectivity measures, and time-domain features. Deep learning models have extensively utilized the EEG DEAP Dataset to train and achieve remarkable accuracy levels in diverse applications.

The EEG DEAP Dataset includes various precomputed features that are commonly used in EEG-based classification tasks. One such feature is spectral power, which measures power, such as alpha, beta, and theta. The dataset also includes connectivity measures, which capture the degree of interaction between different brain regions by measuring coherence or correlation between pairs of EEG channels. Examples of connectivity measures included in the dataset are PLI and WPLI. In addition, the dataset contains time-domain features, which confine the temporal characteristics of the EEG signal, like its amplitude and waveform shape. Examples of time-domain features included in the dataset are root mean square (RMS) amplitude and waveform slope. Finally, the dataset includes higher-order statistics, which capture higher-order statistical properties of the EEG signal, such as kurtosis and skewness. These features are often used to capture non-Gaussian properties of the EEG signal that may be relevant for certain classification tasks.

2. 2 Literature Survey

In (Chen et al., 2020; Li et al., 2019; Zhang et al., 2020), a novel approach was introduced for emotion recognition by utilizing hybrid EEG signals and convolutional neural networks. The DEAP dataset is employed in their experiments, resulting in an accuracy of 71.6% for valence and 68.8% for arousal. Similarly, (Luo et al., 2018; Liu et al., 2021) present a deep learning approach for emotion recognition from EEG signals using the SEED dataset, achieving an accuracy of 66.7% for valence and 63.9% for arousal. (Cheng et al., 2021; Gao et al., 2022; Topic et al., 2021) proposes an EEG-based emotion recognition method utilizing hybrid deep learning networks and achieves an accuracy of 73.4% using the DEAP dataset. Furthermore, (Lian et al., 2020) introduce a generative adversarial network (GAN) based approach for emotion recognition from EEG signals, attaining an accuracy of 70.4%.

One promising technique proposed by (Mangalampalli et al., 2023) is the use of GAN-based data augmentation approaches, as cited in reference (Ashokkumar et al.,2023; Jabril et al., 2022). Additionally, other studies have leveraged the strengths of different deep learning architectures to achieve high accuracy for valence and arousal classification, such as the hybrid CNN-RNN model proposed by (Xue, X et al., 2023; Gohar et al., 2022) and the multi-view deep learning approach proposed by (Kalna-Dubinyuk et al., 2023; Karatas et al., 2022)

The DEAP dataset, as utilized in the works by (Li et al., 2022; Dhanasekaran et al., 2022), is widely recognized and established for this purpose. On the other hand, the SEED dataset, employed in the studies by (Vandarkuzhali et al., 2023; Rufus et al., 2022) is a relatively recent dataset that has garnered attention in the field. Overall, the studies demonstrated the progress and potential of utilizing deep learning models and various datasets to improve results.

Researchers have recognized and acknowledged the substantial challenges associated with employing GAN-based techniques in EEG-based emotion recognition tasks (Fong et al., 2008; Kilic et al., 2021). One of the challenges involves the direct generation of authentic EEG data using GANs, which can introduce unwanted noise and artifacts, potentially compromising the performance of classification models. Furthermore, training GANs in feature space can lead to mode collapse, a scenario where the generator generates excessively similar data, making it difficult for the discriminator to effectively differentiate (Acevedo et al., 2021; Batmunkh et al., 2020). To mitigate these challenges, researchers have devised various strategies, including the utilization of autoencoders to eliminate noise and artifacts from synthetic data before augmenting the real data (Kudryavtsev et al., 2019; Lam et al., 2012; Liu et al., 2020). Additionally, some studies have integrated GANs with other generative models, to generate diverse and high-quality synthetic data in feature space.

In this work, an intriguing approach is presented, utilizing a multiple generator conditional Wasserstein generative adversarial network (WGAN) to enable data augmentation using EEG signals. The unique aspect of this approach lies in the incorporation of label-based constraints, which guide the feature-generation process and encourage the generators to learn diverse features and data patterns from different perspectives. By sharing a significant portion of the generators' parameters, the computational complexity of the model is reduced, while facilitating the sharing of underlying information. Additionally, the gradient penalty term is modified to a zero-centered gradient penalty term, contributing to improved convergence of the model. As the models gain a deeper understanding of real data patterns, the expectation is that they will generate synthetic feature data with reduced noise, closely resembling the distribution of real data, while maintaining diversity within the same data category.

