

Study of Deep Learning Models for the Classification of Epileptic Patients

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Introduction

Epilepsy is a chronic neurological disorder characterized by sudden and abnormal discharges of brain neurons. According to the World Health Organization (WHO), around 50 million people worldwide are affected by this condition, and more than 10% of individuals may experience at least one epileptic episode in their lifetime[1]. Detection of this neurological disorder is typically done through the analysis of electroencephalography (EEG), a non-invasive technique used to record the brain's electrical activity. EEG reveals distinct brain activity patterns in healthy individuals, during seizures, and in people with epilepsy. This makes EEG a valuable tool for the effective detection and monitoring of epilepsy.

Objective

To evaluate and compare various deep learning architectures for classifying epileptic seizures using EEG data.

To identify models that balance accuracy, computational efficiency, and generalizability for potential clinical application.

Proposed Methodology

Dataset Overview: We used the University of Bonn EEG dataset [2]. It includes healthy, epileptic non-seizure, and seizure classes. Each segment is 23.6 seconds long, sampled at 173.61 Hz.

Preprocessing Techniques: Three approaches were applied: raw EEG (no transformation), derivation (to enhance seizure-related changes and suppress noise), and wavelet decomposition to extract both high-frequency spikes and low-frequency rhythms.

Deep Learning Models: We implemented ANN, CNN, and hybrid CNN–LSTM architectures. ANN learns abstract features, CNN captures spatial signal patterns, and CNN–LSTM combines spatial and temporal analysis, making it effective for EEG sequences.

Classification and Evaluation: Several binary and multiclass classification tasks were performed. Performance was evaluated using accuracy, sensitivity, specificity, and training time.

Deployment: The most effective models were integrated into a user-facing interface, allowing EEG signal uploads and real-time classification through a streamlined, interactive application.

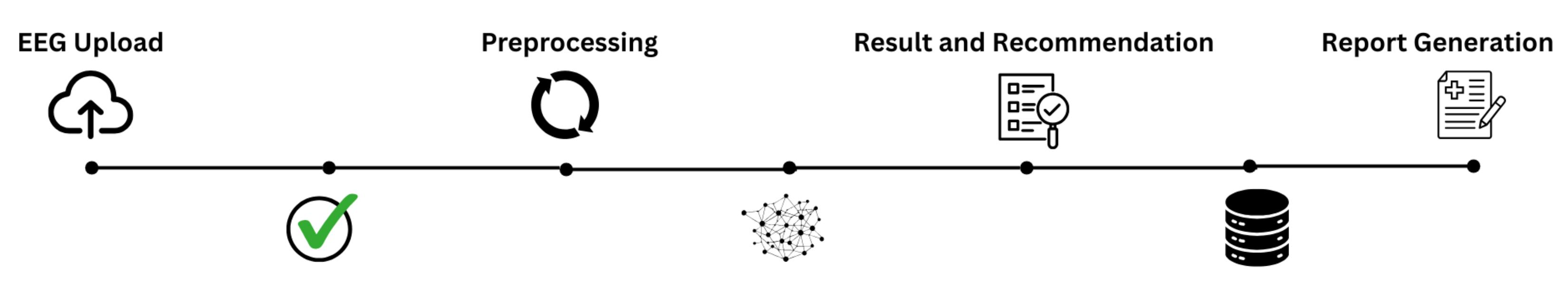


Figure: Workflow of the deployed EEG classification interface.

