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Explainable AI-Driven EEG Channel Selection for Accurate and Interpretable Epilepsy Diagnosis

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ABSTRACT

The study proposes **XLISEE (Explainable LIME-Based Selection of EEG Electrodes)**, a framework that combines **Explainable Artificial Intelligence (XAI)** with machine learning for accurate and interpretable epilepsy detection. Using **LIME** to identify the most relevant EEG electrodes, XLISEE reduces data complexity while maintaining high diagnostic performance. Tested on the **Guinea-Bissau Hospital EEG dataset** with **SVM** and **kNN** classifiers, the model achieved **99.76% accuracy** and **100% sensitivity, specificity, F1-score, and MCC**, demonstrating its efficiency and reliability. By enhancing transparency and reducing computational load, XLISEE supports **real-time, explainable EEG analysis** for clinical and **Brain–Computer Interface (BCI)** applications.

OBJECTIVE

The main objective of this project is to develop an explainable machine learning framework (**XLISEE**) for automated epilepsy detection using EEG signals.

The model aims to:

- Improve diagnostic accuracy and reliability.
- Enhance interpretability through **LIME-based electrode selection**.
- Reduce data complexity and computational load
- Support real-time and transparent EEG analysis for clinical applications.

EXISTING SYSTEM

- **Traditional Methods:** Techniques such as Fourier Transform and Wavelet Transform were used to analyze EEG signals. However, they often failed to capture complex temporal and spatial patterns in brain activity.
- **Machine Learning Approaches**: Methods like SVM, k-NN, and Random Forest used handcrafted features (e.g., entropy, energy, or statistical measures). These approaches achieved moderate accuracy but lacked generalization across subjects and datasets.
- **Deep Learning Approaches:** CNNs, RNNs, and Autoencoders improved feature extraction and classification performance. Yet, they faced issues such as
  1. Poor interpretability of learned features.
  2. High computational complexity.
  3. Limited ability to model dynamic brain connectivity.

DISADVANTAGES

- Limited ability to detect complex or subtle seizure patterns.
- Performance drops when applied to different subjects or datasets (poor generalization).
- High dependency on handcrafted or manually selected features.Still needs **clinical validation** before use in real-world diagnosis.
- Low interpretability — difficult to understand how decisions are made
- High computational cost and long training time for deep learning models.

PROPOSED SYSTEM

Proposed System (Overview & Steps)

Multi-stage architecture: EEG preprocessing → feature extraction → brain connectivity mapping → classification.

1. **EEG Data Input:** User uploads EEG signals.
2. **Preprocessing:** Noise removal, filtering, artifact correction.
3. **Feature Extraction:** Spatial-temporal and frequency-domain features from EEG.
4. **Brain Network Construction:** Functional connectivity networks formed from EEG channels.
5. **Classification:** Deep learning (CNN/LSTM/Transformer) predicts seizure or non-seizure.
6. **Visualization:** Interpretable brain connectivity maps for diagnosis support.
7. **Output:** Accurate seizure detection and brain network interpretation for clinical use.

ADVANTAGES

- High accuracy in seizure detection using deep learning.
- Learns complex spatial–temporal brain patterns automatically.
- Provides interpretable visualization through brain network analysis.
- Reduces manual feature engineering effort.
- Suitable for real-time clinical monitoring.

SYSTEM REQUIREMENTS

HARDWARE REQUIREMENTS

- Monitor type: 15 Inch color monitor
- Processor: Intel i5 / Ryzen 5 or above
- RAM Size: 8GB (minimum)
- Storage: 20GB free space
- GPU: NVIDIA GTX/RTX series (for deep learning acceleration)

SOFTWARE REQUIREMENTS

- Operating System: Windows 10 / 11 or Ubuntu 20.04
- Language: Python (with TensorFlow or PyTorch)
- IDE: PyCharm / Jupyter Notebook
- Application: EEG signal processing and classification tools

