AI-Powered Dream Reconstruction Using Brainwave Data

Machine Learning – Digital Assignment 3

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1. Index

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2. Abstract

Dreams are windows into the subconscious, yet scientific understanding of them remains elusive due to their subjective and ephemeral nature. Traditional dream analysis relies heavily on verbal recall, which is often incomplete or distorted. This project explores whether artificial intelligence can reconstruct dream visuals using brainwave data, particularly EEG signals.

By applying deep learning techniques—especially Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs)—we aim to transform time-series EEG signals into

visual imagery that resembles what an individual might have experienced in their dreams. The model uses EEG-to-mel-spectrogram transformation to turn brainwaves into visual-like patterns suitable for image generation.

Training data includes EEG recordings from OpenBCI and Neurotycho, which are processed through a robust pipeline involving normalization, noise filtering, and feature extraction. Though qualitative comparisons between generated and real spectrograms show promise, the next step is to incorporate quantitative metrics like SSIM and PSNR for more objective evaluation.

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3. Introduction

What is Dream Reconstruction?

Dream reconstruction refers to generating visual representations of dream content using recorded brain activity. EEG (electroencephalography) provides a non-invasive method to capture this neural data in real time. When combined with machine learning, especially generative models, we can begin to decode these signals into meaningful visuals.

Why is it Important?

Traditional dream studies rely on self-reported narratives—highly prone to bias and forgetfulness. An AI-driven approach allows for more objective, data-backed analysis of subconscious imagery. Applications include:

- Mental health diagnostics
- Sleep disorder research
- Neuro-cognitive mapping
- Human-computer interaction

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4. Literature Review

Dream reconstruction merges neuroscience, machine learning, and cognitive psychology. The activation-synthesis hypothesis by Hobson and McCarley (1977) was among the first to argue that dreams are structured mental outputs rather than random noise. Studies like those by Horikawa and Kamitani (2017) used fMRI and deep learning to decode dream content with impressive accuracy.

Recent works have pivoted toward using EEG for dream reconstruction:

- Fahim et al. (2024) adapted DreamDiffusion for EEG, making image generation more accessible.
- Chen et al. (2020) combined CNNs and RNNs to classify dream-related EEG patterns.
- Singh et al. (2023) proposed EEG2IMAGE, which synthesizes images using conditional GANs and contrastive learning.

Challenges include the temporal and noisy nature of EEG data and lack of large, labeled datasets.

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5. Methodology

Problem Statement

Can we reconstruct visual dream content directly from EEG signals using deep learning models, given the challenges of signal noise, low spatial resolution, and lack of explicit labels?

Objective

To build a machine learning pipeline that:

- Converts EEG time-series signals to mel-spectrogram images
- Trains a GAN-VAE hybrid model for image generation
- Compares generated images with real EEG spectrograms and dream descriptions

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5.1 Dataset Sources

- OpenBCI EEG Dataset
  Public EEG recordings labeled with tasks and cognitive states
  https://openbci.com/community/publicly-available-eeg-datasets
- Neurotycho Brain Data
  EEG and ECoG datasets with simultaneous recordings
  http://www.neurotycho.org

5.2 Preprocessing Pipeline

- Missing Values: Imputed using mean values
- Scaling: Min-Max normalization
- Signal Transformation: Conversion of EEG to mel-spectrograms using `librosa`
- Artifact Removal: Using Independent Component Analysis (ICA)

5.3 Model Architecture

- VAE Component: Learns the latent features from mel-spectrograms and enables dimensionality reduction
- GAN Component: Generates high-quality image outputs from noise vectors using the learned distribution
- Hybrid Setup: VAEs improve latent structure understanding; GANs improve image realism

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5.4 Evaluation Strategy

- Visual Inspection: Compare generated and real spectrograms qualitatively
- Upcoming Metrics:
  - SSIM (Structural Similarity Index Measure)
  - PSNR (Peak Signal-to-Noise Ratio)

