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Design and Analysis on Detection and Prediction Model Based on Explainable Artificial Intelligence for Alzheimer's Disease

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ABSTRACT
The Alzheimer's disease (AD) that causes dementia in most people. Its diagnostic and progression-detecting capabilities have been the subject of substantial study. Research findings rarely impact clinical practice, though, and this is due to the following factors: (1) neuroimaging is the primary area of study; (2) the separation of diagnosis and progression detection is common practice; and (3) optimization of complicated machine learning models' performance, not their explainability, is the main emphasis of current studies. This complicates matters and makes it tougher for physicians to have faith in these models. A reliable and understandable model for monitoring the progression of Alzheimer's disease is meticulously constructed in this study. Practitioners are able to give educated recommendations with thorough explanations when they employ this assessment method. The ADNI real-world dataset contains information from 1048 participants, and the model uses eleven different kinds of imaging data from that dataset. Out of the total population, 294 have normal cognitive capacities, 254 have stable moderate cognitive impairment (MCI), 232 have MCI that is getting worse, and 268 have severe symptoms of Alzheimer's disease (AD). Among the several approaches offered by various authors in this book is a two-layer model that makes use of random forest (RF) as a classification technique. To identify early signs of Alzheimer's disease, the model's initial layer use multi-class classification. Layer two of the model uses binary classification to assess the patient's chance of getting Alzheimer's disease (AD) within three years after a moderate cognitive impairment (MCI) diagnosis. A wide variety of biological and clinical characteristics are used to pick essential markers, which improves the model's accuracy. We describe the global and instance-by-instance explainability of the RF classifier's layers using the SHapley Additive exPlanations (SHAP) feature attribution paradigm.

1. INTRODUCTION AND BACKGROUND

Dementia and the slow decline of cognitive capacities and memory are hallmarks of Alzheimer's disease (AD), the most common form of dementia among the elderly. In 2018, more than 50 million individuals across the globe were coping with AD [1]. The estimated 131 million people living with AD in the world in 2050 will result in a societal and economic cost of $9.12 trillion [2]. Classic early indications of AD include forgetting new information, significant dates or events, problems with basic daily tasks, and asking the same questions over and over again. The last step also involves seeing how the patients' behavior changes. Most patients with the condition start experiencing symptoms in their mid-60s. Experts believe that this neurological disorder has multiple causes, including heredity, environmental factors, and lifestyle choices [3]. The damage AD causes is irreversible, and although there are drugs that can help, the disease itself is not treatable. The primary killer of Alzheimer's patients is aspiration pneumonia [4].

Patients these days are more inclined to seek a clinical diagnosis of AD, even if machine learning (ML) is an extremely effective method in this area. Clinical diagnosis, not the prediction of the ML model, is even trusted by doctors. Some 176 people took part in the study, and the results showed that they had less faith in ML and AI models for medical diagnosis and treatment than they did in human doctors. No amount of convincing can increase participants' faith in ML, even when shown that it beats human doctors [5]. The opaque structure of ML models is largely to blame for this mistrust. The best method to earn people's trust, then, is to explain the decision made by the ML models or the aspects that went into making this judgment. With explainable AI, you can annotate a model's judgments and the traits it uses to make those decisions. In most circumstances, it is difficult to get acceptable accuracy when using only neuroimaging data for AD prediction, which is a typical practice. It is already quite dangerous to use single modal data for such vital predictions because it can occasionally yield inaccurate results. In order to address these issues, our work suggests a multimodal ML model that can be explained.

Patients with Alzheimer's disease can greatly benefit from continual assistance, which can greatly enhance their quality of life. But practically everyone in the family is working these days, thanks to capitalism and technology. Their health may deteriorate drastically if they do not receive adequate care and assistance. However, there is also a problem with the lack of institutions that are tailored to care for those with Alzheimer's disease. As a cost-effective method to continually monitor, assist with everyday activities, alert of health deterioration, and arrange for emergency medical care, an AD patient management system that is sensor-based and enabled by the Internet of Things (IoT) can be useful [6, 7]. This report thus provides a framework for the management and monitoring of Alzheimer's patients.

We present the first explainable multimodal technique to our knowledge using the OASIS-3 dataset, which contains clinical, neuroimaging, and psychological data [8].

2. REVIEW

Using a method for multidirectional mapping called Multidirectional Perception-Generative Adversarial Networks (MP-GAN), the key global attributes were captured by Yu et al. [9]. By utilizing the class discriminative map of the generator to transform MR images from one domain to another, the proposed method may differentiate between microscopic lesions. One MP-GAN generator may learn the class-discriminative maps of many classes by combining classification loss, adversarial loss, cycle consistency loss, and L1 penalty. The ADNI found that MP-GAN correctly represents many lesions affected by dementia progression.