LITERATURE SURVEY

TITLE	AUTHOR NAME	YEAR	METHODOLOGY	LIMITATIONS
An Explainable AI Framework Integrating Variational Sparse Autoencoder and Random Forest for EEG-Based Epilepsy Detection	Syed Sajid Hussain, Niyaz Ahmad Wani, Jasleen Kaur, Naveed Ahmad, and Sadique Ahmad	2025	VSAE (VAE + SAE) for feature extraction, Random Forest for classification, and SHAP & LIME for explainability.Top of Form	High computational cost; limited dataset details; interpretability focused on features, not EEG channels.
A Comprehensive Review of EEG-Based Seizure Detection Techniques	Ronneberger, O., Fischer, P., & Brox, T.	2015	Literature review of EEG-based seizure detection methods, datasets, and emerging AI trends..	No experimental validation; lacks detailed performance comparison; broad scope reduces depth..
Review of Methods for EEG Signal Classification and Development of New Fuzzy Classification-Based Approach	Rehman, A., Khan, M. A., Saba, T., et al.	2021	Comparative analysis of EEG classification methods and introduction of a fuzzy logic-based classification model for improved accuracy.	Fuzzy system depends on rule design quality; limited testing on large or varied EEG datasets.
A Novel Method to Predict Laying Rate Based on Multiple Environment Variables	Kamnitsas, K., Ledig, C., Newcombe, V. F. J., et al.	2017	Machine learning regression models using environmental parameters like temperature, humidity, and light for prediction.	Requires large datasets; may perform poorly under unseen conditions; limited model interpretability.

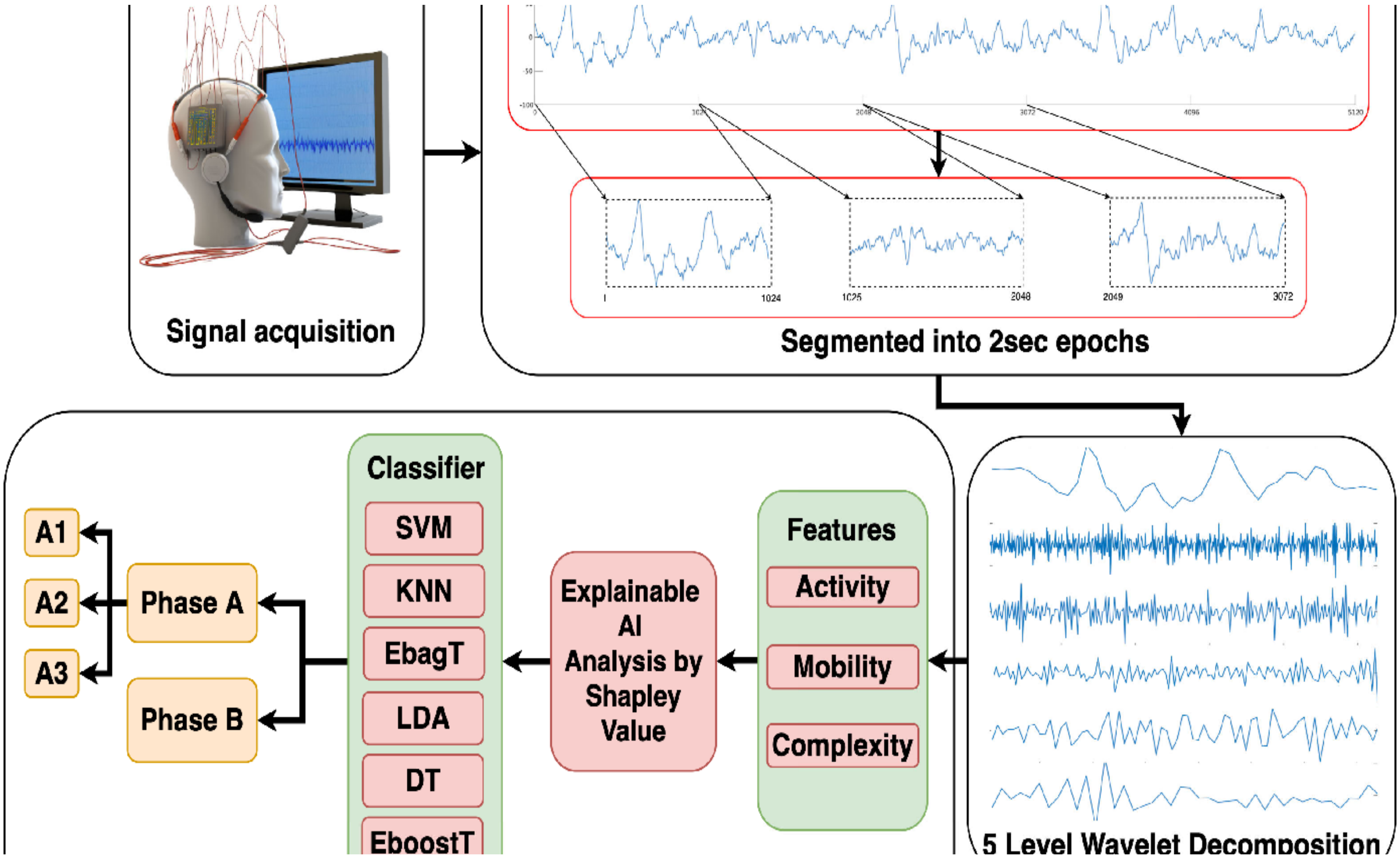
TITLE	AUTHOR NAME	YEAR	METHODOLOGY	LIMITATIONS
ScoreNet: A Neural Network-Based Post-Processing Model for Identifying Epileptic Seizure Onset and Offset in EEGs	Pereira, S., et al.	2016	Neural network (ScoreNet) for refining seizure onset/offset detection using log-dice loss.	Needs pre-detected seizures; high computational cost.
Detection of Epilepsy Disorder Using Spectrogram Images Generated From Brain EEG Signals	Majib, M. S., et al.	2021	EEG converted to spectrograms; classified using CNN models XAI via SmoothGradCAM++.	Needs large datasets; high computational cost; limited performance on noisy EEG data..
Enhancing EEG-Based Schizophrenia Diagnosis with Explainable Multi-Branch Deep Learning	Myronenko, A.	2018	Multi-branch DL model extracts oscillatory and spatial-spectral EEG features with saliency-based explainability	Needs large EEG datasets; computationally heavy; limited cross-dataset generalization.
Cascaded Thinning in Upscale and Downscale Representation for EEG Signal Processing	Oktay, O., et al.	2018	Image-based EEG smoothing using Cascaded Thinning UDR with morphological filtering.	High computational cost; less effective at large line widths.

