Artistic Visualization of Dream using EEG

This project aims to decode dreams from EEG data. The goal is reconstructing visual dream content using EEG Signals.

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Background Research

- EEG (Electroencephalography) captures **brain activity** as **electrical signals**.

- Types of EEG waves

1. Delta (0.5–4 Hz) → Deep sleep, unconscious states
2. Theta (4–8 Hz) → Dreaming, creativity, memory processing
3. Alpha (8–12 Hz) → Relaxation, calm wakefulness
4. Beta (12–30 Hz) → Active thinking, problem-solving
5. Gamma (30+ Hz) → High-level cognition, perception

- Current Solution - DreamDiffusion model.

Dataset Source & Format

The following datasets were used for this project. They consist of EEG data in EDF format accompanied by text files containing dream descriptions. Each dataset originates from a different study and language.

Source	Format	Language
Zhang & Wamsley 2019	EDF and Text files	English
Oudiette_N1Data	EDF and Text files	French
LODE	EDF and Text files	Italian
TWC_USA	EDF and Text files	Conversation-English
Donders	EDF and Text files	Conversation-English

Datasets & Synthetic Data Creation

Diverse EEG Data

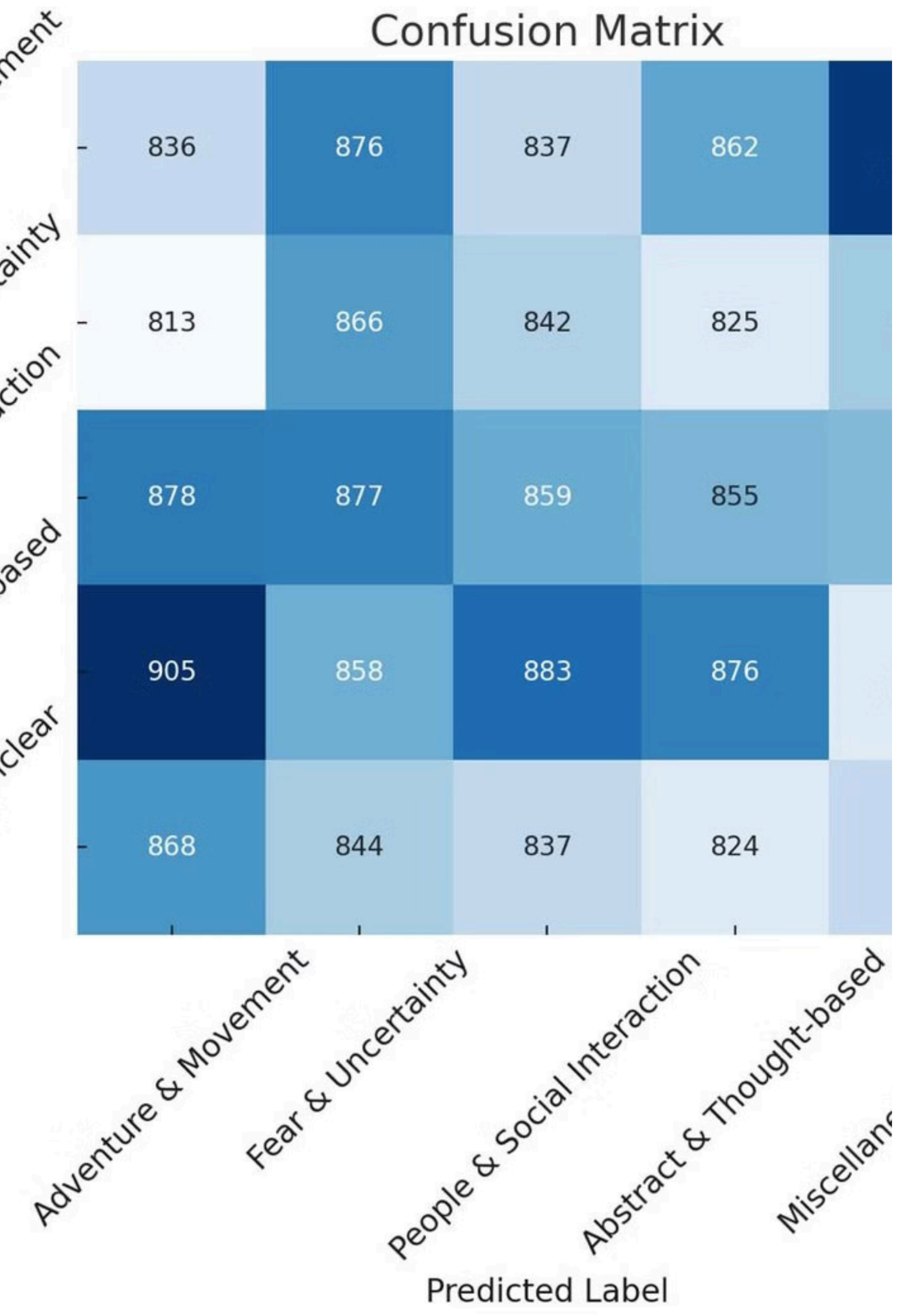
Utilizing 5 different datasets capturing sleep, dream reports, and visual imagery.

