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**Report**

**On**

**“Metadata-Driven Synthetic EEG Signal Generator for  
Multi-Channel Brainwave Simulatio**

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## Problem Statement

Create a robust, configurable synthetic EEG dataset generator that produces physiologically plausible multi-channel EEG recordings tied to participant metadata (age, gender, mental state, long/short-term issues, music exposure).

## Introduction

Electroencephalography (EEG) is one of the most widely used non-invasive neuroimaging techniques for studying brain activity. By capturing the electrical potentials generated by synchronized neuronal firing, EEG provides valuable insight into cognitive processes, emotional states, neurological conditions, and the influence of external stimuli such as music or stress. EEG signals are typically categorized into distinct frequency bands—delta, theta, alpha, beta, and gamma—which correspond to different functional and physiological states of the brain. For example, alpha activity increases during relaxation, beta is associated with alertness or stress, and theta is elevated during fatigue or emotional imbalance.

Despite its importance, **obtaining large, diverse, and high-quality EEG datasets remains a significant challenge**. Real EEG acquisition requires specialized hardware, controlled laboratory environments, strict participant protocols, and careful handling of ethical and privacy considerations. Moreover, EEG signals are highly subject-specific: age, gender, emotional state, health conditions, and even short-term disturbances such as fatigue or infection can substantially alter brainwave properties. As a result, collecting representative datasets for machine learning model training or algorithm benchmarking is often expensive, time-consuming, and limited in scale.

To overcome these barriers, synthetic EEG generation has emerged as an important complementary strategy. A well-designed synthetic generator can simulate realistic,

physiologically inspired EEG signals without requiring actual human subjects. Crucially, synthetic datasets enable rapid experimentation, help validate analytical pipelines, and support model development before real EEG is available.

The **Synthetic EEG Dataset Generator** developed in this project addresses this need by providing a metadata-driven, multi-channel EEG synthesis framework. Instead of producing generic or random EEG signals, the system incorporates **demographic attributes (age, gender), cognitive state (relaxed, stressed, anxious, depressed, drowsy), long- and short-term medical conditions, and music-based modulation** to shape the characteristics of the generated brainwave data. Frequency-band amplitudes and artifacts are influenced by established neurophysiological research, ensuring that the resulting signals resemble patterns observed in real EEG recordings.

Furthermore, the generator produces multi-band data for each standard EEG channel, injects realistic artifacts such as eye blinks and muscle noise, and applies a post-processing RMS alignment technique to ensure that the final band energies closely match the metadata-driven expectations. The output is a raw CSV dataset containing channel-band waveforms, ready for machine learning, visualization, statistical analysis, or feature extraction.

By offering a configurable, reproducible, and extensible framework, this synthetic EEG generator serves as a valuable tool for researchers, students, and developers working in computational neuroscience, affective computing, biomedical signal processing, and EEG-based emotion or health monitoring systems.

## System Overview

Create a robust, configurable synthetic EEG dataset generator that produces physiologically plausible multi-channel EEG recordings tied to participant metadata (age, gender, mental state, long/short-term issues, music exposure).

**The system is a Streamlit-based EEG signal generator with:**

- Metadata-driven control
- Editable multiplier mappings (mental, medical, demographic)
- Band-wise signal synthesis
- Artifact injection
- Music transient effects
- RMS-based post-scaling for band accuracy
- CSV export with all channel-band signals

**It is designed for:**

- Machine learning dataset creation
- Benchmarking classification pipelines
- Research simulations
- Teaching and demonstration purposes

## Metadata Architecture

Category	Parameters
Demographic	Name, Age, Gender
Cognitive / Emotional	Mental state (e.g., relaxed, stressed, anxious, depressed, happy, drowsy)
Health Profile	Long-term issues, Short-term issues
Music-Related	Listening preference, Genre, Onset time, Duration

## Signal Generation Pipeline

The generator creates EEG data in five major steps:

### 1 Time-base creation

A time vector is produced according to duration and sample rate:

```
time = 0 → duration (resolution = 1/srate)
```

### 2 Band-specific waveform synthesis

For each channel-band pair:

- 1–3 sinusoids chosen randomly within band frequency range
- Amplitude modulation simulates natural variability
- Low-level Gaussian noise added
- Channel scaling introduces inter-channel variability

### 3 Music transient envelope

If music is enabled:

- Time-local amplitude boosts applied during onset → duration
- Genre-specific bands enhanced (e.g., classical: alpha↑, rock: beta↑/gamma↑)

### 4 Artifact injection

Simulated eye-blinks and muscle artifacts are inserted into channel-level signals:

- Eye blinks → large, slow Gaussian bumps
- Muscle bursts → short, high-frequency noise bursts

Artifacts are then redistributed proportionally into band components.

## 5 RMS alignment (post-processing)

After synthesis:

1. Compute observed RMS per band across channels.
2. Compare with metadata-derived target band distribution.
3. Apply conservative amplitude scaling ( $0.7\text{--}1.4\times$ ) to nudge RMS closer to expected values.

This ensures metadata meaningfully influences the generated data.

## Raw CSV Dataset (Final Output)

The final output is a **single CSV file** containing all synthesized EEG samples.

### CSV Structure

The CSV includes:

#### Time column

`time`

#### Channel-band signal columns

Format:

`<Channel>_<Band>`

Example:

`Fp1_delta, Fp1_theta, Fp1_alpha, Fp1_beta, Fp1_gamma  
Fp2_delta, Fp2_theta, ...`

These contain floating-point amplitudes ( $\mu\text{V}$ ) for each timestamp.

