DOI: 10.1002/alz70860_106904

PUBLIC HEALTH

POSTER PRESENTATION

Alzheimer's & Dementia®
THE JOURNAL OF THE ALZHEIMER'S ASSOCIATION

EPIDEMIOLOGY

Developing Foundation Model for Early Detection of Alzheimer's Disease and Related Dementias (ADRD) from midlife

Samuel O. Danso[1,2] | Ibrahim Alqatawneh[3] | Adewale Samuel Owo[4] | Tamlyn J Watermeyer[5,6] | Joe Butler[7,8] | Poorna Gunasekera[9]

[1]School of Computer Science and Engineering, University of Sunderland, Sunderland, England, United Kingdom

[2]University of Edinburgh, Edinburgh, United Kingdom

[3]University of Sunderland, Sunderland, England, United Kingdom

[4]University of Sunderland, Sunderland, United Kingdom

[5]Edinburgh Dementia Prevention, Centre for Clinical Brain Sciences, College of Medicine and Veterinary Medicine, University of Edinburgh, Edinburgh, United Kingdom

[6]University of Northumbria, Newcastle upon tyne, England, United Kingdom

[7]School of Psychology, University of Sunderland, Sunderland, United Kingdom

[8]National Institute of Health Applied Research Collaboration North East & Cumbria, Newcastle-Upon-Tyne, England, United Kingdom

[9]Unviversity of Plymouth, Plymouth, England, United Kingdom

Correspondence
Samuel O. Danso, School of Computer Science and Engineering, University of Sunderland, Sunderland, England, United Kingdom.
Email: sam.danso@sunderland.ac.uk

Abstract

Background: While recent development of Artificial Intelligence (AI)-based approaches have demonstrated to be effective in predicting risk of ADRD, these have mostly focused on AD subtype, aged and homogenous populations (Grueso et al, 2022; Rahim et al., 2023), thereby limiting their applicability to other types of ADRD and younger populations. Inspired by earlier work (Danso et al 2021), we propose an AI-based deep-learning framework for early detection of ADRD based on heterogeneous and diverse population from midlife (Figure 1).

Method: We obtained two datasets from the European Prevention of Alzheimer's Dementia- EPAD (n = 2096) and PREVENT Dementia Programme (n = 700) available online (AD workbench, 2020). Following procedures described in Danso et al (2018) a harmonised cohort was curated containing individuals with no diagnosis of dementia. We then created three risk groups (High risk = ApoE4 allele and family history of AD; Medium risk = ApoE4 allele but no family history of AD; Low risk = no ApoE4 allele and no family history of AD) following the risk definition by Ritchie & Ritchie (2012). Convolutional Neural Network (CNN) and Long- Short Term Memory (LSTM) models were developed using 5-fold cross validation and then applied optimisation procedures to obtain optimal parameters for the trained models.

Result: The harmonisation resulted in a cohort (n = 2796; mean age =62; range = 40 – 89years; female =57.5%, Caucasian = 95%), containing medical history, physiological, lifestyle, neuroimaging, and sociodemographic features. Overall, CNN outperformed LSTM by 7% points for accuracy and f1-score (Table 1), with mean AUROC scores of 97% and 94% respectively (Figure 2), and mean validation loss scores (CNN = 0.36; LSTM =0.46).

Conclusion: The superior performance of CNN is consistent with the literature and the relatively low validation loss demonstrates its generalisability. While this model is currently optimised for AD with limited features, a Transfer Learning paradigm is being employed to further train the CNN model to predict risk of other AD sub-types after including BioHermes dataset into pipeline. Future work will also explore modifications of the CNN architecture for multimodal features with explainability capabilities.