Data Combination & Categorization

Matching EEG segments to dream content keywords and categorizing them under 5 classes

Different Approach For Data Collection

Data collection approaches varies in terms of - language of text data, method of conversations and approach of Data Sampling



Data Categories

- **Adventure & Movement** (e.g., "going," "went," "see," "where") – Dreams about traveling, exploring, or movement.
- **Fear & Uncertainty** (e.g., "no," "think," "thought," "didn’t") – Dreams involving fear, confusion, or distress.
- **People & Social Interaction** (e.g., "she," "him," "people") – Dreams with conversations, relationships, or interactions.
- **Abstract & Thought-based** (e.g., "thinking," "know," "say") – Dreams focused on thoughts, realizations, or abstract ideas.
- **Miscellaneous & Unclear** (e.g., "some," "something," "things") – Dreams that don’t fit neatly into one category.

EEG Data Preprocessing

1. ## Feature Extraction

   - Highpass and Bandpass filter applied to extract waves
   - Filename,Channel,Band,PSD_Mean,PSD_Std,Mean,Variance,Skewness,Kurtosis

2. ## Data Cleaning

3. ## Handling Missing Values

Text Data Preprocessing

1. Converted txt file to CSV
2. Translate text to english
3. Extracted Keywords to Classify them into 5 categories
4. Combined all the 5 csv dataset in single csv

Model Development: Baseline (Random Forest)

1

Data Split

Train/Test/ Validation split: Training Set: (85521, 10) Validation Set: (21381, 10) Test Set: (11878, 10)

2

Model

Random Forest: simple, interpretable, handles non-linearity.

3

Metrics

```
✅ Validation Accuracy: 0.8819
✅ Test Accuracy: 0.8797

Classification Report (Validation Set):
               precision    recall  f1-score   support

           0       0.83      0.97      0.90      9019
           1       0.95      0.75      0.84      2712
           2       0.99      0.67      0.80       458
           3       0.95      0.80      0.87      3709
           4       0.91      0.87      0.89      5483

    accuracy                           0.88     21381
   macro avg       0.93      0.81      0.86     21381
weighted avg       0.89      0.88      0.88     21381

✅ Model saved successfully!
```