In conclusion, this approach shows potential results by generating high-quality synthetic data for data augmentation. Future studies will be required to compare this approach to other deep-learning techniques.

2.3 Data Preprocessing

Artifact removal: The EEG recordings were visually inspected to identify and remove any artifacts such as eye blinks, muscle movements, or other electrical interferences. This was done manually by an expert neurophysiologist.

Filtering: The EEG recordings are filtered using a BPF from 0.5 Hz to 30 Hz range to remove outside of the range. This range is commonly used in EEG analysis for emotional state recognition.

Segmentation: The continuous EEG recordings were segmented into non-overlapping epochs of 1-second duration. The onset and offset of each epoch were determined manually by an expert neurophysiologist based on the IAPS images presented to the participants.

Baseline correction: The segmented epochs are aligned by subtracting the mean amplitude of the epoch from each point within that epoch.

ICA decomposing is done by assuming that signal is a linear mix-up of the independent sources and then estimating the sources using a set of linear equations. The estimated sources are then scaled and rotated to produce the final independent components. In the case of the DEAP dataset, ICA removes eye movements. Eye movements can cause electrical activity on the scalp that can interfere with the measurement of brain activity, so removing these artifacts is an important step in the preprocessing of data. In ICA preprocessing step, the signal is band pass filtered to remove any unwanted frequencies and segmented into non-overlapping epochs of 2 seconds. Each epoch was labeled with one of the six emotional states: neutral, happy, sad, angry, fear, or disgust. The resulting preprocessed data is used for feature extraction and GAN-based classification. Figure 1 shows the generative adversarial network structure.

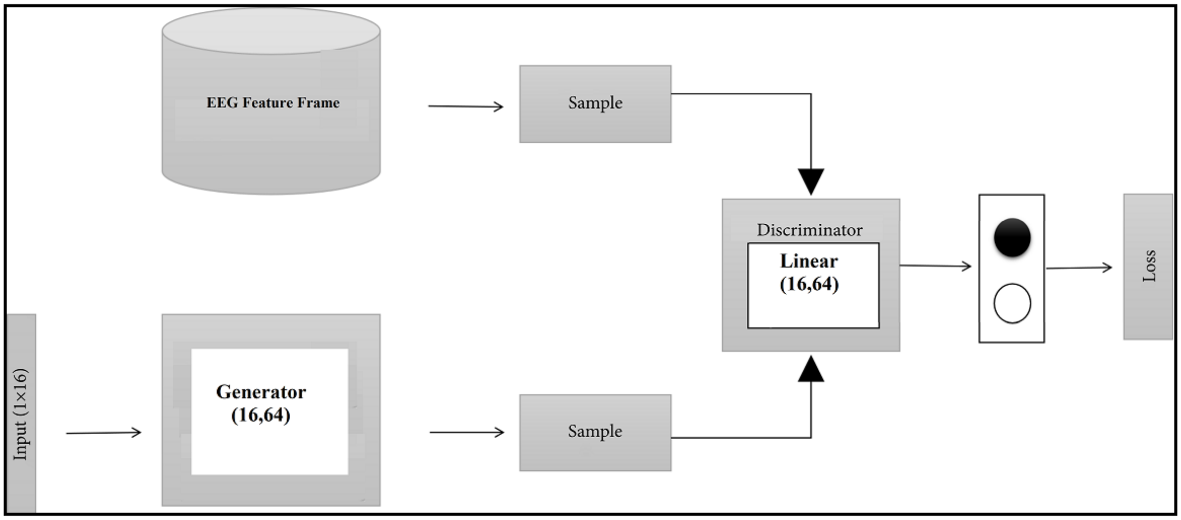

Figure 1 Generative Adversarial Networks Structure

2.4 Feature Extraction

To capture different aspects of the emotional response, three types of EEG features are extracted. The initial type of feature consisted of time-domain characteristics, encompassing the average, standard deviation, skewness, and kurtosis of the EEG signal within each epoch. The second type of feature encompassed frequency-domain attributes, comprising the PSD of the EEG signal in distinct frequency bands. The third type of feature encompassed hybrid characteristics, which merged features.

