University of Kelaniya

Faculty of Science

Department of Statistics and Computer Science

Research Proposal for Bachelor of Science in Computer Studies (Special) Degree

COST 43238 – Research Project

Research Proposal

on

Enhancing Alzheimer's Disease Prediction through Multimodal Fusion-Enabled Ensemble Learning Using Deep Learning Algorithms

By

M. C. Kularatne

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1. Introduction

1.1. Background Study

Alzheimer's Disease is a progressive and debilitating neurodegenerative disease that is more common with adults older than the age of 65. Alzheimer's disease causes the brain to shrink and brain cells to eventually die. It is estimated that at least 44 million people are suffering from Alzheimer's disease worldwide. Cognitive decline, memory loss, and a variety of behavioral and psychiatric problems are among its key features.

1.2. Problem Statement

Still there is no proper treatment to cure a patient with Alzheimer's Disease (AD) back to normal. The only available treatment is used to decelerate mild cognitive impairment (MCI) patient from being an AD patient. Patients in the phase of MCI have a risk of converting to AD in a very less time period but some are not. Therefore, it is very important to identify Alzheimer's disease in its early stages. Since there are no reliable biomarkers or laboratory testing for Alzheimer's disease, diagnosing it in its early stages can be difficult. Currently, a diagnosis is made via clinical measures, such as cognitive testing, medical history, and neuroimaging, which can be a time-consuming and expensive process. Hence, developing an accurate model for early Alzheimer's prediction would be a significant task in the history of the medical field.

1.3. Aims and Objectives

1.3.1. Aims

The primary aim of this research is to develop a system which can be used to identify AD in early stages. Furthermore, the system will also recommend personalized medicine as per the stage. By harnessing the power of deep learning algorithms and multimodal fusion techniques, aim to create a powerful predictive model.

1.3.2. Objectives

Develop a model using deep learning algorithms to predict Alzheimer's disease.

Identify AD patients in their early stages.

Create individualized care plans for better treatments.

Provide healthcare professionals with reliable predictive models that assist in making clinical decisions consist of diagnosis, prognosis and treatment selection.

1.4. Significance of your Research

For my final year research, I'm planning to develop a model that can predict Alzheimer's Disease in its early stages. This can help in millions of people who are in the age of 65 or above having chance of getting MCI. Enhanced Alzheimer's disease prediction can lead to better-informed clinical decisions. It can assist healthcare professionals in identifying at-risk patients earlier, allowing for timely interventions and treatment planning. Beside all of this, a system like this can drastically reduce the cost associated with long-term hospitalization supervision. This research provides a positive impact in the field of healthcare by enhancing the Alzheimer's disease prediction through AI techniques.

2. Literature Review

Alzheimer's Disease (AD) is a relentless neurodegenerative disorder that affects millions of individuals globally, particularly those over the age of 65. In this literature review, we explore several notable studies that employ multimodal deep learning techniques to predict AD, highlighting their methodologies, datasets, and key findings. In their research, Venugopalan and colleagues utilized a multimodal approach, combining 3D Convolutional Neural Networks (CNNs) for neuroimaging data (ADNI1) with Stacked Denoising Auto-encoders for clinical and genetic data (ADNI1, ADNI2, ADNI GO). They achieved an accuracy of 0.87, emphasizing the potential of deep learning in AD prediction. However, a limitation of this study was the use of a limited dataset (Venugopalan et al, 2021).

Qiu and his team introduced a multimodal deep learning approach that integrated CNNs for image data and CatBoost for clinical data, combining demographics, medical history, neuropsychological testing, and functional assessments. With an impressive accuracy of 95%, their model showcases the power of combining diverse data sources. However, it is important to note that their dataset lacked confirmed cases of atypical AD (Qiu et al, 2022).