Model Development: CNN with Spectrograms

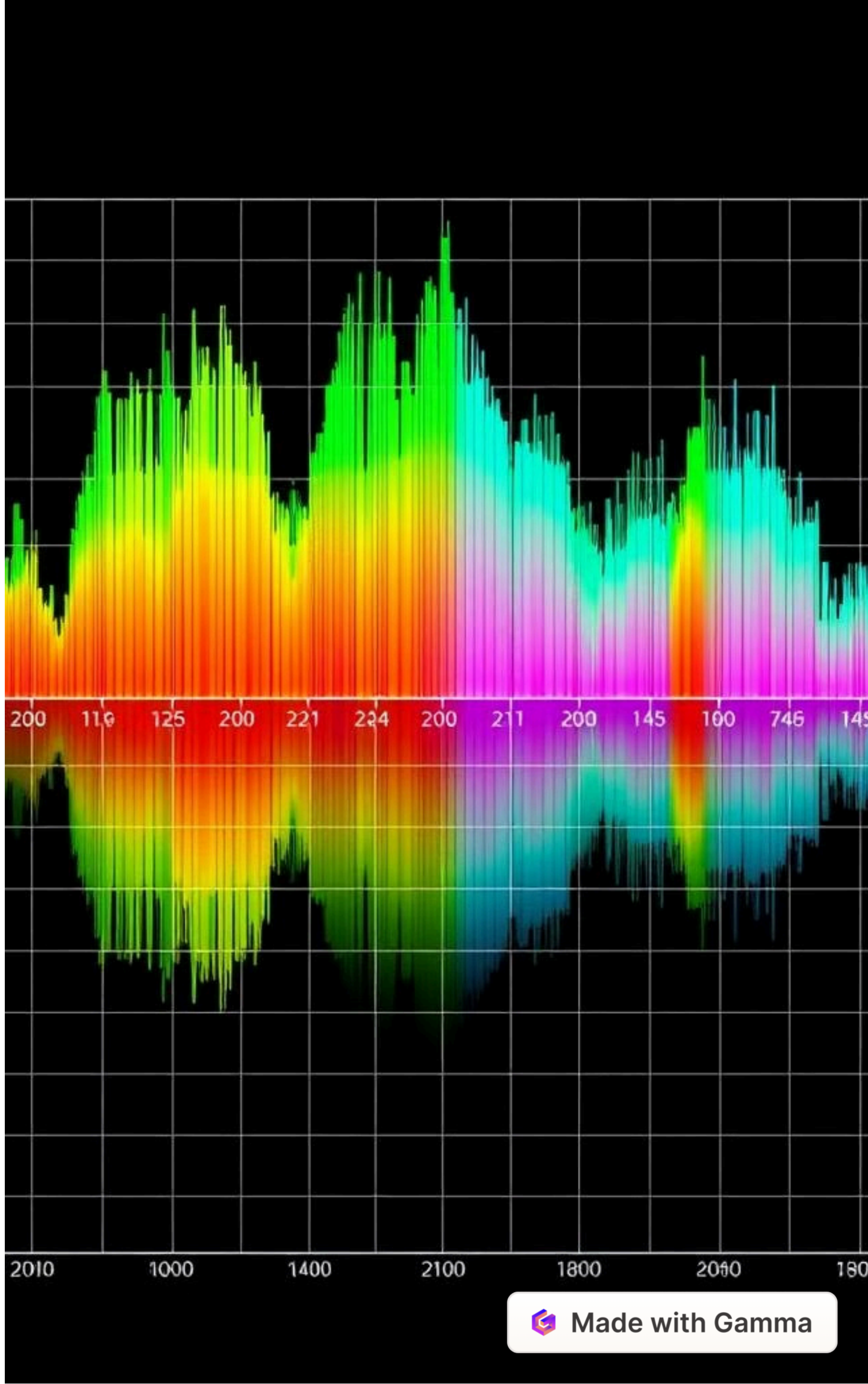
- **EEG Transformation**: Converted EEG time-series to time-frequency representations using STFT or Wavelet Transform.
- **Spectrogram Purpose**: Visualizes how signal frequency content changes over time, revealing hidden patterns in EEG signals.
- **Non-Stationary Nature**: EEG signals change over time; spectrograms show how frequency bands behave during dreams.
- **Dream State Classification**: Different dream states may have distinct frequency distributions, aiding classification.

Dataset Changes for CNN

1. Spectrogram
   - Converting EEG signals into spectrogram images.
   - Each EDF file can create multiple spectrograms, one for each EEG channel.
   - If an EDF file contains 32 EEG channels, it will generate 32 spectrograms. -
   - Total number of spectrograms = number of EDF files × number of EEG channels per file.