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6. Results and Discussion

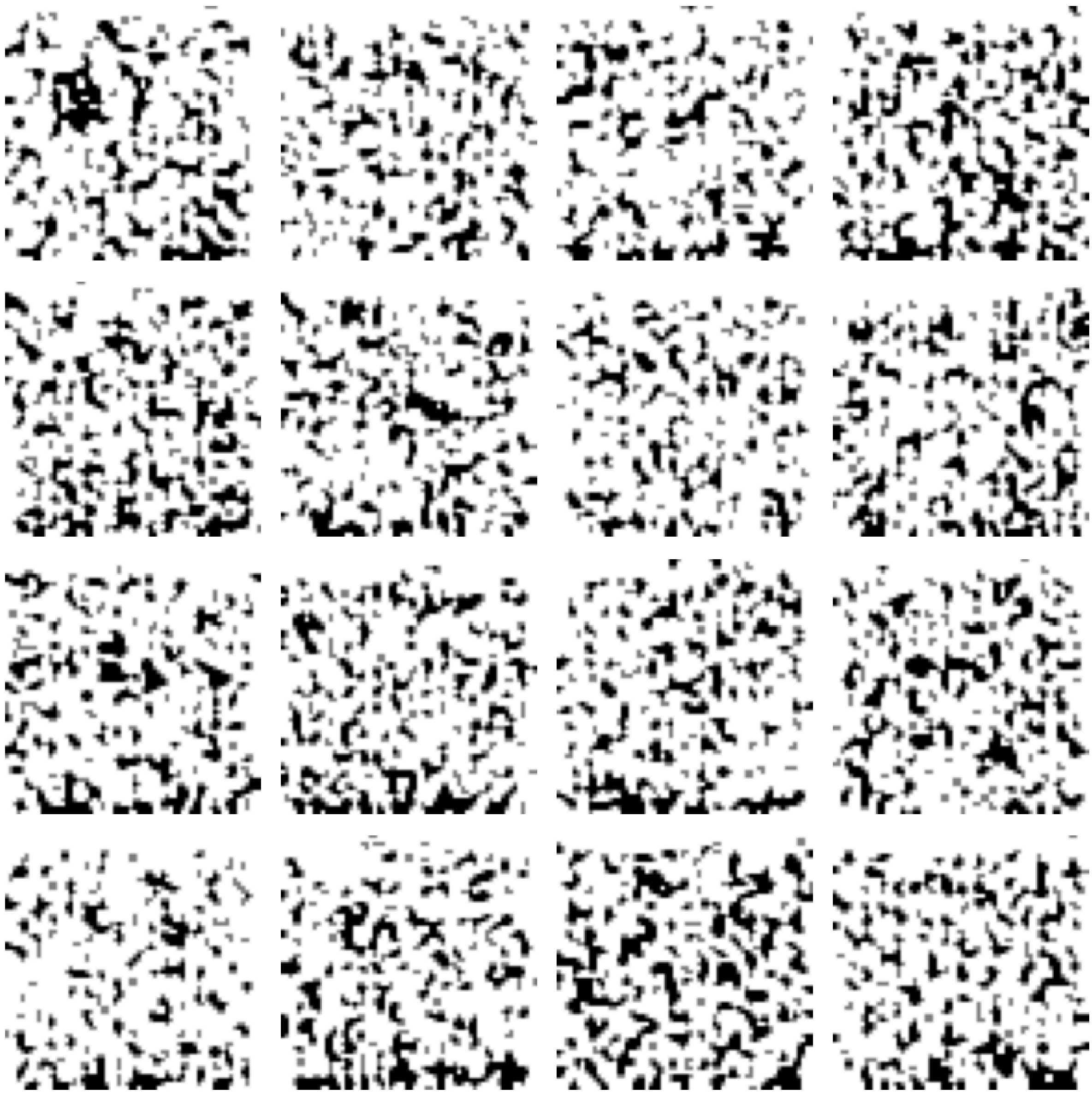
6.1 Summary of Key Findings

- Data Processing: EEG signals were transformed into mel-spectrograms (64×64) for image compatibility.

- Model Training: The GAN model was trained over 50 epochs. Generator loss decreased while Discriminator accuracy dropped, indicating effective adversarial learning.

