1ST WORKSHOP ON ARTIFICIAL INTELLIGENCE
FOR BIOMEDICAL DATA - AIBIO

Self-Attention as a Predictor of EEG Anomalies

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MANOLO
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Overview

Introduction & Background

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- EEG signals are highly sensitive, low-amplitude recordings easily contaminated by **artifacts** (noise not generated by brain activity).
- Artifacts may arise from physiological (muscle tension, sweating) or technical sources (electrode detachment).
- What counts as “noise” is often **task-dependent**: a feature irrelevant for one application may be meaningful for another.
- Traditional denoising via **reconstruction/prediction errors** (Autoencoders, LSTMs) ignores contextual relevance.
- **Our idea:** Train attention-based models on a downstream task (e.g., sleep stage classification) and use its attention patterns to infer anomalies without explicit artifact labels.

Research Methodology

Self-Attention as a Predictor of EEG Anomalies

Research Methodology

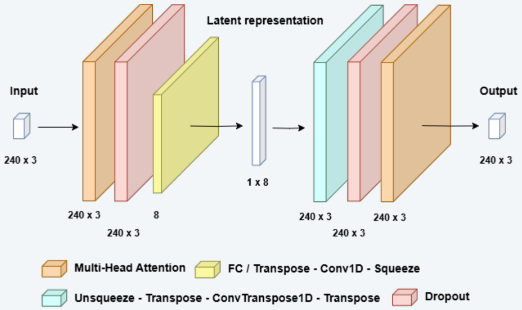
- Traditional anomaly detection uses **reconstruction or prediction errors**, but these often miss **context-specific anomalies**.
- **Reconstruction error** can fail because models may learn to reproduce artifacts if trained on contaminated data (false negatives).
- **Prediction error** can incorrectly flag unpredictable but normal variations as anomalies (false positives).
- The **attention-based approach** assumes that **low-attention regions** correspond to noisy or irrelevant segments.

Hypothesis: during a task (e.g., reconstruction or prediction), the model learns to ignore artifacts that hinder performance.

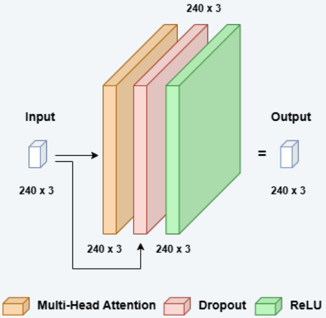
Research Methodology

Acronym	*Architecture*	*Detection*
LSTM *C-LSTM* *AE_err*	LSTM Autoencoder Convolutional LSTM Autoencoder Attention-based Autoencoder	Reconstruction error
TP_err	Transformer Predictor	Prediction error
AE_att *TP_att*	Attention-based Autoencoder Transformer Predictor	Attention
MNE	IIR filter	

Research Methodology



AE_err/AE_att architecture



Left:

TP_err/TP_att architecture

Experiments

Data Preprocessing

Our approach was evaluated using the **BOAS dataset**:

- EEG signals recorded from a **two-channel headband** at **128 Hz**.
- Signals segmented into **30s epochs**, each labeled into five sleep stages (Wake, N1, N2, N3, REM).
- **56 overnight recordings** from different users in total; 43 train, 3 validation, 10 test.
- Data normalized using **median and IQR** for robustness (skipped for MNE to preserve signal shape).
- Ground truth from Bitbrain's **proprietary artifact estimation algorithm**.

Note: 6 test recordings have minimal noise; comparisons focus on the remaining 4.

Training Process & Hyperparameters

- We pass the test dataset through each class-specific autoencoder, then classify the restyled outputs using the original classifier.
- High **classification accuracy** on restyled signals indicates the autoencoders have learned the patterns that the classifier uses for each sleep stage.

Metric	N1	N2	N3	REM
Accuracy	0.9997	0.9998	0.9260	0.9986

Results & Discussion

Results & Discussion

We use the **BOAS EEG dataset**, with 128 full-night recordings from 2 channels (256 Hz), to explain classifier errors across 4 sleep stages (N1, N2, N3, REM).

- **EEG Data:**
  - 30s epochs ($n_s = 7680$ samples, $n_c = 2$).
  - FFT $\rightarrow$ 0.4-30 Hz filtering $\rightarrow$ segment into $n_s' = 300$ spectral slices.
  - Extract 3 features per slice (frequency, phase, amplitude).
- **Classifier:** Two-stage convolutional network over sequences of $k = 5$ epochs:

$$X_t^f = [e_{t-k+1}, \ldots, e_t] \rightarrow \hat{y}_t$$

- **Autoencoders:** Hybrid networks with convolutional and attention layers:

$$X_f^t = e_t \oplus \text{pos} \longrightarrow \hat{X}_f^t \text{ (reconstructed input)}$$

Conclusion & Future Work

Conclusion

- **xSTAE** explains classifier errors by restyling misclassified EEG instances into correctly classified ones.
- Autoencoders balance **identity loss** (keep instance similar) and **classification loss** (push to correct label), revealing features the classifier missed.
- Contributions:
  - Ground counterfactual explanations in time-series EEG classification.
  - Identify spectral representations suitable for EEG signals.
  - Validate on open BOAS dataset and release full experimental setup.

Future Work

- Explore **alternative identity losses** to highlight meaningful changes (e.g., bigger local changes, selective brainwave bands).
- Conduct **expert trials** to refine interpretability of restyled EEGs.
- Investigate linking insights from misclassifications to **actionable guidance** at the data or confidence level, keeping xSTAE model-agnostic.

Thank you for your attention!

Thank you for your attention! Any questions?

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