Graph Attention Networks Enhance Epilepsy Detection from EEG Using Accessible Hardware in Low-Resource Settings

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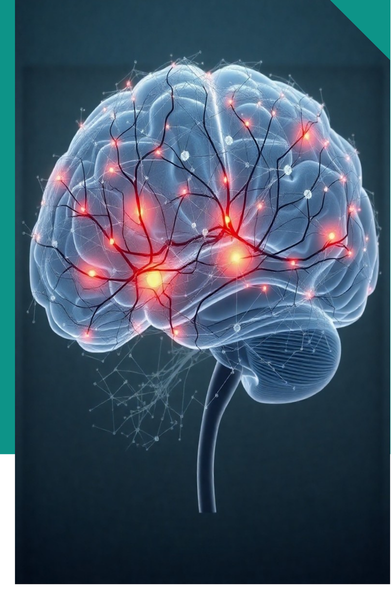
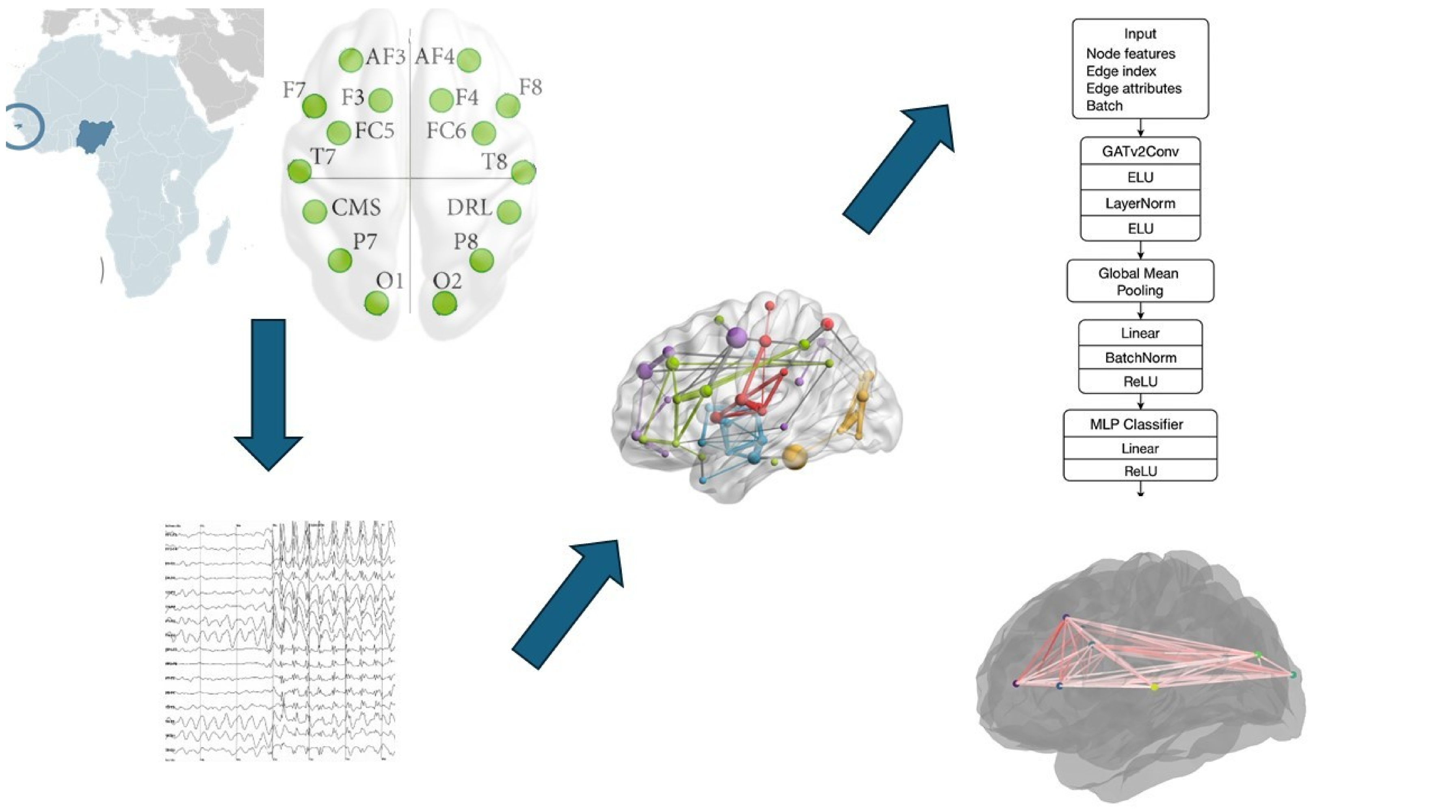


Background

- Epilepsy affects 50–60 million people worldwide, predominantly in low- and middle- income countries (LMICs) which account for 80% of cases, and these regions experience higher mortality and stigma.
- Diagnosis relies on EEG pattern detection, but challenges include costly EEG devices and stigma, limiting accessibility in low-resource environments. especially restricting their practical use in LMICs.
- This study aims to use graph attention networks (GAT) on low-cost EEG data to classify epilepsy versus controls, focusing on model explainability and importance of brain connectivity edges.



