NEURO SIGNAL ANALYSIS OF ALZHEIMER'S DISEASE

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INTRODUCTION

- Alzheimer’s disease (AD): Most common neurodegenerative cause of dementia, affecting millions globally.
- Diagnosis challenge: Overlap in clinical presentation with normal aging and other disorders complicates early detection.
- EEG as a tool: Noninvasive, affordable, and provides direct insight into neural function.
- Need for advanced analytics: Subtle EEG changes in early AD require sophisticated, multivariate analysis.
- Deep learning opportunity: Models like BiLSTM with attention can automatically learn complex patterns for AD diagnosis.
- Project goal: Classify AD vs. cognitively normal (CN) controls using EEG features and demographic data with a Bilstm-Attention model.

LITERATURE REVIEW

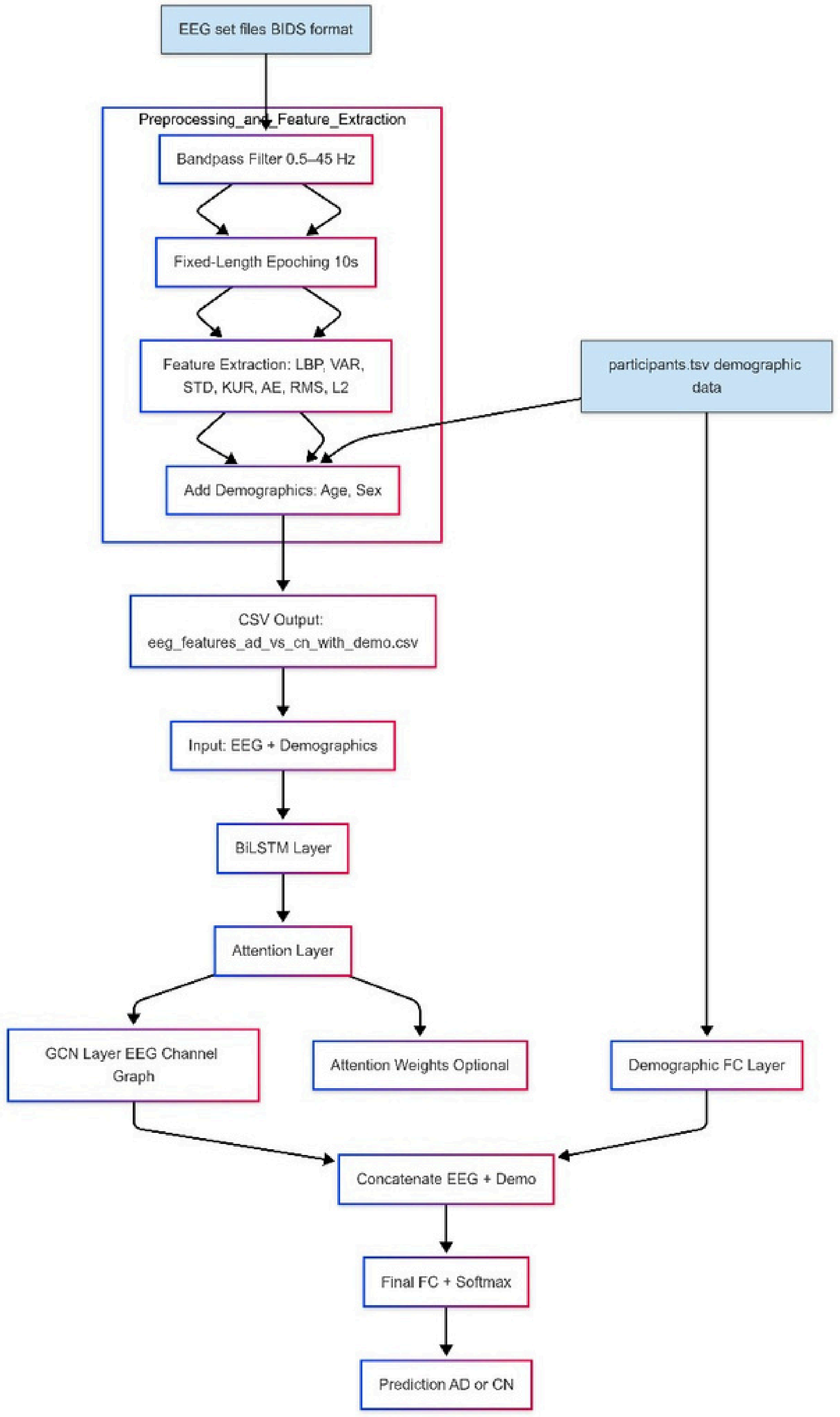
- EEG as a biomarker: AD patients show more slow-wave (delta, theta) and less fast-wave (alpha, beta) activity 2,4,52,4,5.
- Traditional methods: Spectral and time-domain features have limited power, especially for early AD.
- Machine/deep learning advances: Multivariate models (CNN, LSTM, attention) improve performance by integrating multiple features 1,3,61,3,6.
- Challenges: Inter-individual variability, class imbalance, and demographic effects (age, sex) impact EEG and must be addressed 7−97−9.

