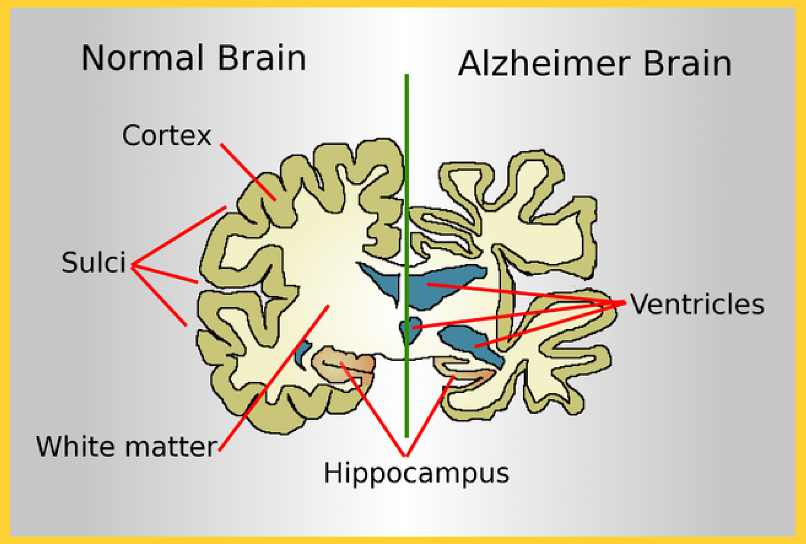
Developing a Deep-Learning Tool to diagnose early stage Alzheimer's Disease using EEG Signals

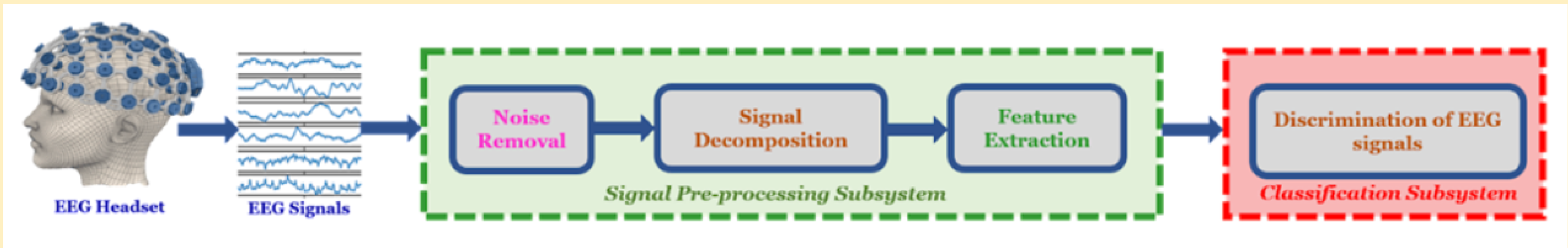
By Bhavana Akilan - Laidlaw Leadership and Research Scholar, University of Toronto
Supervised by Dr Shankar Sriram and Dr Anila Glory, SASTRA Deemed University, Thanjavur

Introduction



- Alzheimer's Disease (AD) is a devastating, incurable form of dementia with no established diagnostic method, posing significant treatment access challenges.
- Early detection and diagnosis of AD are crucial to prevent brain damage and enable timely biomedical interventions.
- Among available biomarkers, EEG stands out as a cost-effective and temporally precise option for AD diagnosis.
- The non-linear nature of EEG signals complicates interpretation by physicians, prompting the exploration of Artificial Intelligence for a deep-learning tool to aid in early AD diagnosis.
- This research aims to leverage AI to improve the accuracy and accessibility of AD diagnosis, potentially revolutionizing early intervention and treatment outcomes.

Materials and Methods



Data Acquisition and Preprocessing

- Multi-channel EEG signals recorded with 19 electrodes.
- Dataset accessed through Kaggle, featuring 19 nodes and 1024 time points per participant.
- No artifact removal techniques employed to enhance DL model robustness.

AD Diagnosis

- Comprehensive feature set enables accurate classification between healthy controls and dementia stages.
- Incorporation of entropy-based features enhances the understanding of signal complexity.

Model Performance

- Multi-channel EEG signals recorded with 19 electrodes.
- Dataset accessed through Kaggle, featuring 19 nodes and 1024 time points per participant.
- No artifact removal techniques employed to enhance DL model robustness.

Feature Extraction

- Capturing time and frequency domain, dynamic complexity, synchronization, and more.
- Extraction of 22 features, including Hjorth parameters, entropy-based features, and more.
- Daubechies wavelet decomposition (db10, level 5) used for signal analysis.
- Extraction of entropy features to measure complexity and regularity.
- Row-wise and column-wise features extracted pre- and post-decomposition for higher analysis accuracy.

Model Training and Validation

- Features labeled for dementia (1) and non-dementia (0).
- 70:30 train-test split ratio, followed by 10-fold cross-validation for model assessment.
- Metrics include precision, recall, f1-score, and support for each label, along with macro and weighted averages.
- RNN, with 10 layers including LSTM and GRU, used to detect overfitting.
- Training with Adagrad optimizer, batch size of 64, and 100 epochs.