Clinical Alzheimer's disease scores were predicted by Lei et al. [10] using a hybrid architecture and deep learning. We intend to decrease dimensionality and screen for features in AD-related brain regions using a feature selection method that merges group LASSO with correntropy. Here, we look at the relationship between connections between brain areas and longitudinal data using multi-layer independently recurrent neural network regression. The suggested mixed deep learning network may be able to forecast the clinical score by analyzing the relationship between the two. The anticipated clinical score values allow for efficient and rapid treatment of patients' health issues.

A novel tensorizing GAN with high-order pooling was proposed by Yu et al. [11] for the purpose of assessing AD and MCI. Thanks to the high-order pooling strategy used by the classifier, the proposed model may fully utilize the second-order statistics of integrated MRI. In an early effort to employ MRI classification for the diagnosis of Alzheimer's disease, the Tensor-train, High-order Pooling, and Semi-Supervised GAN (THS-GAN) was developed. The THS-GAN outperformed state-of-the-art methods in exhaustive trials conducted on the ADNI dataset. Tensor training and pooling showed promise for improving classification outcomes as well.

Using gene databases and magnetic resonance imaging (MRI) scans, Kamal et al. [12] trained a Convolutional Neural Network (CNN) to identify Alzheimer's disease (AD). The scientists used SVC, XG boost, and K-Nearest Neighbor (KNN) to classify diseases after they had collected microarray gene expression patterns. The authors applied the LIME method to describe their findings, which were based on a combination of gene and picture data rather than either method alone. While SVC performs better than competing methods for gene-expensive data, CNN achieves an accuracy rate of 97.6% when classifying MRI images.

A two-layer explainable ML model was proposed by El Sappagh et al. [13] for the aim of AD classification. In this multimodal approach, data were gathered from eleven distinct modalities. Among these were cognitive tests, neuropsychological assessments, medical records, MRIs, PET scans, cognitive batteries, and more. In this case, the SHAP framework was used to explain the results that were obtained from the initial multiclass classification layer's Random Forest (RF) classifier. Binary classification resulted from a shift in Layer 2 from probable mild cognitive impairment to Alzheimer's disease. The accuracy rate was 93.94% and the cross-validation F1-score was 93.95% for the first layer and the multiclass classifier, respectively. The second layer was 87.08% accurate, according to the F1-score. The authors can improve the model's accuracy and F1 score by using the deep learning technique. In any case, this model achieved respectable results in the lab, not in the real world.

A multimodal Recurrent Neural Network (RNN) model was introduced by Lee et al. [14] to forecast AD from MCI. The authors used this strategy to merge demographic data with neuroimaging scans taken at different points in time and biomarkers for cognitive performance extracted from CSF samples taken over time. Here, we retrieved all of our data from the ADNI website. There were two levels to the suggested model. In the first layer, there are four GRUs, or Gated Recurrent Units, and each of these houses a single data modality. A feature vector with a fixed size was generated from the first layer.

3. MACHINE LEARNING BASED PREDICTION MODEL FOR ALZHEIMER'S DISEASE

Loddo et al. (2022) [15] created a deep learning approach to identify Alzheimer's disease using brain imaging. Automated deep-ensemble classification of dementia levels is recommended after extensive examination of deep learning models. This article summarizes the present status of machine learning algorithms for the diagnosis and classification of Alzheimer's disease (AD), with a focus on neuroimaging, and examines the challenges of early AD detection. Results demonstrate that deep learning approaches show promise for Alzheimer's disease identification, even though no novel algorithms have been investigated. All of the aforementioned research projects use various DL and ML methods to aggregate data from various sources in order to make AD predictions. However, they pay little attention to how to interpret the results of these models and instead concentrate solely on how well the models function.

This study does double-duty by creating a novel model and then analyzing its performance. A two-layer model can be constructed using RF, according to El-Sappagh et al. (2021) [16]. Results for each layer are explained at both a high level and a more detailed level in the SHapley Additive exPlanations (SHAP) design. 22 explainers are used to support each RF choice at each tier, in addition to decision trees and fuzzy rule-based systems. Danso et al. (2021) [17] build an explanation-generating framework for dementia risk prediction models by integrating transfer learning and ensemble learning methods. The final forecast is based on the risk variables, which are represented by SHAP.

Kakutani et al. (2019) [18] highlighted the potential danger of dementia and how drinking tea may lower that risk. A higher risk of mild cognitive impairment and Alzheimer's disease has been linked to poor sleep quality, according to studies done by Brachem et al. (2018) [19] and Shi et al. (2020) [20].