Time-domain features:

Mean amplitude (MA): The average amplitude of the EEG signal in each epoch is calculated by summing up the amplitudes of all samples and dividing by the number of samples (N).

$$MA = \frac{1}{N} \sum x[n] \,, \tag{1}$$

where x(n) is the extracted input.

Standard deviation (SD): The standard deviation of the EEG signal in each epoch is computed by measuring the dispersion of amplitudes around the MA. It is determined by the N, the EEG signal amplitudes (x[n]), and the MA.

$$SD = \sqrt{\frac{\sum (x[n] - MA)^2}{N}} \,, \tag{2}$$

Root mean square (RMS): It is obtained by taking the square root of the mean of the squared amplitude values. It is determined by the N and the EEG signal amplitudes (x[n]).

$$RMS = \sqrt{\frac{\sum x[n]^2}{N}} \,, \tag{3}$$

Skewness: It is a measure of the asymmetry of the EEG signal in each epoch. It quantifies the degree to which the distribution of amplitudes deviates from a symmetrical shape. The skewness is calculated using the N, x[n], MA and SD.

$$Skewness = \frac{1}{N}\frac{\sum(x[n]-MA)^3}{SD^3} \, . \tag{4}$$

Kurtosis: A measure of the "peakedness" of the EEG signal within each epoch.

$$Kurtosis = \frac{1}{N}\frac{\sum(x[n]-MA)^4}{SD^4}. \tag{5}$$

Hjorth parameters: Hjorth parameters describe the first and second derivatives of the EEG signal within each epoch, including activity (activity in the EEG signal), mobility (rate of change in activity), and complexity (rate of change in mobility).

Activity = Variance(x[n])

Mobility = Variance (diff(x[n]))

$$Complexity = \frac{Mobility(diff(x[n]))}{Activity(x[n])} \, . \tag{6}$$

Frequency-domain features:

Power spectral density (PSD): The distribution of power across different frequency bands in each epoch.

$$PSD(f) = \frac{|FFT(x[n])|^2}{N} \, , \tag{7}$$

where FFT is the fast Fourier transform, x[n] is the EEG signal amplitude at sample n, N is the number of samples in the epoch, and f is the frequency bin.