PROPOSED METHOD

- Three main stages:
- **Feature extraction:** Compute statistical and nonlinear features from EEG epochs.
- **Data preprocessing**: Clean, segment, and scale data; append demographic variables.
- **Classification**: Use a BiLSTM-Attention neural network for final prediction.
- Goal: Leverage both EEG and demographic information for robust classification.

MODEL ARCHITECTURE

- Input: For each sample, a matrix (channels × features) + demographic features (age, sex).
- BiLSTM: Two bidirectional LSTM layers (128 hidden units, dropout) to model temporal dependencies across channels.
- Attention mechanism: Learns which channels and features are most informative for classification.
- Classifier head: Concatenates attention context with demographics, passes through two fully connected layers (256, 128 units, ReLU, dropout), and outputs binary prediction via sigmoid activation.



DATASET DESCRIPTION

- Source: OpenNeuro ds004504, resting-state, eyes-closed EEG.
- Subjects: 65 included (37 AD, 28 CN), ages 49–80+.
- EEG recording: 19 channels (10–20 system), segmented into 10-second epochs.
- Sample count: ~2,900 AD epochs, ~2,300 CN epochs.
- Demographics: Age and sex included for each subject.

PREPROCESSING AND FEATURE EXTRACTION

- Preprocessing:
- Bandpass filtering (0.5–45 Hz), re-referencing, artifact removal.
- Segmentation into non-overlapping 10s epochs.
- Feature extraction (per channel, per epoch):
- Log Band Power (LBP)
- Variance (VAR)
- Standard Deviation (STD)
- Kurtosis (KUR)
- Average Energy (AE)
- Root Mean Square (RMS)
- L2 Norm
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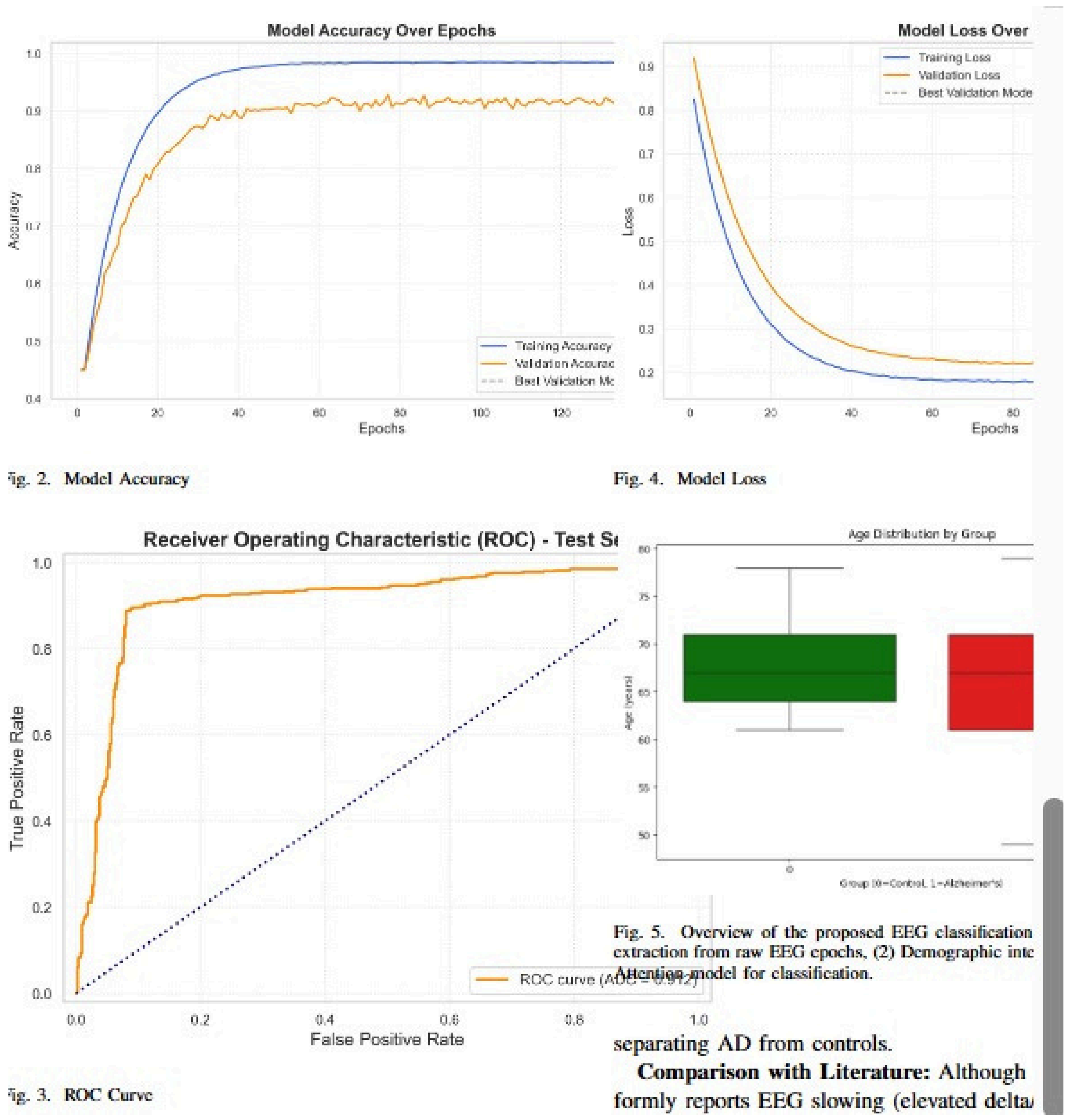