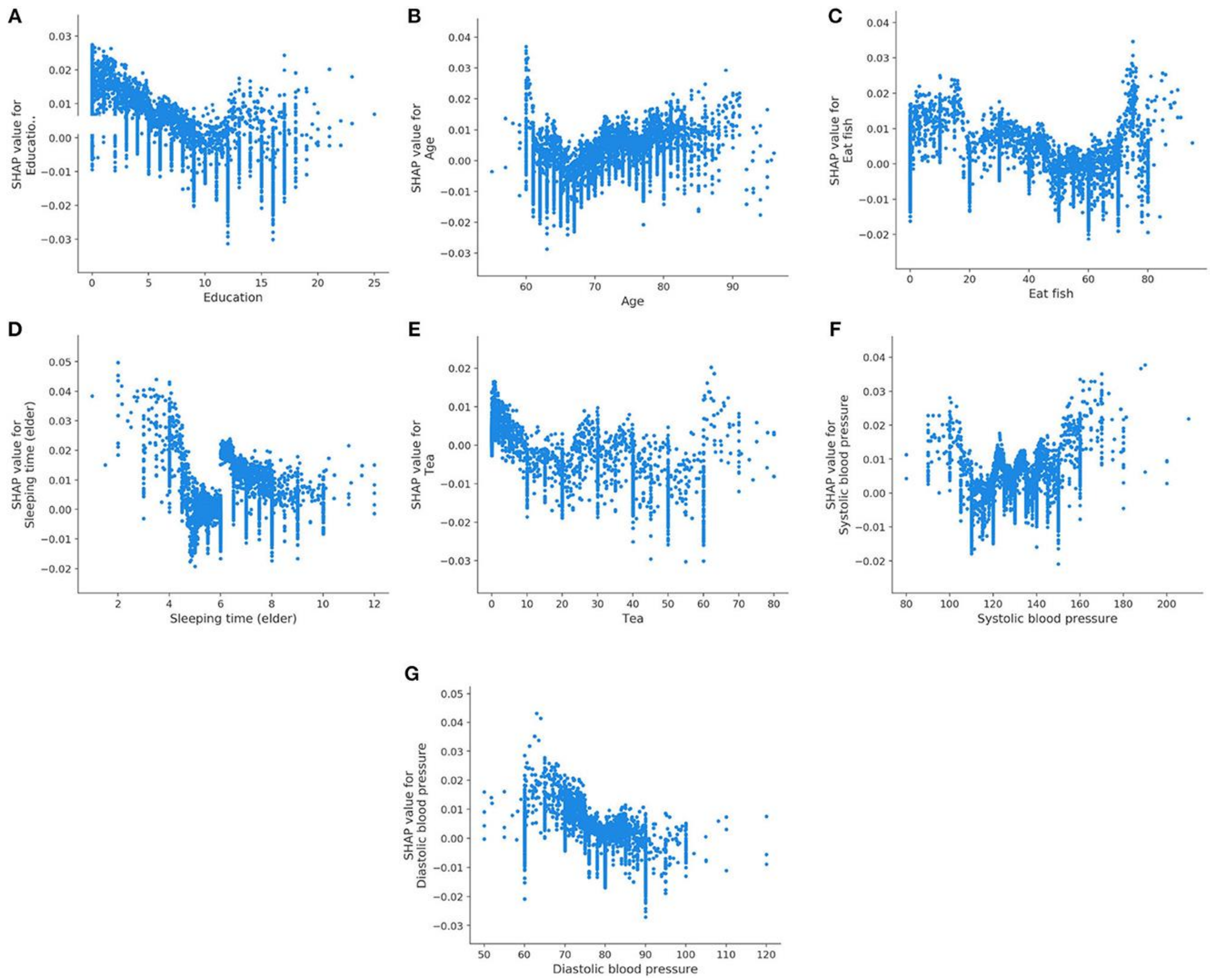

Figure 1. SHAP dependency plots for MCI class. (A) Education, (B) age, (C) eat fish, (D) sleeping time (elder), (E) tea, (F) systolic blood pressure, (G) diastolic blood pressure.

The findings of the aforementioned articles support the rationality of our concept, as illustrated in Figure 1. In addition to previous studies that support this idea, our results add to the increasing amount of evidence that AD is a complex disease impacted by several factors, both internal and external. We can identify the mixture of these contributing features using a unified machine learning framework and enhanced feature selection.

CONCLUSION

Our proposed ML model, which is based on an RF classifier, is both very accurate and easy to understand in this review paper. We demonstrated the viability of using multimodal RF classifiers for the identification and progression prediction of AD. Predictions obtained from integrated multimodalities perform better than predictions obtained from any individual modality for both binary and multi-class classification problems. An explainable multimodal strategy to AD prediction is proposed in this work. Three genre-specific datasets are fused at the data level in this multimodal technique. In this study, we pull from OASIS-3 mental health records, MRI segmentation numerical data, and ADRC patient records. To make ML and ML algorithms' prediction abilities better, we implement the feature selection procedure here. This involves identifying important variables and deleting any irrelevant or redundant features. For five different classifications, this multimodal technique yields an RF classifier accuracy of 98.81%.

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