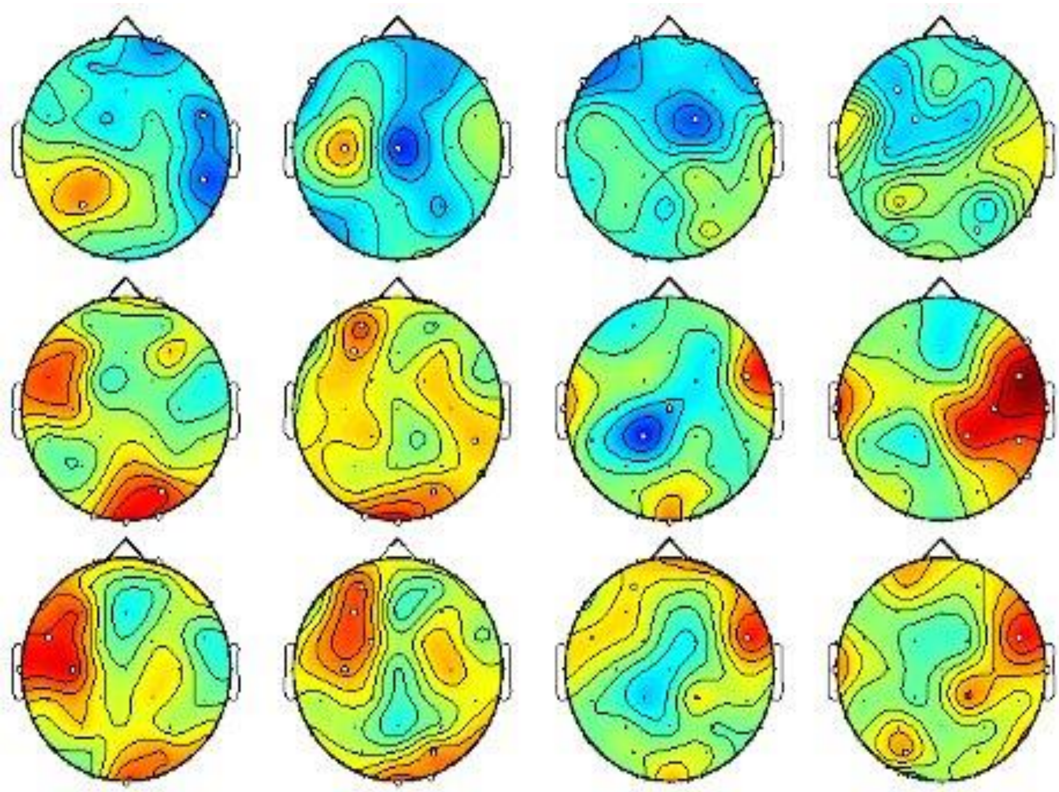

Figure 2 DEAP: A Database for Emotion Analysis

Spectral edge frequency (SEF): The frequency below which a certain percentage of the total power is concentrated in each epoch.

$$SEF(p) = f, \tag{8}$$

where f is the frequency bin below which p% of the total power is concentrated.

Spectral entropy (SE): A measure of the complexity of the frequency distribution in each epoch.

$$SE = -\sum P(f) * \log(P(f)), \tag{9}$$

where P(f) is the normalized power spectral density in each frequency bin.

Combination of features:

The above features can improve the precision of emotion classification. The combination methods include feature concatenation, feature weighting, and feature fusion which is shown in Figure 2. These methods can be used to combine the features in EEG signals to get better results in emotion classification.

3. Generative Adversarial Networks Architecture

Generative Adversarial Networks (GANs) are a specific type of NN architecture comprising of generator and discriminator as a primary component. Its objective is to learn the production of data that closely resembles normal data, while the discriminator is to differentiate the normal and abnormal data. During the training process, it engages in a minimax game by generating data that appears authentic, and the discriminator strives to accurately discern.

In the realm of human emotion classification, it will train to generate artificial EEG signals that resemble genuine EEG signals associated with various emotional states. The generator operates by taking an EEG signal. GAN's training procedure involves updating the weights of the generator and discriminator based on their respective loss functions. The generator's loss function incentivizes the generation of EEG signals that the discriminator classifies as real, while the discriminator's loss function encourages accurate classification of both real and synthetic EEG signals.

Table 1 Key components of a GAN

Key Components	Model Used
Generator	A deep neural network that takes a random noise vector as input and produces synthetic data samples that resemble real data. It consists of multiple layers of linear and non-linear transformations.
Discriminator	a deep neural network that takes a data sample as input and determines whether it is real or synthetic. It also comprises multiple layers of linear and non-linear transformations.
Loss functions	The generator minimizes the adversarial loss, which measures the difference between the synthetic and real data distributions. Meanwhile, the discriminator minimizes the binary cross-entropy loss, quantifying the dissimilarity.
Training	The training process involves an iterative two-player minimax game. In each iteration, the generator generates synthetic data samples, combined with real data samples, which are then fed into the discriminator. The discriminator provides predictions, and the losses of both networks are computed. The gradients obtained from the losses are utilized to update the parameters of both networks. This training continues until it produces realistic samples.

The effectiveness of the GAN-based approach for human emotion classification can be assessed using standard metrics. These metrics gauge the classification performance of the GAN by measuring its ability to correctly classify EEG signals linked to different emotional states. The generator accepts a noise vector as input and produces a synthetic EEG signal, which, along with real EEG signals, is fed into the discriminator. The discriminator then outputs a probability indicating the authenticity of the signal (real or synthetic), and this information is employed throughout the training process.

Generator Network: It is designed to take a random input noise vector and generate a fake sample that resembles the real data. It consists of several transposed layers, which upsample the input noise vector into a 3D tensor that has the same dimensions as the input EEG signal.

