

Evaluating the Performance of Generative Adversarial Networks for EEG Signal Synthesis: A Comparative Analysis

University of Hertfordshire **UH**

Mahendra Nath Reddy E; Diego Resende Faria
School of Physics, Engineering & Computer Science
E-mail: ml.mahendranath@gmail.com

Introduction

The complexity of EEG data arises from its high temporal resolution and the intricate patterns it captures from brain activity. This makes it a valuable but challenging signal to analyze and model.

The scarcity of high-quality EEG data poses significant limitations for machine learning applications, as most models require large datasets to generalize effectively.

GANs offer a promising solution to these challenges by enabling the generation of synthetic EEG data that can augment existing datasets.

Unlike traditional augmentation methods, GANs are capable of capturing the complex temporal and spatial dependencies in EEG signals.

Research Question

- How effectively can GAN architectures generate realistic EEG data for mental state classification tasks?

Objectives

- Investigate and compare GAN architectures for generating realistic EEG data for two mental states: Concentrating and Relaxed.
- Generate synthetic EEG data for Concentrating and Relaxed mental states using multiple GAN architectures.
- Evaluate the quality of synthetic data using visual, statistical, and loss-based metrics.
- Compare the performance of GAN models to identify strengths and weaknesses.

Methodology and Development

Dataset:

- Source: Bird et al. (2018).
- Preprocessed EEG data for mental states: Concentrating and Relaxed.

Preprocessing Steps:

- Normalization: Ensured consistency across datasets.
- Temporal Alignment: Reduced noise/discrepancies.
- Channel Selection: Retained TP9, AF7, AF8, TP10, Right AUX.

GAN Architectures Evaluated:

- Standard GAN
- Dual GAN
- Deep Convolutional GAN (DCGAN)
- Wasserstein GAN with Gradient Penalty (WGAN-GP)

GAN Models Overview

Key Features:

- Standard GAN: Baseline model.
- Dual GAN: Two generators and discriminators for improved quality.
- DCGAN: Convolutional layers for stability and enhanced output quality.
- WGAN-GP: Gradient penalty and Earth Mover's Distance for addressing mode collapse and instability.

Training Details:

- Epochs: 5000 (Dual GAN: 500 in sequence)
- Latent Dimension: 100
- Batch Size: 64
- Learning Rate: 0.2

| Feature | WGAN | Vanilla GAN | Improved Vanilla GAN | DCGAN | Dual GAN |
|------------------------|----------------------|----------------------|------------------------------|----------------------|---------------------------------|
| Loss Function | Wasserstein distance | Binary cross-entropy | Binary cross-entropy | Binary cross-entropy | Binary cross-entropy |
| Stability Enhancements | Weight clipping | None | Batch normalization, Dropout | Batch normalization | Independent training for states |
| Network Type | Fully connected | Fully connected | Fully connected | Convolutional | Fully connected |
| Applications | General-purpose | General-purpose | General-purpose | Image-like data | Multi-modal data |

Result Analysis

Metrics Evaluated:

- Pearson Correlation Coefficient (PCC):** Measures correlation strength.
- KL Divergence:** Assesses distribution matching.
- Spectral Similarity:** Frequency content alignment.
- Signal Energy:** Intensity of generated signals.
- Peak Signal-to-Noise Ratio (PSNR):** Noise and clarity.
- Fréchet Inception Distance (FID):** Realism of generated signals.

Key Findings:

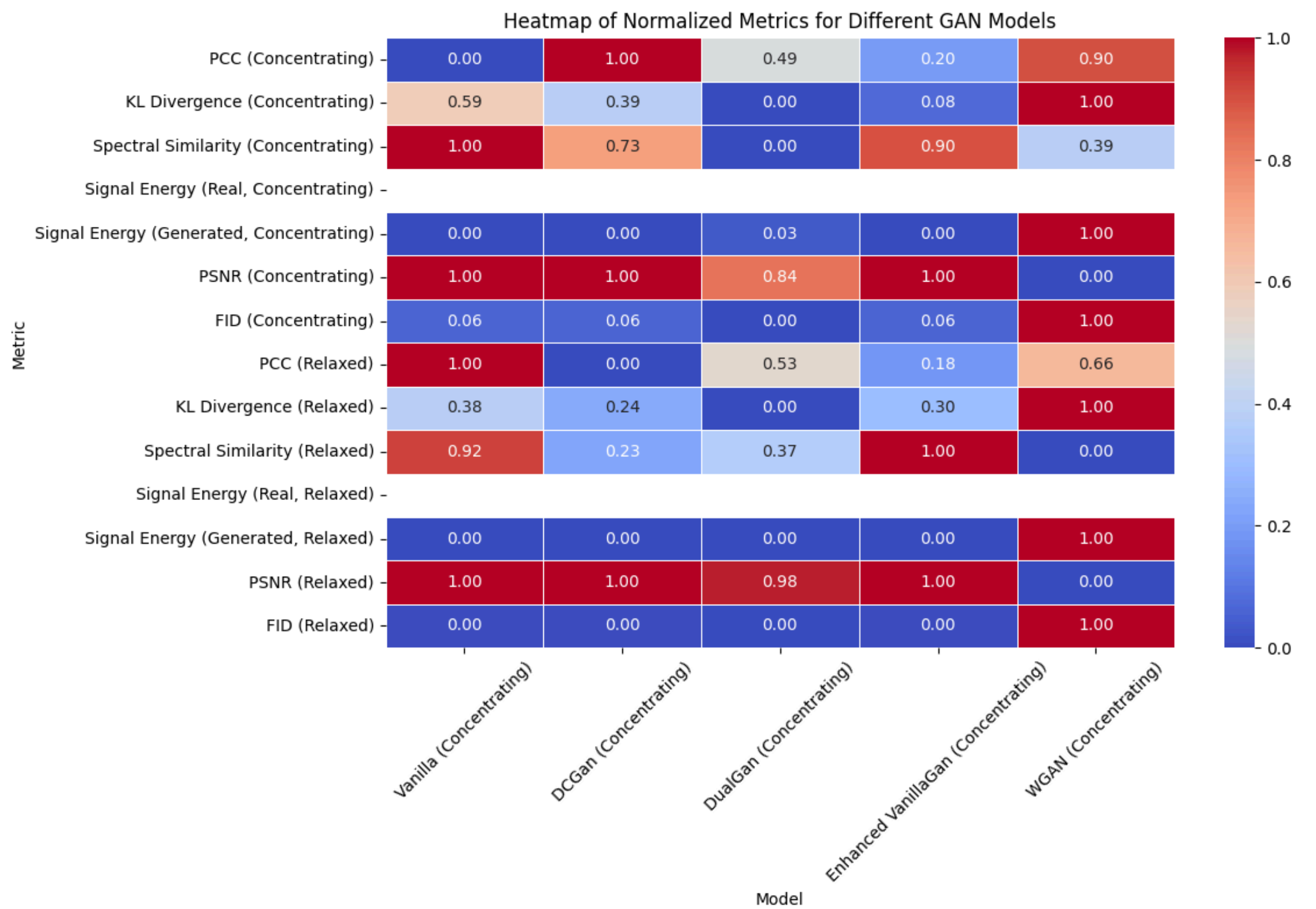
- WGAN-GP:** Most stable with high signal fidelity.
- Dual GAN:** Excels in distribution alignment and statistical similarity.
- Vanilla GAN:** Struggles with instability and overfitting.
- DCGAN:** Good spectral similarity but less robust in overall metrics.

Observations:

- Dual GAN leads in KL Divergence and FID for distribution alignment.
- WGAN-GP demonstrates high signal energy and stability during training.
- Enhanced Vanilla GAN excels in preserving spectral characteristics.
- Vanilla GAN exhibits significant challenges with overfitting.
- Negative PSNR values for WGAN-GP in some cases.
- Instability in Vanilla GAN training.

The combined score measures overall model performance. It averages multiple metrics across "Concentrating" and "Relaxed" states.

The **WGAN (Concentrating)** model achieves the highest combined score: **0.662363**.



Evaluating Model Performance

The discriminator loss, generator loss, and Kolmogorov-Smirnov (KS) test provide valuable insights into the quality of the models' outputs. WGAN exhibits significantly negative discriminator and generator losses, which is an indication of its strong ability to distinguish between real and fake data, as well as generate samples that align closely with the true data distribution. These extreme values suggest that WGAN is successfully minimizing both the loss functions to an exceptional degree.

| Model | Discriminator Loss (Final) | Generator Loss (Final) |
|----------------------|----------------------------|------------------------|
| WGAN | -46325.38 | -40421.15 |
| Vanilla GAN | 0.036112 | 9.579382 |
| DCGAN | 0.596716 | 1.12449 |
| Enhanced Vanilla GAN | 0.622476 | 0.737003 |
| DualGAN | 0.691442 | 0.709464 |

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