2. Mapping with Categories

3. New .csv file for CNN



CNN Model Training

Architecture : CNN

- 3 convolutional layers (extracting spatial patterns in spectrograms).
- Max pooling layers (reducing spatial dimensions while preserving features).
- Fully connected (dense) layers (classifying the image into 5 categories).
- Dropout layer (preventing overfitting).

Optimizer & Loss

- Model is trained using the Adam optimizer and CrossEntropy loss for 30 epochs.
- Training accuracy and loss are plotted to analyze model performance.

Training Time

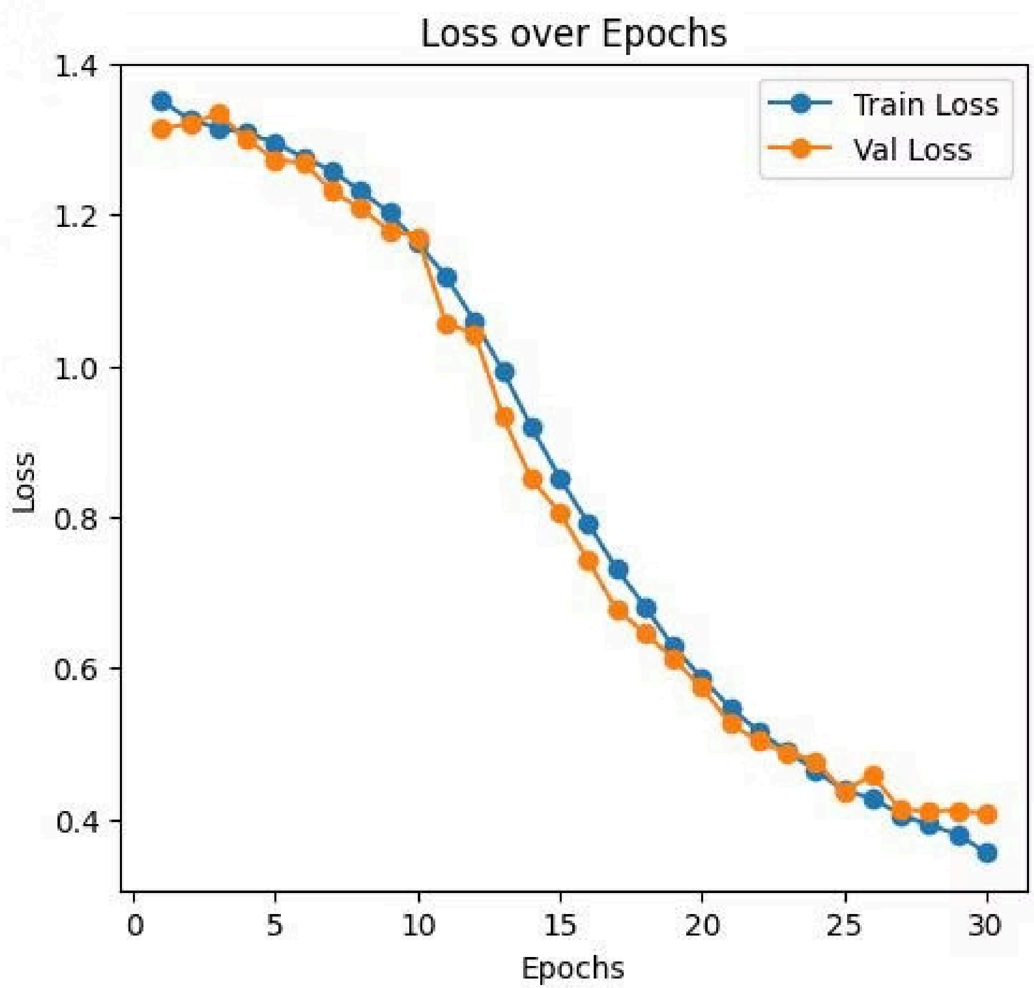
Approximately 4 hours for 30 epochs.