Dataset

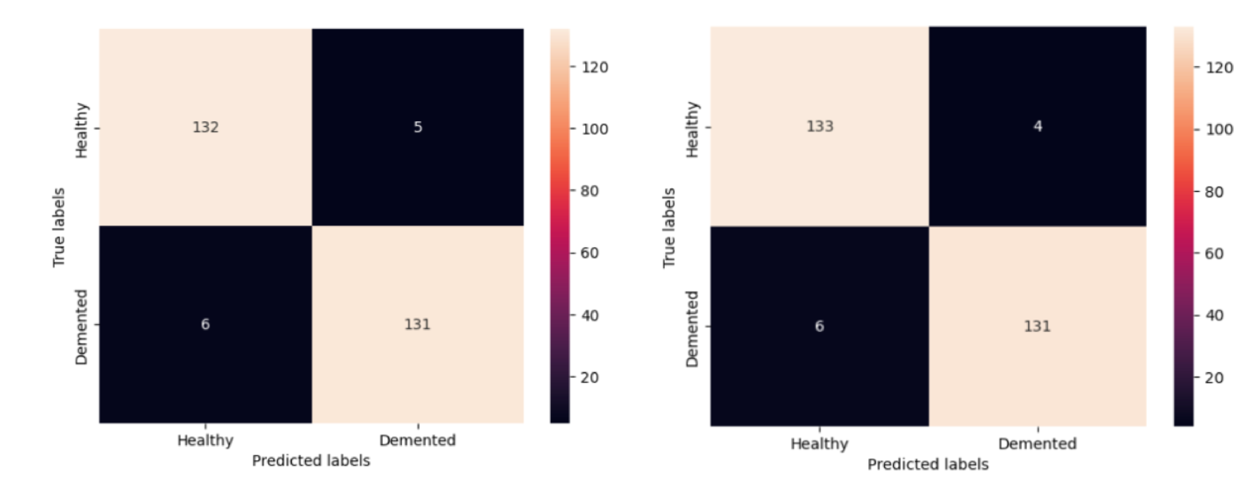
Pineda, A. M., Ramos, F. M., Betting, L. E., & Campanharo, A. S. (2020). Quantile graphs for EEG-based diagnosis of Alzheimer's disease. Plos one, 15(6), e0231169.

Results and Discussion

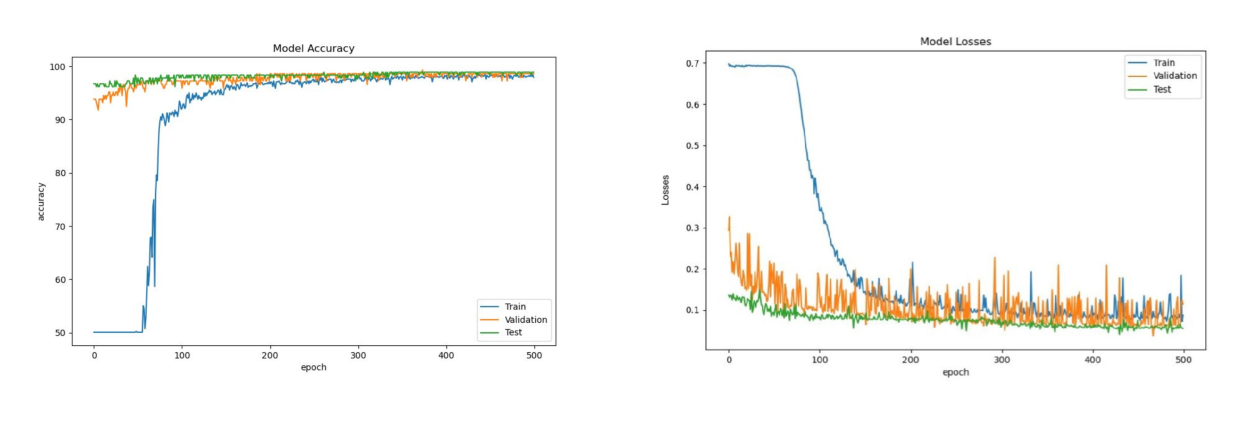
The results show a surprising accuracy of 98+/-2% while using classifiers such as Multi-Layer Perceptron and Random Forest. To ensure there was no overfitting, a Recurrent Neural Network was subsequently implemented.

Classifier	Accuracy for column-wise extracted features	Accuracy for column-wise extracted features + decomposed wave features
MLP	77.0 +/- 7.5 %	98.1 +/- 1.5 %
GNB	61.4 +/- 4.8 %	90.3 +/- 2.8 %
Decision Tree	71.9 +/- 4.6 %	92.5 +/- 2.9 %
KNN	73.7 +/- 6.8 %	93.3 +/- 2.9 %
Logistic Regression	72.9 +/- 5.8 %	96.6 +/- 2.1 %
MNB	60.5 +/- 5.7 %	79.6 +/- 5.7 %
SVM	66.5 +/- 4.9 %	93.9 +/- 2.6 %
Random Forest	97.5 +/- 2.4 %	98.0 +/- 2.0 %

Classifier	*Precision*	*Recall*	*F1-Score*
MLP	0.963235	0.956204	0.959707
Random Forest	0.970370	0.956204	0.963235



Confusion matrices for MLP and Random Forest Classifiers



Model Accuracy and Model Losses for RNN

ACCURACY: 98+/-2%

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Related Literature:

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- Bhat, S., Acharya, U. R., Dadmehr, N., & Adeli, H. (2015). Clinical neurophysiological and automated EEG-based diagnosis of the alzheimer's disease. European neurology, 74(3-4), 202-210.
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