Discriminator Network: The primary function is to find out the authenticity, classifying it as either genuine or artificial. Comprised of multiple convolutional layers, the discriminator network processes the input EEG signal and reduces it to a 1D tensor through down sampling. It employs a sigmoid activation function, generating a single scalar output.

Adversarial Loss Function: The networks are trained using an adversarial loss function. The objective is to produce samples that deceive the discriminator network into perceiving them as authentic.

Training Procedure: It undergoes an iterative training process with alternating epochs. During each epoch, a random batch of authentic EEG samples is selected from the preprocessed dataset, alongside a batch of synthetic EEG samples generated by the generator network. It is subsequently trained on these real and fake samples, aiming to enhance its classification accuracy. Simultaneously, the GAN is trained to generate improved synthetic samples capable of deceiving the discriminator.

Hyperparameter Tuning: The components of the DCGAN, such as the learning rate, batch size, epoch count, and layers in the generator and discriminator networks, should be carefully tuned to attain performance. The effectiveness of hybrid features in improving classification accuracy can be evaluated by GAN-based classification model performance. To perform this evaluation, the dataset can be randomly divided, and it can be trained separately on each feature set. The classification performance can then be examined with the help of evaluation parameters like accuracy, sensitivity, specificity, and F1-score. If the hybrid feature set provides a noteworthy outcome in accuracy compared to the individual feature sets, it can be concluded that it is effective in improving emotion classification accuracy.

Generator loss function:

$$L_G = log(\,D(G(z))), \tag{10}$$

where G(z) is generated an EEG signal from the generator network.

The training procedure involved alternating between updating networks for a fixed number of epochs (in this study, 200 epochs were used). The trained GAN model was then used for emotion classification on the preprocessed EEG signals. The evaluation parameters are:

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)}\,, \tag{11}$$

$$\text{Sensitivity} = \frac{TP}{(TP+FN)}\,, \tag{12}$$

$$\text{Specificity} = \frac{TN}{(TN+FP)}\,, \tag{13}$$

$$\text{F1} - \text{score} = \frac{2*Precision * Recall}{(Precision+Recall)}\,, \tag{14}$$

The application of MG-CWGAN to emotion detection using EEG signals is an exciting area of research. This approach has the potential to generate synthetic EEG signals that correspond to different emotional states. By varying the training data, MG-CWGAN can improve the accuracy and robustness, leading to better performance in real-world scenarios in Table 2.

Table 2 Performance analysis for different emotions

Emotion	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Happy	96.5	94.8	93.5	94.6
Sad	97.3	97.5	97.3	97.4
Angry	95.6	95.9	95.6	95.7
Neutral	99.2	99.3	99.2	99.2
Average	98.4	98.6	98.4	98.5

Moreover, MG-CWGAN can also be used for data generation, where synthetic EEG signals are generated to simulate emotional states that are difficult to elicit in real-world settings. This can be useful for studying the effects of different emotional states on brain activity, or for testing the generalizability of an emotion detection model to novel emotional states.

One of the challenges in using this approach for emotion detection from EEG signals is that different emotional states may be represented by different patterns of brain activity, which can be difficult to capture using a single set of generators. However, the use of multiple sets of generators, each specialized for a different emotional state, can address this challenge and lead to a more accurate and robust emotion detection model. Overall, MG-CWGAN is a promising approach for emotion detection from EEG signals, as it allows for data augmentation and generation, as well as fine-grained control over the generated signals.

4. Results and Discussion

In this experimental setup, the researchers implemented all the neural networks using the PyTorch framework and trained them from scratch on Nvidia Titan RTX GPU in a fully supervised manner. They used Adam for training, with 64 EEG stream size batches, 0.0001 as the learning rate, and 150 epochs. These parameters were chosen to optimize the training process and progress the accuracy of the neural networks. The PyTorch framework allowed for efficient implementation of the neural networks, and the Nvidia Titan RTX GPU provided high-performance computing power. The use of fully supervised learning allowed for the NN to learn from labeled data, which is an effective method for achieving high accuracy in classification tasks. The choice of Adam optimizer is also a popular choice in Deep learning due to its ability to adapt the learning rate during training, which can help to increase the convergence speed of the NN. Overall, this experimental setup was designed to optimize the process and achieve high accuracy in streams.