Results

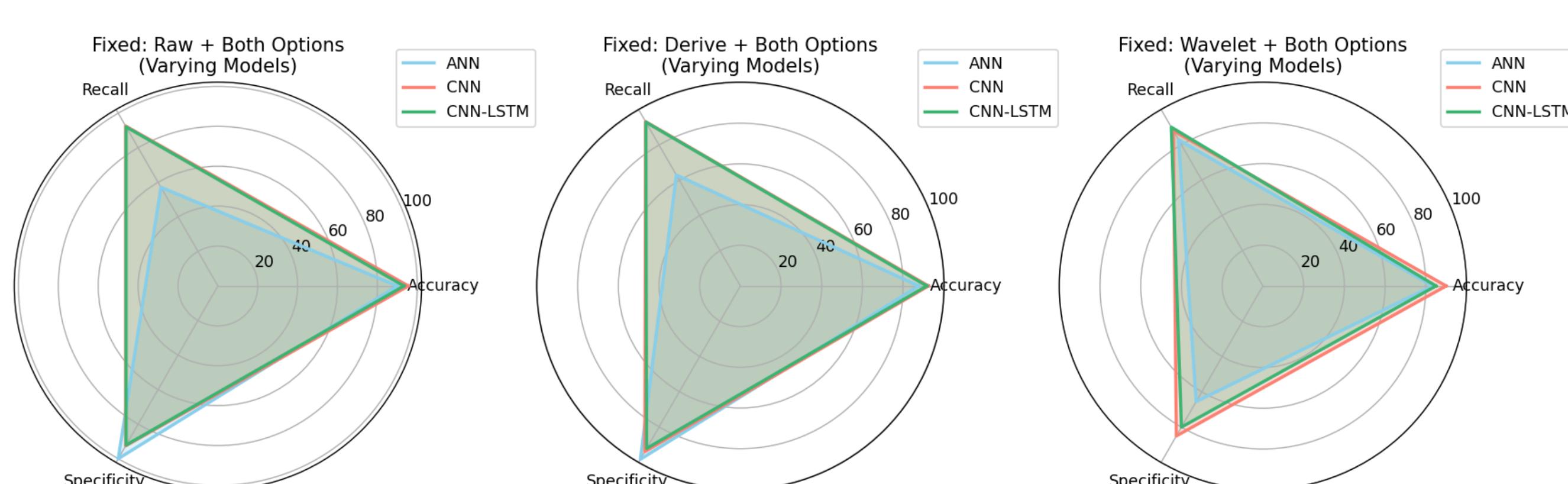


Figure: Classification performance ranges.

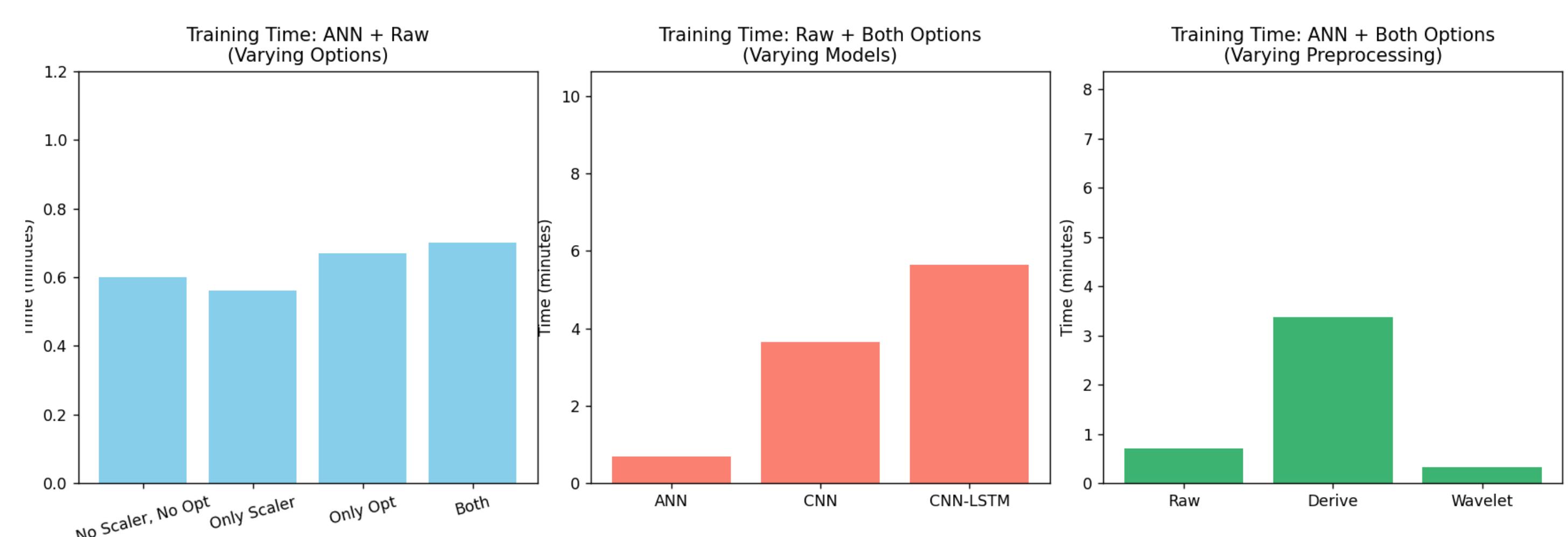


Figure: Comparison of Execution Time.

- We analyzed how training choices like data scaling and optimizer tuning affect model performance. These improvements led to better accuracy, sensitivity, and training speed across ANN, CNN, and CNN–LSTM models.
- CNN provided the best balance of performance and speed. ANN was faster but less reliable, while CNN–LSTM offered slightly higher sensitivity at the cost of longer training time.
- Wavelet decomposition improved results with minimal overhead, making it ideal for real-time use. Derivative-based features boosted sensitivity but required more time and reduced accuracy slightly.

Conclusions and Future Work

This study shows that, despite the complexity of EEG signals, preprocessing techniques and deep learning models can effectively classify seizures and extract features. In the future, we plan to apply this approach to other biomedical signals and improve the interface for doctors. This will include adding features like training models with new patient data to support personalized clinical decision-making.

Bibliography

[1] El-Sayed A Hemdan EE Ein Shoka AA, Dessouky MM. Eeg seizure detection: concepts, techniques, challenges, and future trends. national library of medicine.

[2] Universitätsklinikum Bonn, “Epileptology - Universitätsklinikum Bonn.” <https://www.ukbonn.de/en/epileptology/>, 2025.