Velazquez and Lee proposed a multimodal ensemble model utilizing CNNs for image data and Random Forest for patient biometric and neuropsychiatric test score features. Achieving an accuracy of 98.81%, their model demonstrated remarkable predictive capabilities. Nonetheless, the study faced limitations due to a restricted dataset (Velazquez and Lee, 2022).

Spasov and colleagues developed a parameter-efficient deep learning approach that utilized CNNs with MRI, demographic, neuropsychological, and genetic data. Their model achieved an accuracy of 86%, indicating its potential for AD prediction. However, the study was constrained by the size of the dataset (Spasov et al, 2019).

Lee and his team employed Recurrent Neural Networks (RNNs) to predict AD progression, incorporating demographic information, neuroimaging phenotypes from MRI, cognitive performance, and CSF measurements. They achieved an accuracy of 68.5%, albeit with some limitations related to single-modality feature optimization and GRU parameter updates (Lee et al, 2019).

Abrol and co-authors used Support Vector Machines (SVM) to fuse structural MRI and functional MRI data. Although the study yielded limited accuracy (0.0013), it highlighted the need for a unified multimodal fusion approach. However, the research was hampered by a small sample size and limited comparisons with other deep learning approaches (Abrol et al, 2019).

Yang and colleagues employed XGBoost for raw T1-weighted MRI data and Cox models for multiple clinical variables. They achieved an accuracy of 0.915 using ensemble learning and 0.922 with the Cox model, indicating the potential of their multimodal approach (Yang et al, 2021).

The possibility of using several deep learning algorithms in the prediction of Alzheimer's disease is highlighted by all of these studies, in conclusion. Despite the fact that much progress has been made, there are still problems to be solved, such as the requirement for vast and diverse datasets and dataset limits. However, these advancements mark a significant step in enhancing the early detection and treatment of Alzheimer's disease, which might impact the field of AD research and clinical practice.

3. Research Methodology

3.1. Brief Idea about Research Method

As for my research I'm doing "Enhancing Alzheimer's Disease Prediction through Multimodal Fusion-Enabled Ensemble Learning Using Deep Learning Algorithms". In the past there has been done research using multimodal data fusion. I'm planning to use MRI images as well as clinical and genetic data. As a novelty I'm using ensemble learning in both data models.

3.2. Plan for the Data

I'm planning to use online available dataset obtained from Alzheimer's Disease Neuroimaging Initiative (ADNI) database and Open Access Series of Imaging Studies (OASIS) database. The ADNI is a longitudinal multicenter study designed to develop clinical, imaging, genetic, and biochemical biomarkers for the early detection and tracking of Alzheimer's disease (AD). ADNI began in 2004 under the leadership of Dr. Michael W. Weiner. OASIS is aimed at making neuroimaging datasets freely available to the scientific community. Previously released data for OASIS-Cross-sectional (Marcus et al, 2007) and OASIS-Longitudinal (Marcus et al, 2010) have been utilized for hypothesis driven data analyses, development of neuroanatomical atlases, and development of segmentation algorithms. From this I'm planning to use ADNI 3 and OASIS 3 datasets.

3.3. Tools and Technologies

I'm using intel i7-10510U 1.80GHz processor computing workstation for image processing and non-imaging data processing. Python (version 3.11) and PyTorch (version 2.0) are planning to use according to the necessity. Other Python libraries that I'm hoping to use for data analysis include pandas (version 2.1.1), scipy (version 1.11.1), tensorflow (version 2.14.0) and scikit-learn (version 1.3).

3.4. How you plan Experiments and Validation

As I mentioned earlier, I'm using both images and structured data. I'm planning to use ensemble learning in both data models separately. For the images I'm planning to use ResNet, VGG and Xception as the deep learning algorithms. For the structured data I'm planning to use Radial Basis Function Networks (RBFN) and Restricted Boltzmann Machines (RBM). As the ensemble method Stacking will be used for both data types. Then using late fusion, I hope to get the final accuracy combing both data types.

4. References

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