NEUROSKY–EPI: The First Open Single–Electrode Epilepsy EEG Dataset with Context–Aware Modeling and Clinically Grounded Metadata

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Abstract

We introduce **NEUROSKY–EPI**, to our knowledge the *first open* single–electrode EEG dataset for epilepsy. The resource contains **25 patients** and **2,032** labeled **1 s** windows captured with an off–the–shelf NeuroSky MindWave Mobile 2 headset, accompanied by clinically interpretable metadata (seizure type, antiepileptic drugs, comorbidities, adherence, education, socioeconomic status). We propose a simple, reproducible evaluation for handy devices: train EEGNet using **CHB–MIT** windowed into **12,009 8 s** segments from **24 patients** on a **single Fp1** channel to mirror the consumer lead, then evaluate directly on NEUROSKY–EPI band–power features. This practical setup yields $\sim$60% test accuracy; augmenting inputs with a **16–dim** context vector from an autoencoder that summarizes resting$\leftrightarrow$awake responsiveness improves performance to $\sim$68%. Patient–level embeddings from EEGNet's penultimate layer also show stronger unsupervised separability with context (KMeans: 54.17% $\rightarrow$ 66.67%). We will release de–identified data, code, and concise dataset/model cards to enable clinically grounded, low–compute epilepsy analytics and fairness–aware studies on single–electrode recordings.

1 Introduction

Across many regions, access to clinical multi–channel EEG is limited, follow–up is irregular, and compute resources are constrained. We therefore ask whether *single–electrode, low–cost* recordings from an off–the–shelf headset can support actionable epilepsy analytics when paired with a compact, reproducible evaluation protocol.

This work proposes a dataset–first evaluation with a handy consumer device and establishes a simple benchmark others can replicate. To our knowledge, **NEUROSKY–EPI** is the *first open single–electrode EEG dataset for epilepsy*. It contains **25 patients** and **2,032** labeled **1 s** windows (256 Hz) captured with NeuroSky MindWave Mobile 2 and paired with clinically interpretable metadata (seizure type, AEDs, comorbidities, adherence, education, socioeconomic status). For supervised supervision we use **CHB–MIT** windowed into **12,009 8 s** segments from **24 patients**, training EEGNet on a **single Fp1 channel** to mirror the consumer device, and then evaluating on NEUROSKY–EPI.

Contributions. (1) **NEUROSKY–EPI:** an open, single–electrode epilepsy dataset (25 patients; 2,032 windows, 1 s) with medical+social metadata to enable clinically grounded and fairness–aware analyses. (2) **Practical evaluation protocol:** a minimal, reproducible benchmark for handy devices–standardized windowing, single–lead (Fp1) training on CHB–MIT, and direct evaluation on

NEUROSKY–EPI—suited to low compute and limited clinical infrastructure. (3) **Context–aware enhancement:** adding a 16–dim autoencoder context vector to band features improves supervised accuracy from ∼60% to ∼68% and boosts patient–level KMeans clustering from 54.17% to 66.67%. (4) **Open release:** de–identified data, code, and concise dataset/model cards to facilitate reuse and extension.

2 Datasets

CHB–MIT (training source; brief). We use the CHB–MIT scalp EEG database for supervised training (PhysioNet: CHB–MIT Scalp EEG Database). We window CHB–MIT into **12,009** segments of **8 s at 256 Hz** drawn from **24 patients**. To match our consumer device, we *restrict training to a single Fp1 channel* (or closest available lead).[1]

NEUROSKY–EPI (this work; evaluation set). **Cohort:** 25 patients from a South Asian Country. **Device:** NeuroSky MindWave Mobile 2 at Fp1 with ear–clip reference **Windows: 2,032** labeled windows of **1 s** . Data were taken in two phases - resting and awake phase. Both were taken for 1 minute each. Labels inherit contemporaneous patient seizure status (seizure-positive vs. seizure-free at visit). **Metadata:** age, gender, education, socioeconomic status, age of onset, seizure type (e.g., generalized tonic–clonic, absence), current AEDs (e.g., carbamazepine, valproate, levetiracetam), treatment duration, comorbidities (e.g., tuberculosis, diabetes, ADHD, depression), seizure–frequency change, satisfaction, adherence, occupation. Identifiers are de–identified; linkage keys are hashed prior to release.