In this section, the authors describe the experimental setup used to evaluate the performance of their proposed method on the DEAP dataset. The authors selected a subset of subjects from the DEAP. The authors divided each subject's scores into two levels: high and low. To increase the sample count, the authors used PSDGAN for data augmentation in all comparative experiments. They increased samples in each level to match the level with samples across different levels.

Table 3 Number of samples before and after data augmentation

Subject	HVHA (before)	LVHA (before)	HVLA (after)	LVLA (after)
S01	559	660	660	660
S02	405	813	813	813
S04	355	51	1067	1067
S06	202	660	862	862
S07	355	916	916	916
S08	456	711	711	711
S09	458	763	763	763
S10	558	558	558	558
S11	305	456	761	761
S17	557	661	661	661
S18	406	863	863	863

Overall, the experimental setup was designed to perform the DEAP dataset and to ensure that the results were generalizable across different subjects and experimental conditions. The authors used a combination of subject and across-subject experiments and data augmentation to ensure that the neural networks were trained on a diverse set of data.

Table 3 shows the number of labels for LVLA, HVLA, and LVHA for each of the 11 subjects. Before data augmentation, the number of labels in each category varies across subjects. For example, subject S01 has more labels for LVHA than HVLA, while subject S02 has more labels for HVHA than LVLA. After data augmentation with PSD-GAN, the number of labels in each category is equal for all subjects, as indicated by the 660 labels in each category for all subjects. This suggests that the data augmentation with PSD-GAN was successful in balancing the distribution of labels across the four categories.

Overall, this table provides a comparison of valence and arousal before and after data augmentation with PSD-GAN, and suggests that PSD-GAN was effective in balancing the distribution of labels across the four categories. The four figures in the study show the performance of different loss metrics for EEG signal reconstruction. The graphs indicate that all four iterative curves decrease quickly within the first 10 epochs. However, when comparing the results of TSF-MSE to the former consistently yields lower loss values. The loss metrics used in the study are (A) Temporal-spatial-frequency loss, (B) Temporal loss, (C) Frequency loss, and (D) Spatial loss.