TITLE	AUTHOR NAME	YEAR	METHODOLOGY	LIMITATIONS
Deep Learning Approaches for EEG-Motor Imagery-Based BCIs: Current Models, Generalization Challenges, and Emerging Trends	He, K., et al.	2016	Systematic review of 68 DL-based EEG-MI studies; analysis of models, generalization, and ethical aspects using XAI, FL, and neuromorphic trends.	No experimental validation; relies on secondary data; reproducibility and dataset diversity issues.
Explainable Depression Classification Based on EEG Feature Selection From Audio Stimuli	Zhao, L., & Jia, K.	2016	Review of 68 EEG-MI DL studies; analyzed CNN/RNN models and trends in XAI, FL, and neuromorphic computing.	No experimental validation; relies on secondary data; dataset and reproducibility limitations.
A Novel EEG-Based Hypergraph Convolution Network for Depression Detection: Incorporating Unified Brain Network and Multi-Segment Spatiotemporal EEG Features	Raut, G., et al.	2020	Combined Graph Convolutional GRU and Hypergraph Convolution Network (HGCN) for hierarchical fusion of spatial–temporal EEG features in depression detection	High model complexity; requires large computational power and EEG data for reliable performance
Effect of Inverse Solutions, Connectivity Measures, and Node Sizes on EEG Source Network: A Simultaneous EEG Study	Zikic, D., et al.	2012	Simultaneous EEG-SEEG study; compared inverse solutions and connectivity measures; simulated node size effect	Limited dataset; computationally intensive; lacks deep-brain or non-EEG modality validation.