3 Method

Goal: transfer supervision from clinical CHB–MIT (8 s windows) to consumer single–electrode inputs (1 s windows) while exploiting state context.

3.1 Stage 1: Bands → Generator Head → EEGNet (single Fp1)

For each window x, we compute **10** NeuroSky–compatible features: *Attention, Meditation, Theta, Delta, LowAlpha, HighAlpha, LowBeta, HighBeta, LowGamma, MidGamma* ($b(x) \in \mathbb{R}^{10}$). A small **generator head** $g : \mathbb{R}^{10} \to \mathbb{R}^{2048}$ (MLP→reshape→upsampling) maps features to an *EEGNet-length sequence* . This allows a single architecture to handle both 8 s CHB–MIT and 1 s NEUROSKY–EPI by up-mapping the latter.

3.2 Training & Cross–Domain Inference

We train EEGNet (5) for **50 epochs** on CHB–MIT (post–g, **single Fp1 channel**), reaching ∼**75%** validation accuracy. Applying the trained model to NEUROSKY–EPI (1 s $\to b(x) \to g(\cdot) \to$ EEGNet) yields ∼**60%** test accuracy.This phase is done without context vectors involved as inputs.

3.3 Stage 2: Context Autoencoder and Fusion

An autoencoder (8; 7) produces a **16–dim context vector** $c(x)$ summarizing resting↔awake responsiveness and also all rest and awake phase values. We concatenate $[c(x);\, b(x)] \in \mathbb{R}^{26}$, feed through the same $g(\cdot)$, and retrain for **50 epochs**, observing ∼**85%** CHB–MIT–style validation and ∼**68%** test accuracy on NEUROSKY–EPI. Optimization uses Adam (6) with early stopping.

3.4 Stage 3: Patient Embeddings & Unsupervised Evaluation

From EEGNet's penultimate layer we extract a $16 \times 1 \times 64$ map per window, mean–pool per patient, then cluster (KMeans (11), Agglomerative/Ward (12), GMM with EM (10), Spectral (9)) into two groups; accuracy uses direct label assignment.

[1] If CHB–MIT uses bipolar montages, the Fp1-derived channel is chosen for parity with NeuroSky Fp1.

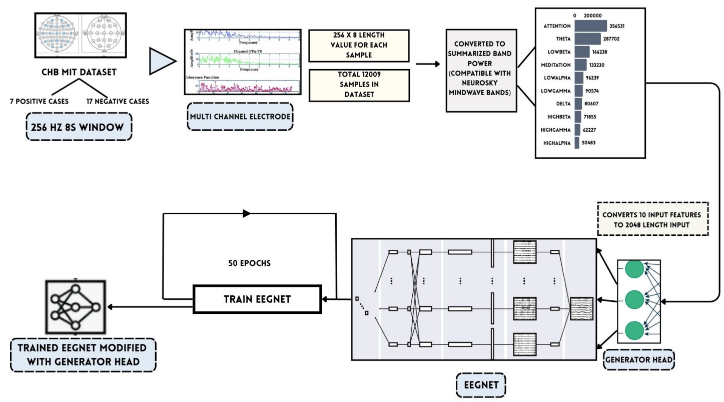

Figure 1: Stage 1: 10–D band power → generator head → EEGNet trained on CHB–MIT (single Fp1).

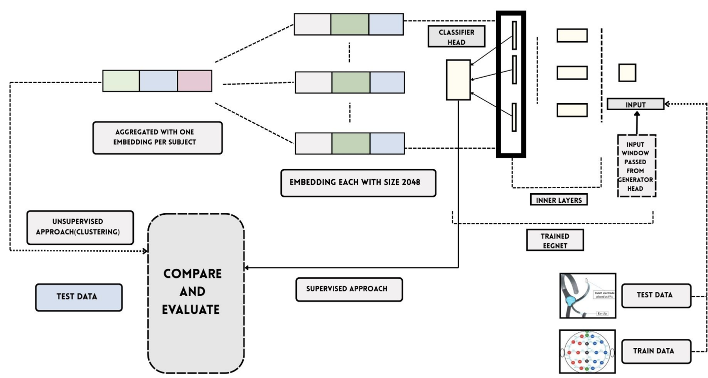

Figure 2: Stage 2: Inference with trained EEGNet. Here no context vector is used. Supervised classification is evaluated with the classifer's output against our collected data. And for unsupervised analysis, the embeddings of the second last layer are collected and then aggregated for unsupervised clustering.