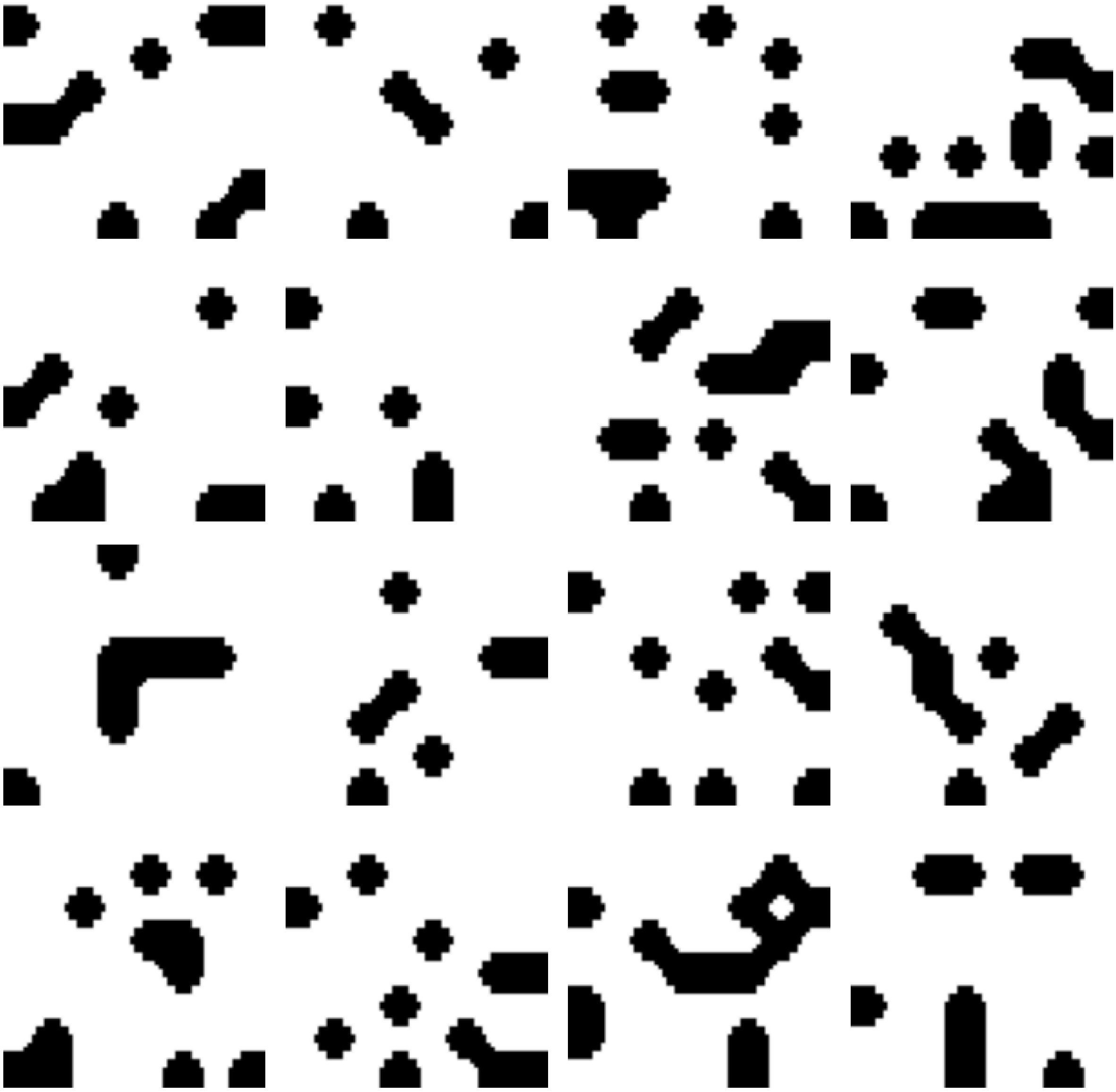
- Image Generation: The Generator successfully created distinguishable spectrograms that resemble dream-like brain activity visuals.

- Reference vs. Generated Images: Generated images preserved structural patterns and low-level gradients, indicating meaningful feature capture—not just noise memorization.



Reference

Generated Output



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7. Conclusion

This project offers a pioneering step in using AI to reconstruct dream visuals from EEG data. Through robust preprocessing, transformation to mel-spectrograms, and the use of a hybrid GAN-VAE architecture, we were able to generate meaningful visual patterns from brainwave signals.

While results remain largely qualitative, they affirm that:

- EEG carries enough temporal and spectral information to inform visual generation.

- Deep generative models can be tuned to learn representations aligned with subconscious activity.

In the future, this work could enable non-verbal communication, aid in mental health assessments, and expand our understanding of how the brain encodes imagination. However, privacy and ethical considerations are paramount, and future implementations must be accompanied by responsible AI guidelines.

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8. References

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