RESULTS

- Train/validation/test split: 80/20, with 15% of train for validation.
- Best model test set results:
- Accuracy: 0.82
- AD Precision/Recall/F1: 0.84/0.83/0.84
- CN Precision/Recall/F1: 0.79/0.80/0.79
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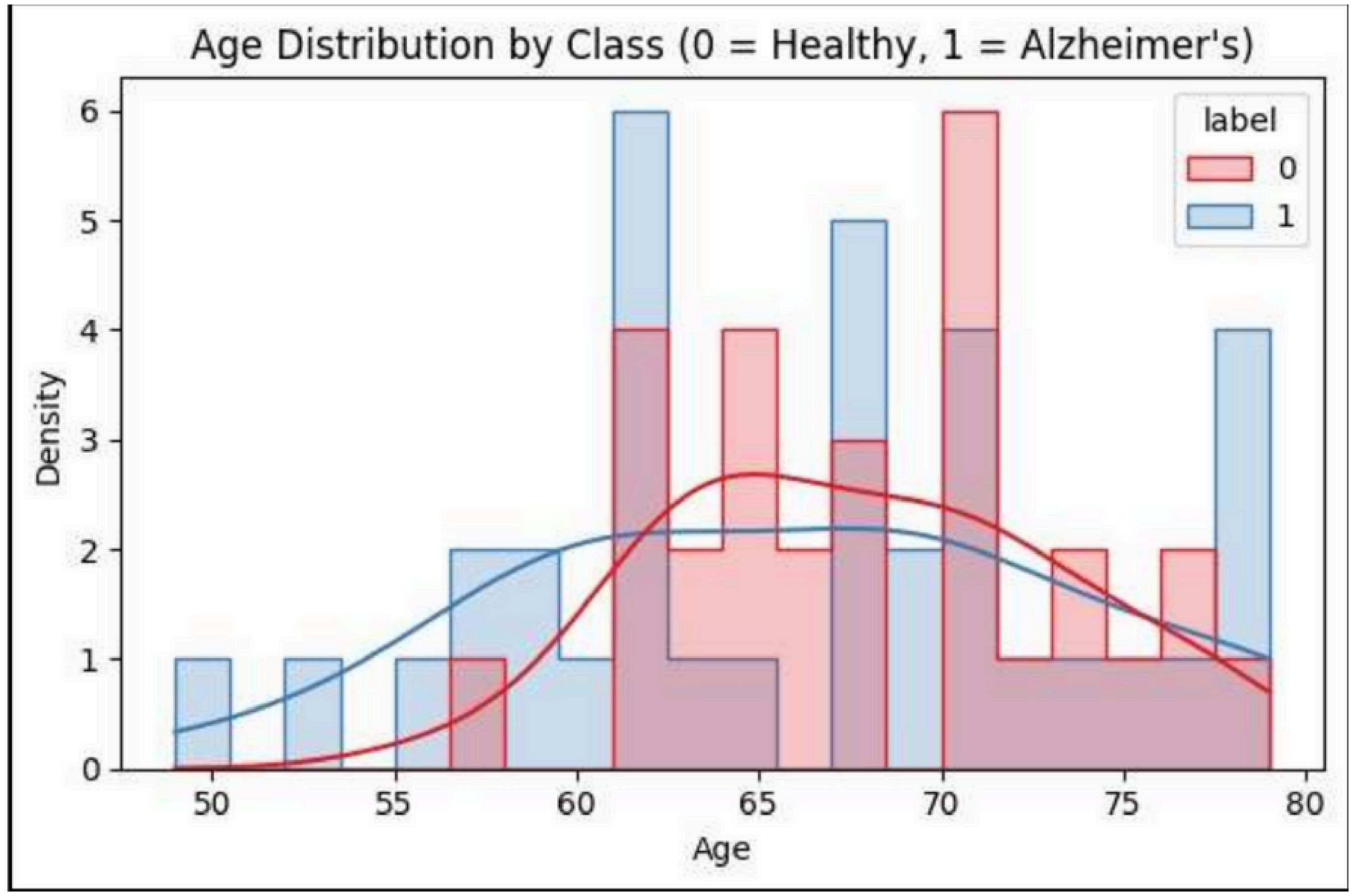

CONCLUSION

- Summary: BiLSTM-Attention model accurately classifies AD from resting-state EEG using multichannel time-domain features and demographics.
- Strengths: Captures distributed, subtle EEG patterns; robust to demographic confounds.
- Limitations: Small dataset, only time-domain features used.
- Future work: Incorporate frequency-domain features, expand dataset, move toward clinical application.

REFERENCE

- W. Xia et al., Heliyon, 2023.
- S.-K. Kim et al., Scientific Reports, 2024.
- A. Alzahrani et al., Frontiers in Human Neuroscience, 2023.
- M. Saeed and A. Alzahrani, Bioengineering, 2023.
- X. Li and Y. Chen, Applied Sciences, 2023.

THANK YOU