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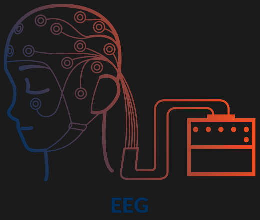

NeuroDetectNet: Advanced EEG Classification for Neurodegenerative Disease

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Problem Definition and Literature Review

Problem Definition

To classify neurodegenerative diseases such as Alzheimer's Disease (AD), Frontotemporal Dementia (FTD), and Healthy Subjects using routine EEG data employing deep learning.

Main Base Paper

Title

EEG-Based Neurodegenerative Disease Classification using LSTM Neural Networks (1)

Published in

IEEE Statistical Signal Processing Workshop, 2023

Methodology

1. Uses LSTM Recurrent Neural Networks (RNN)
2. A final accuracy of 75.3% was achieved

Other Base Papers

1.EEG-Based Alzheimer's Disease Recognition Using Robust-PCA and LSTM Recurrent Neural Network (2)

Published on: May 2022

2.EEG-based classification of Alzheimer's disease and frontotemporal dementia: a comprehensive analysis of discriminative features (3)

Published on: July 2024

Dataset

Dataset Paper
A Dataset of Scalp EEG Recordings of Alzheimer's Disease, Frontotemporal Dementia and Healthy Subjects from Routine EEG (4)
Dataset Link: OpenNeuro Dataset
Dataset Characteristics
1. EEG Data Collection: This includes recordings from 88 subjects (36 AD, 23 FTD, 29 healthy control) that were collected in a clinical setting.
2. EEG Setup: 19 scalp electrodes arranged per the 10–20 international system, 500 Hz sampling rate.
3. Each recording lasted approximately 13.5 minutes for AD group (min=5.1, max=21.3), 12 minutes for FTD group (min=7.9, max=16.9) and 13.8 for CN group (min=12.5, max=16.5).
4. Data Preprocessing: Artifacts were removed using a Butterworth band-pass filter, followed by Independent Component Analysis (ICA) for noise reduction.

Proposed Solution Architecture

Hybrid CNN-LSTM Architecture

Convolutional Layers: Inclusion of CNN layers before the LSTM layers to capture demographic features from EEG channels. Convolutions can extract local features across the demographic dimensions of EEG signals, making the architecture better suited to capture demographic dependencies.

LSTM Layers: Retain the LSTM layers to capture temporal dependencies, as these are essential for modeling the time-series nature of EEG signals.

Attention Mechanism

Integrating an attention layer after the LSTM layers can help the model selectively focus on the most informative temporal segments of the EEG data, allowing it to differentiate between signal noise and relevant patterns more effectively.

Performance Metrics

Accuracy Improvement

With hybrid model and attention mechanism , we expect a notable improvement over the 75.3% baseline

Class	Sensitivity (%)	Precision (%)	F1-score (%)
N	73.2	73.6	73.4
AD	67.3	71.3	69.3
FTD	83.9	83.9	83.9
LBD	73.5	66.9	70.0

Figure: Base paper performance metrics

References

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[2] ——, "Eeg-based alzheimer's disease recognition using robust-pca and lstm recurrent neural network," *Sensors*, vol. 22, no. 10, p. 3696, 2022.

[3] M. Rostamikia, Y. Sarbaz, and S. Makouei, "Eeg-based classification of alzheimer's disease and frontotemporal dementia: a comprehensive analysis of discriminative features," *Cognitive Neurodynamics*, pp. 1–16, 2024.

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