#### Metadata columns (repeated on each row)

```
patient_name
age
gender
mental_state
long_term_issues
short_term_issues
wants_to_listen
music_genre
music_onset
music_duration
```

### Example header

```
time, Fp1_delta, Fp1_theta, Fp1_alpha, Fp1_beta, Fp1_gamma,
Fp2_delta, Fp2_theta, ... , F7_theta, F7_alpha, F7_beta,
...
patient_name, age, gender, mental_state, long_term_issues,
short_term_issues, wants_to_listen, music_genre,
music_onset, music_duration
```

### Units

All voltage samples are in **microvolts ( $\mu\text{V}$ )**.

### Row count

**Number of rows = duration × sample\_rate.**

## Deterministic Generation & File Naming

### Reproducible seeds

If no seed is provided, a deterministic seed is computed from:

```
name + age + gender + mental_state + music_genre
```

so regenerating with identical metadata yields identical synthetic EEG.

### Filenames

Files follow the pattern:

```
synthetic_eeg_<Name>_YYYYMMDD_HHMMSS.csv
```

## Batch Generation

A batch metadata CSV can be uploaded to generate multiple EEG datasets at once:

- One output CSV per participant
- All files stored in `generated_batch/`
- Optional deterministic seeding (`seed = 1000 + i`) ensures reproducibility

## Experimental Behavior & Observations

### Band distribution patterns

Metadata strongly influences RMS distribution:

- Relaxed  $\rightarrow \uparrow$  alpha
- Stressed  $\rightarrow \uparrow$  beta
- Drowsy  $\rightarrow \uparrow$  delta/theta
- Music (classical)  $\rightarrow \uparrow$  alpha/theta during onset-duration
- Long-term issues (e.g., epilepsy)  $\rightarrow$  broad-band increases

### Artifact characteristics

Artifacts appear as:

- Sharp amplitude peaks (eye-blink-like)
- Short high-frequency distortions (muscle bursts)

These resemble real EEG noise sources.

# Synthetic EEG Dataset Generator ↗

## Actions

Generate single dataset (use current metadata)

Generate batch (from uploaded batch CSV)

## Preview

No dataset generated. Click 'Generate single dataset'.

*Figure 1 : Home Interface of the Synthetic EEG Dataset Generator*



## Participant metadata (enter values then press Generate)

Name

Age

25

-

+

Gender

Male



Mental state

relaxed



Add mental state (type & press Add)

Add mental state

Figure 2 : Participant Metadata Input Section

## Long-term issues (multi-select; add new then select)

Add long-term issue

Add long-term issue

Long-term issues

Choose an option



## Short-term issues (multi-select; add new then select)

Add short-term issue

Add short-term issue

Short-term issues

Choose an option



Figure 3 : Long-Term and Short-Term Issue Configuration Panel

---

## Music options

Wants to listen?

True ▼

Genre

classical ▼

Time of day

morning ▼

Music onset (s)

10.00 – +

Music duration (s)

30.00 – +

---

*Figure 4 : Music Exposure Configuration Section*

## Recording settings

Recording duration (s)

60.00

– +

Sample rate (Hz)

256

▼

Template CSV (optional)



Drag and drop file here

Limit 200MB per file • CSV

Browse files

Batch metadata CSV (optional)



Drag and drop file here

Limit 200MB per file • CSV

Browse files

☐ Create .docx report

Figure 5 : Recording Settings and Template Upload Panel

>

Synthetic EEG Dataset Generator

Deploy

Actions

Generate single dataset (use current metadata)

Generated: synthetic\_eeg\_Darshan\_20251212\_094839.csv

Generate batch (from uploaded batch CSV)

Preview

First 6 rows of last generated file:

	time	Fp1_delta	Fp1_theta	Fp1_alpha	Fp1_beta	Fp1_gamma	Fp2_delta	Fp2_theta	Fp2
0	0	-8.8528	12.3055	9.6394	0.7987	1.9137	-3.333	19.1407	
1	0.0039	-5.5651	6.8764	5.4803	0.4747	-2.2347	-4.2156	18.7491	
2	0.0078	-3.2166	3.1908	2.5423	0.182	-1.4017	-3.9383	16.7945	
3	0.0117	-4.6591	3.9677	3.4871	-0.1304	1.0411	-3.2652	12.5401	
4	0.0156	-2.5535	1.4297	1.2852	-0.2494	1.4677	-2.6435	9.5335	
5	0.0195	6.0295	-1.3793	-1.9904	1.0383	-0.4302	-0.9298	2.3182	

Download CSV

Figure 6 : Dataset Generation Confirmation and CSV Preview

Per-channel RMS (summary):

	delta	theta	alpha	beta	gamma
Fp1	12.498	19.061	12.74	4.893	3.516
Fp2	13.378	9.151	5.225	6.032	1.151
F3	10.966	15.865	3.857	3.481	2.535
F4	5.065	9.866	17.279	5.4	3.22
F7	12.288	14.172	3.633	7.829	1.502
F8	11.065	16.904	16.338	4.344	2.726
Fz	9.141	13.308	7.06	6.826	2.03
C3	6.287	10.547	13.586	6.19	2.704
C4	8.512	3.368	14.015	7.099	0.634
Cz	10.323	4.18	6.044	8.813	1.973

Figure 7 : Per-Channel RMS Summary Table

## **Acknowledgement**

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