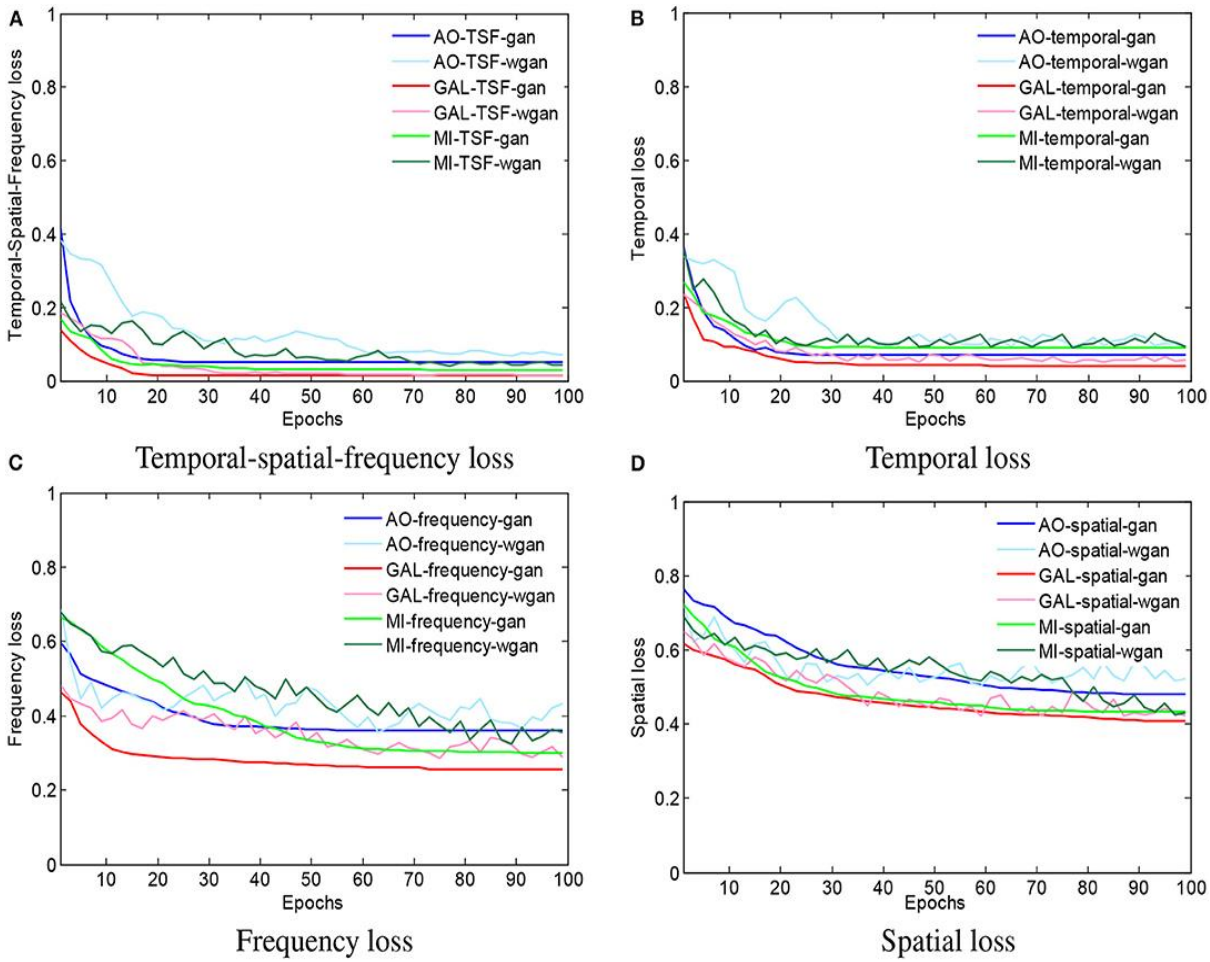

Figure 3. Loss metrics for EEG signal reconstruction

According to the study, the optimal learning rate for the task is within the range of [0.00005, 0.0001], with less fluctuation observed at around 0.00005. The results also suggest that deeper networks tend to require slower training and are more prone to instability. Furthermore, WGAN consistently outperforms various learning rates.