Overall Pipeline: Data are collected with an affordable portable EEG in low-income countries (left), they are preprocessed and used to create brain connectivity matrices (center). Then, classified using graph attention networks, and the used weights are investigated to shed some lights about epilepsy biomarkers (right). In this figure the electrodes labels for the Epoc EEG device and the used GAT architecture are also shown.

Results

Classification Performance

Graph Attention Network (GAT) achieved area under the receiver operating characteristic curve (AUROC) of 0.78 for Nigerian data and 0.82 for Guinea-Bissau dataset.

GAT outperformed both random forest and graph convolutional network (GCN) classifiers; performance differences confirmed statistically significant via DeLong test ($p < 0.05$).

Training completed efficiently (~30 minutes per dataset) on Google Colab, with subsequent successful deployment on low-cost hardware.

Attention Weights and Connectivity

Strong attention edge weights localized in fronto-temporal brain regions including electrodes AF3, AF4, F3, F4, FC5, and FC6.

Connectivity patterns consistent across Nigerian and Guinea-Bissau datasets despite observed variation in overall performance.

Visualization of attention weights in multiple brain views reinforced emphasis on bilateral fronto-temporal connectivity.

Node-level Importance and Architecture Tuning

Optimal architecture included 6 attention heads and 32 hidden units; fewer heads or units decreased classification accuracy, while additional complexity increased computational cost without performance gains.

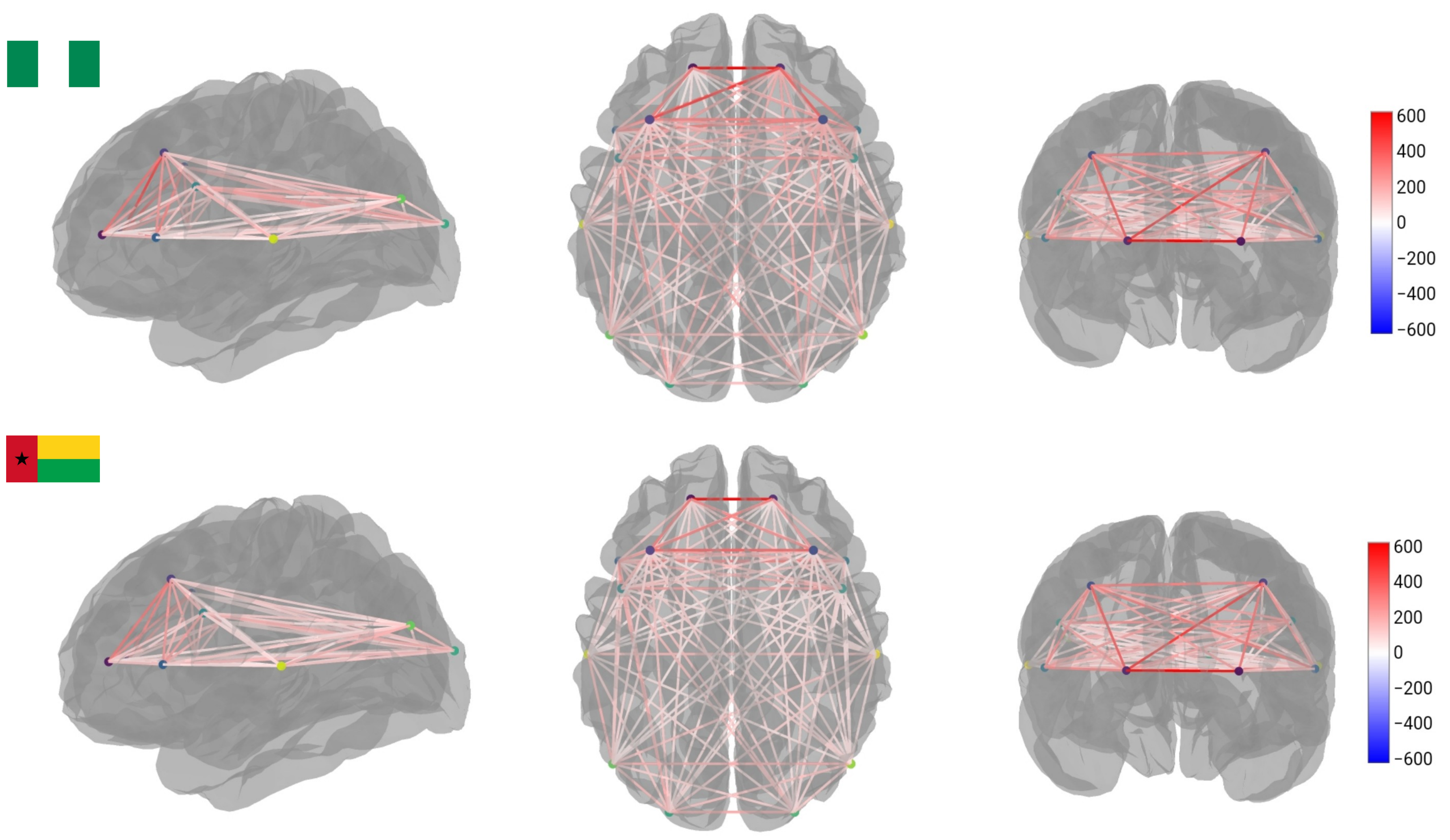
Model feasible to run on affordable, low-resource hardware platforms, supporting practical deployment.