4 Experiments & Results

Setup. 50 epochs, Adam, early stopping; generator head trained jointly. Two–cluster evaluation for unsupervised methods.

4.1 Supervised (window–level)

Bands only (1 s $\rightarrow b(x) \rightarrow g(\cdot) \rightarrow$ EEGNet): $\sim$**60%** test on NEUROSKY–EPI; CHB–MIT val $\sim 75\%$. **Bands + context** (16–D + 10–D): $\sim$**68%** test; CHB–MIT–style val $\sim 85\%$.

4.2 Unsupervised (patient–level)

Without context.

Method	Accuracy	Cluster sizes (0/1)
KMeans	0.5417	10 / 15
Agglomerative	0.5833	12 / 13
GMM	0.5417	10 / 15
Spectral	0.5833	12 / 13

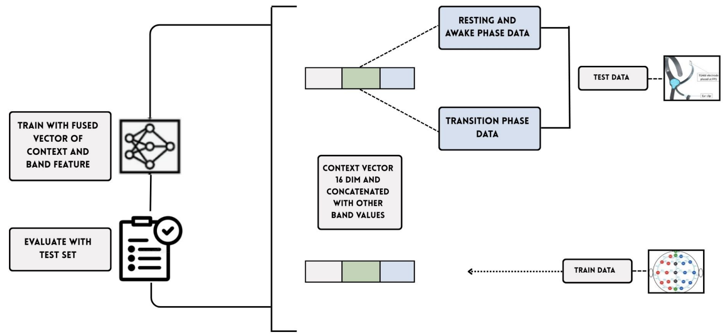

Figure 3: Stage 3: Experiments with context vectors as concatenated input along with band signal values. Then it undergoes same steps of stage 2 which include supervised and unsupervised classifications

With context.

Method	Accuracy	Cluster sizes (0/1)
KMeans	**0.6667**	14 / 11
Agglomerative	0.6250	18 / 7
GMM	0.5000	10 / 15
Spectral	0.5000	15 / 10

Summary. Context improves KMeans by +12.5 pp; others are mixed, suggesting gains from stronger aggregation and representation learning. We also note that discrepancies between CHB–MIT training and NEUROSKY–EPI evaluation are partly attributable to limited sample size and class imbalance; expanding the dataset with more balanced cohorts is expected to further reduce this gap.

5 Clinical Relevance, Release, and Ethics (Concise)

Clinical linkage. Metadata support analyses of seizure phenotype, age of onset, AED regimens (with satisfaction/adherence), comorbidities (e.g., tuberculosis, diabetes, depression, ADHD), and social determinants (education, socioeconomic status) which enable medically grounded modeling and fairness auditing.

Release. We will provide 10–D features per window, labels, hashed patient keys, de–identified metadata, and code. A dataset card and model card accompany the release.

Ethics/limits. All data were collected under ethical clearance of Ethical Review Board. Single–electrode signals lack spatial resolution; window labels inherit patient status; $N{=}25$ limits generalization. Release is de–identified and not intended for stand–alone clinical decision–making.

6 Conclusion

We introduced **NEUROSKY–EPI**, the first open single–electrode epilepsy EEG dataset, and showed that even a single Fp1 lead from a consumer device can support meaningful seizure analytics when paired with EEGNet. Contextual embeddings improved both supervised accuracy and patient clustering, highlighting the value of capturing state responsiveness.

This work demonstrates that low–cost, handy devices can extend neurological monitoring to under–resourced settings. Future efforts will expand the cohort, pursue longitudinal data, collect more amount of data, and benchmark against clinical EEG. By releasing NEUROSKY–EPI and code, we aim to foster reproducible, globally representative research on accessible epilepsy monitoring.

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