Figure 1: Overview of approach to developing Foundation model for ADRD

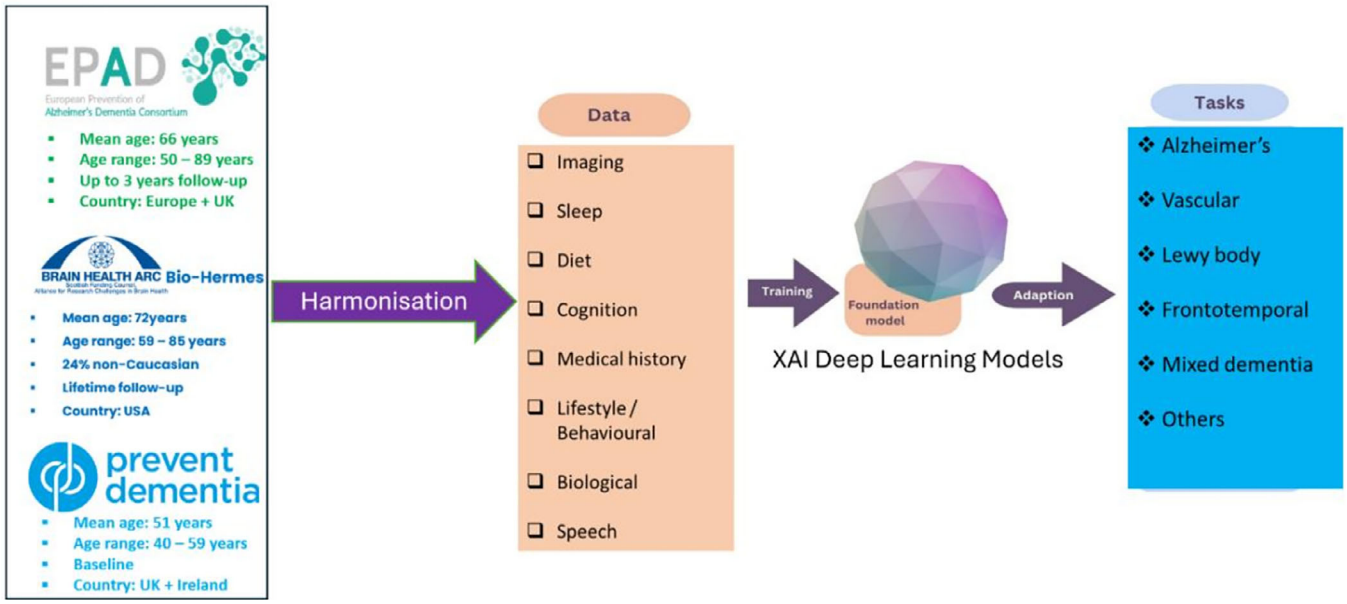
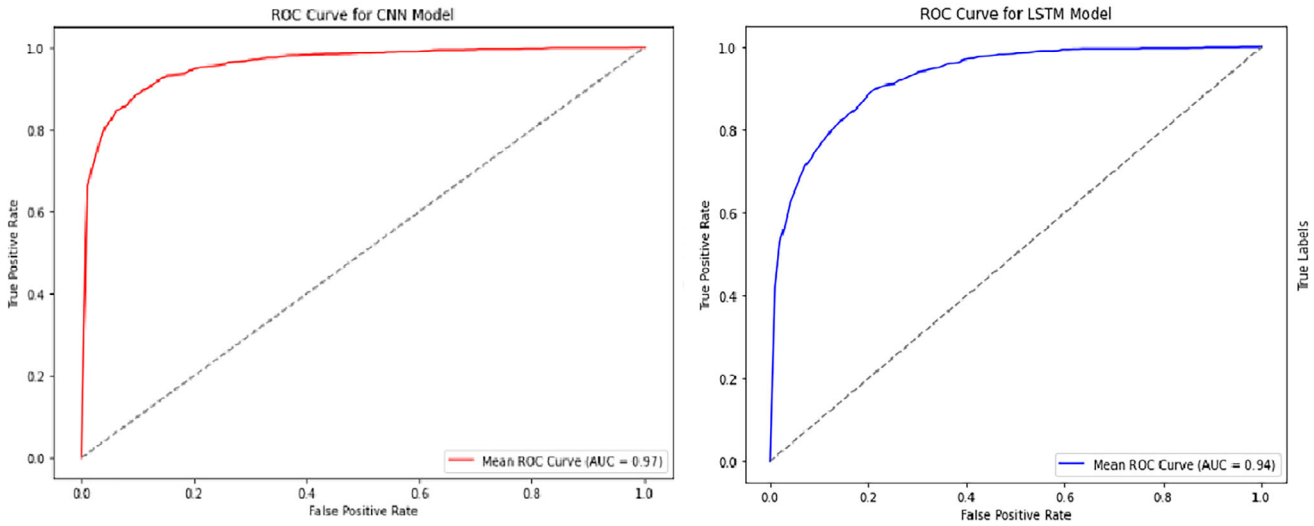


Figure 2: ROC curves for CNN and LSTM



Alzheimer's & Dementia®
THE JOURNAL OF THE ALZHEIMER'S ASSOCIATION

RESULT TABLE								
Model	Class	Precision	Sensitivity	F1-Score	Weighted Average Precision	Weighted Average Recall	Weighted Average F1-Score	Accuracy
CNN	Low	0.88	0.90	0.89	0.88	0.88	0.88	88%
	Mid	0.89	0.83	0.86				
	High	0.86	0.91	0.88				
LSTM	Low	0.79	0.86	0.83	0.81	0.81	0.81	81%
	Mid	0.82	0.74	0.78				
	High	0.81	0.83	0.82				