TABLE I. Nigeria Dataset Classification Report Comparison (Random Forest, GCN, GAT).

Metric	Random Forest		GCN		GAT	
	Control	Epilepsy	Control	Epilepsy	Control	Epilepsy
Precision	0.72	0.67	0.55	0.64	0.67	0.72
Recall	0.77	0.62	0.46	0.72	0.60	0.77
F1-score	0.74	0.65	0.50	0.67	0.64	0.75
Accuracy	0.70		0.61		0.70	
Macro avg F1	0.70		0.59		0.69	
Weighted avg F1	0.70		0.60		0.70	
AUROC	**0.70**		**0.64**		**0.78**	

Methods

- EEG data acquired from 301 participants in Nigeria and Guinea-Bissau using a 14- channel Epoc portable headset; data were filtered and segmented into overlapping 5- second epochs.
- EEG data modeled as complete spatio-temporal graphs weighted by phase locking values; nodal features included fractal dimension and band energy within delta, theta, alpha, and beta frequency bands.
- Designed a lightweight GAT architecture consisting of two GATv2Conv layers with 6 attention heads and 32 hidden channels using LeakyReLU activations; softmax output used for classification with Adam optimizer and leave-one-out cross- validation.
- Explainability achieved by averaging attention coefficients across heads to quantify edge importance; and node relevance assessed by Grad-CAM analysis.
- Model training conducted on Google Colab; successfully deployed on Raspberry Pi 4 (8GB RAM) to demonstrate feasibility in low-resource environments.



Attention weights related to the brain connectivity for the Nigeria (top) Guinea-Bissau (bottom) dataset: Sagittal, axial, and coronal view, showing stronger weights in the fronto-temporal area. The color code marks the dark red connections as most relevant as those among AF3, AF4, F3, F4, FC5 and FC6. .

TABLE II. Guinea-Bissau Dataset Classification Report Comparison (Random Forest, GCN, GAT).

Metric	Random Forest		GCN		GAT	
	Control	Epilepsy	Control	Epilepsy	Control	Epilepsy
Precision	0.66	0.73	0.65	0.72	0.69	0.76
Recall	0.79	0.59	0.72	0.55	0.75	0.71
F1-score	0.72	0.66	0.72	0.61	0.75	0.71
Accuracy	0.69		0.61		0.73	
Macro avg F1	0.69		0.59		0.73	
Weighted avg F1	0.69		0.60		0.73	
AUROC	**0.76**		**0.70**		**0.82**	

Key Findings

- Graph Attention Networks outperform traditional classifiers in detecting epilepsy from low-cost EEG data in low-resource settings.
- GAT model AUROC scores of 0.78 (Nigeria) and 0.82 (Guinea-Bissau) demonstrate significant diagnostic performance gains.
- Explainability analyses identify fronto-temporal brain regions as critical connectivity biomarkers consistent across geographically distinct datasets.
- Demonstrated feasibility of deploying the model on affordable hardware platforms supports scalable epilepsy diagnosis in LMICs.

Mazurek, S., Blanco, R., Falcó-Roget, J. and Crimi, A., 2024, "Explainable graph neural networks for EEG classification and seizure detection in epileptic patients". In 2024 IEEE International Symposium on Biomedical Imaging (ISBI) (pp. 1-5).

Mazurek, S., Moore, S. and Crimi, A., 2025. "Graph Attention Networks for Detecting Epilepsy from EEG Signals Using Accessible Hardware in Low-Resource Settings". arXiv preprint arXiv:2507.15118.

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