TITLE	AUTHOR NAME	YEAR	METHODOLOGY	LIMITATIONS
An Attention Mechanism-Based Interpretable Model for Epileptic Seizure Detection and Localization With Self-Supervised Pre-Training	Chen, W., et al.	2006	Self-supervised EEG pre-training with attention and fine-tuning on limited labeled data.	Depends on pretext design and careful tuning of attention.
Explainable Depression Classification Based on EEG Feature Selection From Audio Stimuli	Taheri, S., et al.	2010	EEG feature extraction from audio stimuli, selected relevant features, used explainable AI for depression classification.	Focuses mainly on accuracy; limited analysis of feature-model association; dataset diversity not specified.
Machine Learning Algorithms for Epilepsy Detection Based on Published EEG Databases: A Systematic Review	Choudhury, C. L., et al.	2020	Systematic review of EEG-based epilepsy detection studies, focusing on signal processing, feature extraction, and classification trends.	No experiments; limited by study scope and data quality.
E-RXAI-IoT: A Systematic Evaluation Framework of Rule-Based XAI Methods for Anomaly Detection in IoT Systems			Systematic evaluation of rule-based XAI methods (Anchor, RuleFit) across RF, DT, DNN, and SVM using IoT datasets	Limited to two datasets; focused only on rule-based XAI; may not generalize to all IoT applications

TITLE	AUTHOR NAME	YEAR	METHODOLOGY	LIMITATIONS
Automated Explainable Detection of Cyclic Alternating Pattern (CAP) Phases and Sub-Phases Using Wavelet-Based Single-Channel EEG Signals	Chen, W., et al.	2006	Wavelet-based Hjorth features from single-channel EEG; KNN and ensemble classifiers; SHAP for explainability	Limited to single-channel EEG; performance may vary for different sleep disorders; relies on quality of CAP database
Level-set segmentation of brain tumors using a threshold-based speed function	Taheri, S., et al.	2010	A traditional image processing technique using a level-set algorithm to evolve a contour and outline the tumor boundaries.	Highly sensitive to initial settings and image noise; less automated and generally less robust than learning-based methods.
Brain tumor detection and classification using convolutional neural network...	Choudhury, C. L., et al.	2020	Developed an Artificial CNN (ACNN) to classify MRI scans as either having a tumor (positive) or not (negative).	The model was designed for classification only and does not perform segmentation to outline the tumor's location or shape.

ARCHITECTURE DIAGRAM



MODULE

- Data Acquisition Module
- Preprocessing Module
- Feature Extraction
- Classification Module
- Result Visualization Module
- System Interface Module

MODULE DESCRIPTION

Data Acquisition Module:

- **Function:** Collect EEG signals from open-source datasets or real-time EEG devices.
- **Tools:** EEG headset or public datasets (e.g., CHB-MIT, Bonn EEG).
- **Output:** Raw EEG signals.

MODULE DESCRIPTION

Preprocessing Module:

- **Function:** Remove noise and artifacts (like eye blinks, muscle activity).

- **Techniques:**
- Bandpass filtering (0.5–60 Hz)
- Independent Component Analysis (ICA)
- Normalization/scalings.

- **Output:** Clean EEG data ready for analysis

MODULE DESCRIPTION

Feature Extraction:

- **Function:** Extract meaningful features that represent brain activity

- **Techniques:**
  - Wavelet Transform
  - Statistical features (mean, variance, entropy)
  - Hjorth parameters
  - Frequency band power (delta, theta, alpha, beta, gamma)

- **Output:** Feature vector.

MODULE DESCRIPTION

Classification Module :

➢ **Function:** Classify EEG signals as **normal** or **epileptic**.

➢ Techniques:

•CNN / RNN / Transformer-based neural networks
•SVM or Random Forest (for smaller datasets)

➢ **Output:** Predicted class (e.g., seizure/non-seizure)..

MODULE DESCRIPTION

Result Visualization Module:

- **Function:** Display classification results and brain activity patterns.

- **Tools:**
- Matplotlib / Seaborn for plots
- Real-time dashboard for seizure alerts

- **Output:** User-friendly visual output.

MODULE DESCRIPTION

System Interface Module:

- **Function:** Provide interaction between user and system.

- **Tools:**

- GUI using Tkinter / PyQt
- Displays signal graphs, detection status, and reports.

CONCLUSION

The proposed EEG-based epilepsy detection system accurately identifies seizures using deep learning.

It enhances diagnostic efficiency and reduces reliance on manual analysis.

The model’s automation ensures faster and more consistent results.

Overall, it supports early detection and improved clinical decision-making.

THANK YOU!!!!