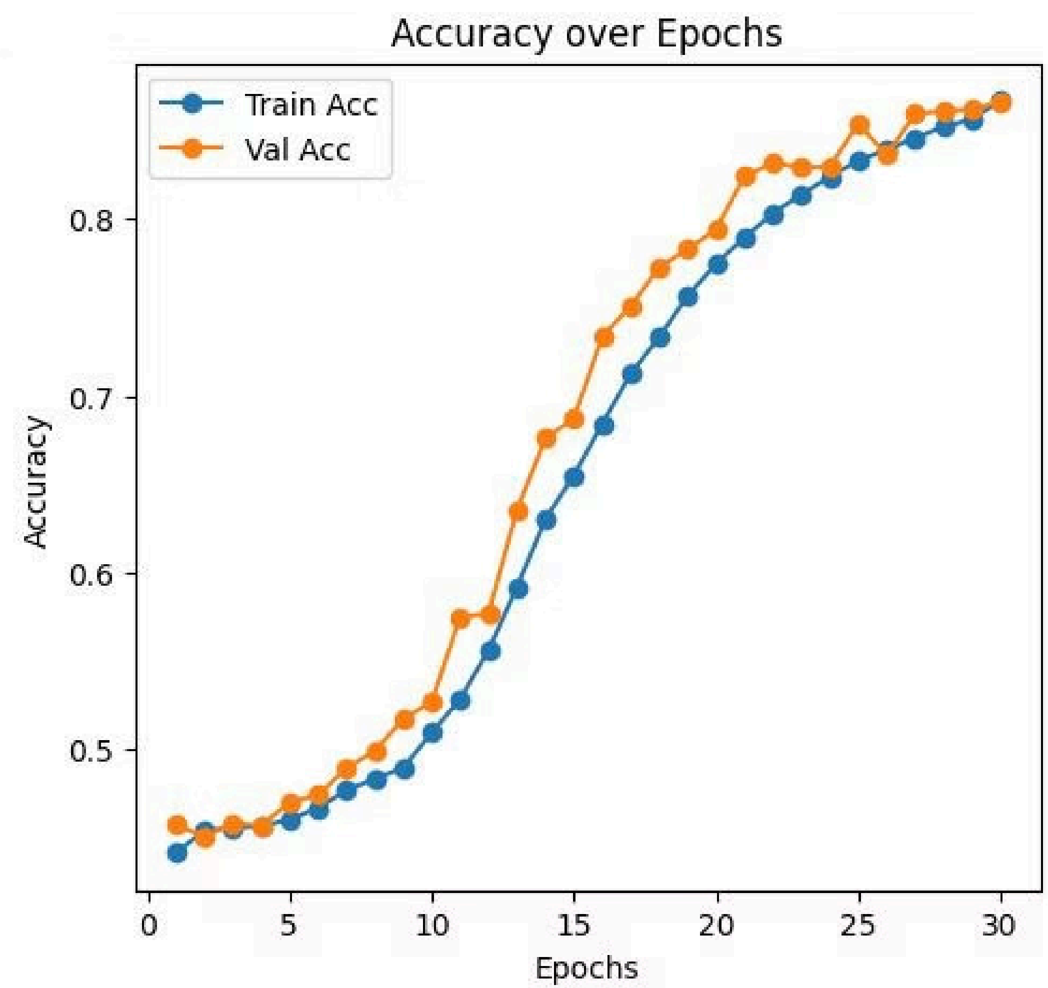
Generated Image

Category : Adventure and Movement

- Characterized by dynamic scenes involving travel, exploration, or physical activity.
- EEG signals fed into the CNN model, which processed spectrograms of the brain activity.
- CNN extracted relevant features, high activity in frequency bands linked to visual processing and motor imagery, suggesting an adventurous and active dream scenario.
- Output from the CNN was then used as input for DALL-E 3, a powerful text-to-image generation model.

Results & Evaluation





Test Accuracy: 87.7895%

Limitations & Future Work

Limitations

Limited EEG resolution, individual variability, data scarcity.

Future Directions

Develop personalized dream decoding models.

Goal

Real-time dream visualization systems.