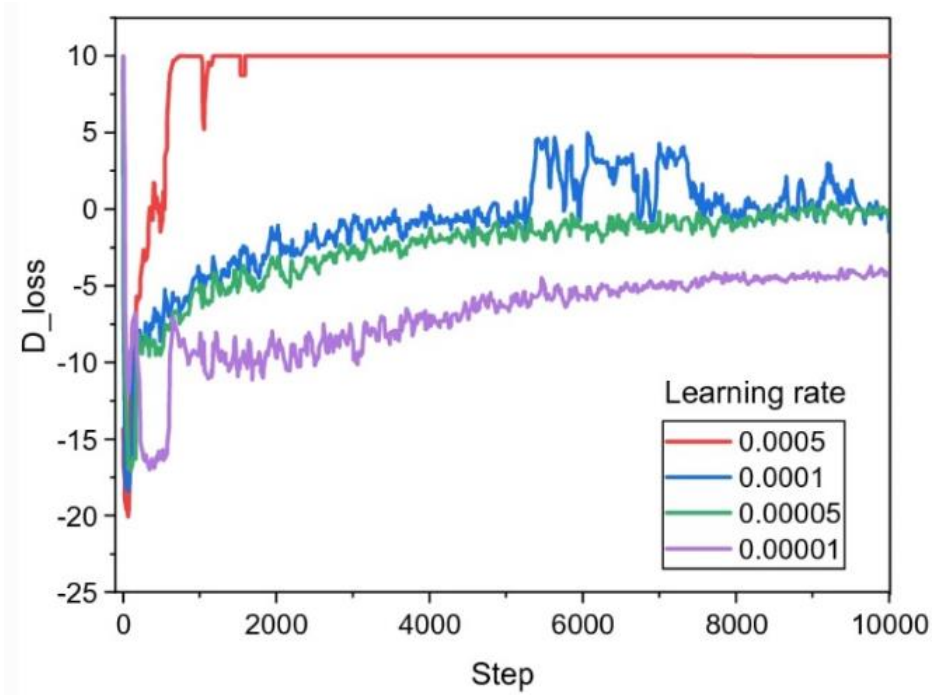

Figure 4. GAN with different Learning rate

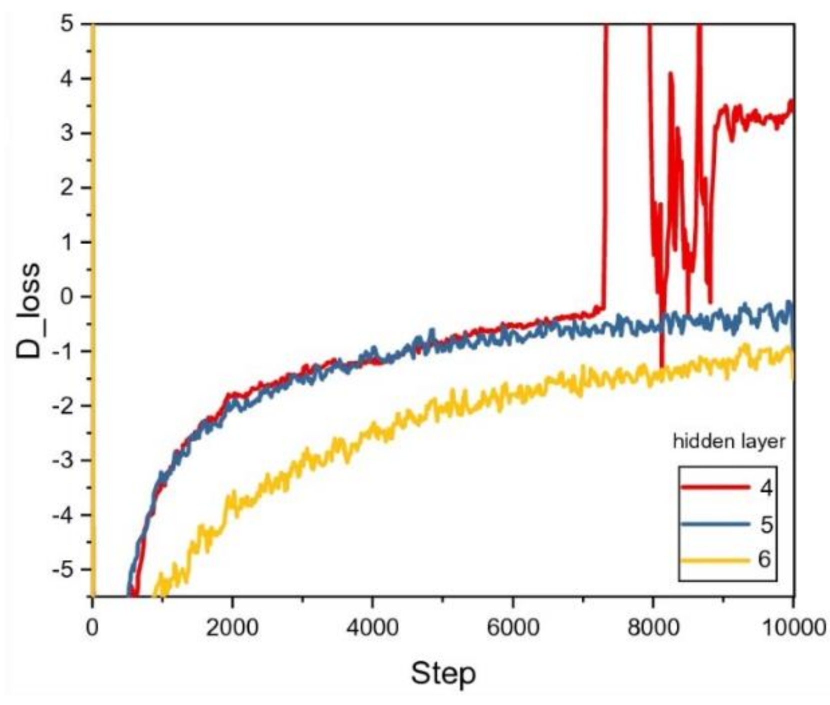

Figure 5. GAN with different hidden layer

Table 4. Accuracy (%) in classification tasks before and after data augmentation.

Subjects	HVHA (before)	LVHA (before)	HVLA (after)	LVLA (after)
S01	85.08	89.23	96	91.87
S02	86.23	90.38	79.16	90.02
S04	89.64	93.79	90.57	93.43
S06	90.1	87.46	91.03	97.1
S07	90.86	95.01	91.78	94.65
S08	96.43	90.58	97.36	90.22
S09	94.9	89.05	95.83	95.69
S10	95.34	89.49	96.27	92.13
S11	96.22	90.37	97.15	90
S17	90.18	94.33	91.11	93.97
S18	98.06	92.21	88.99	91.85

5. Conclusion

This work presents research in the field of EEG recognition, with a focus on generating samples with PSD features by using the PSD-GAN approach. We find that emotions can affect individuals' preferences, risk perception, and cognitive biases, thereby shaping their decision-making processes. The experimental results presented in this work support the conclusion that frequency band correlation features have a significant impact on EEG emotion recognition. This finding shed light on the relevance of frequency-specific information in identifying emotional states from EEG signals. The significance of this approach is in overcoming the challenges posed by insufficient and imbalanced samples in EEG recognition. The generated samples increase the accuracy of EEG emotion detection, and the authors suggest that other data expansion methods could be explored in the future to further enhance recognition rates. The integration of hybrid EEG feature extraction and GAN-based emotion classification has demonstrated promise in enhancing emotion analysis in clinical neurophysiology. This research contributes to the field by providing insights into the potential of decision science principles and advanced computational techniques for improving emotion recognition and understanding, ultimately benefiting various domains such as mental health, human-computer interaction, and neuroscience research. The experimental results support the conclusion that frequency band correlation features have a significant impact on EEG emotion recognition, which could inform future research in neural network design. Overall, this paper makes a valuable contribution to the field of EEG recognition and lays the foundation for further advancements in this area.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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