Detection Of Dementia

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Abstract— Detection of dementia is a pressing challenge in modern healthcare, as timely diagnosis significantly improves patient care, treatment outcomes, and resource management. This paper presents a comprehensive approach integrating convolutional neural networks (CNNs) for MRI-based neuroimaging analysis with machine learning algorithms applied to patient data, including cognitive test scores and demographic information. The hybrid model is designed to increase predictive accuracy and reliability. The paper explores the system architecture, problem statement, methodology, testing strategies, and evaluation results. We also discuss future enhancements and challenges in deploying such systems in real-world healthcare environments.

Keywords—Dementia Detection, Early Diagnosis, Convolutional Neural Network (CNN), Deep Learning, MRI Analysis, Machine Learning, Cognitive Assessment, Healthcare AI

I. INTRODUCTION

Dementia refers to a group of neurological disorders characterized by the progressive decline in memory, reasoning, and cognitive abilities. The World Health Organization estimates that over 55 million people are currently living with dementia worldwide, with nearly 10 million new cases emerging annually. Alzheimer's disease is the most common cause of dementia, followed by vascular and mixed dementia subtypes. The economic and social burden of dementia is immense, affecting not only patients but also their families and caregivers. Early detection is therefore critical in slowing disease progression, providing timely treatment, and planning long-term care strategies.

Traditional diagnostic methods rely on clinical interviews, neuropsychological tests, and manual interpretation of MRI scans. However, these approaches are time-intensive, subject to human error, and may miss subtle early-stage indicators. Advances in artificial intelligence, particularly deep learning and machine learning, have enabled automated systems capable of analysing large-scale medical datasets with improved precision and speed. This research proposes an integrated dementia detection system combining MRI-based deep learning and structured patient data classification for enhanced diagnostic support.

II. RELATED WORK

Researchers across the world have investigated different approaches for the early detection of dementia. Traditional diagnostic methods have relied on clinical interviews, cognitive assessments, and manual MRI interpretation, which, while effective, are timeconsuming and prone to subjectivity [1,2]. Early computational approaches used handcrafted features such as texture, volumetric measurements, and statistical brain region analysis, combined with classifiers like Support Vector Machines (SVM) and Naïve Bayes, to predict cognitive decline [3,4]. The emergence of Deep Learning marked a breakthrough in dementia detection. Convolutional Neural Networks (CNNs) can automatically extract spatial features from MRI scans without manual intervention, significantly improving diagnostic accuracy. Sarraf and Tofighi (2016) demonstrated the effectiveness of CNNs in detecting Alzheimer's disease from fMRI scans [5]. Similarly, Basaia et al. (2019) trained deep learning models on structural MRI data to distinguish between Alzheimer's disease, mild cognitive impairment (MCI), and healthy controls, achieving high classification accuracy [6]. Recent works also explored multimodal approaches that integrate MRI scans with cognitive test scores such as MMSE and CDR, along with demographic data, to further enhance robustness and reliability [7,8].

The proposed Dementia Detection System builds upon these studies by implementing a CNN-based MRI classifier integrated with a patient attribute classifier (e.g., Random Forests or Naïve Bayes). Unlike prior works, this system emphasizes usability and accessibility, enabling clinicians and researchers to upload MRI scans and patient records, receive real-time dementia predictions, view explainable Grad-CAM heatmaps, and generate structured PDF reports. This dual-model approach not only enhances accuracy but also ensures clinical interpretability, bridging the gap between AI-driven research and real-world healthcare applications [9,10].

III. METHODOLOGY

The methodology defines the structured approach for building the dementia detection framework. It encompasses data collection, preprocessing, model development, training, validation, and reporting. By combining MRI-based deep learning with tabular patient recorded data classification, the system aims to achieve a holistic and accurate prediction model.

A. Data Collection and Preprocessing

MRI Dataset: Acquire MRI image datasets from Kaggle categorized into multiple classes representing dementia severity (non-demented, very mild demented, mild demented, moderate demented).

Patient Attribute Dataset: Collect patient attribute data including age, gender, MMSE, ASF, eTIV, CDR, normalized brain weight, and relevant attributes from reliable sources or clinical databases.

B. Preprocessing

MRI Image Preprocessing: Standardize image sizes and formats for consistency. Normalize pixel values, perform resizing, and apply techniques like augmentation to enhance the dataset for robust CNN model training. b. Attribute dataset Preprocessing: Clean and preprocess patient attribute data by handling missing values and normalizing numerical features for the classifying algorithm.

C. Model Development

For building our models, we take two approaches. First, for MRI images, we construct a deep learning model using TensorFlow and Keras. It's like crafting a puzzle with layers of filters and patterns to decode the images. We train it on diverse data, tweaking settings like brightness and angle to improve accuracy. Then, for patient attributes, we explore different algorithms, sort of like trying out various tools to solve a problem. We train and test each method on our cleaned- up data to find the best fit for predicting dementia.

D. User Interface Development

Design a user-friendly interface enabling the admin to upload MRI images for CNN analysis. Input patient details for the classifying algorithm model. Manage system functionalities and inputs seamlessly.

E. **Report Generation**

Develop a mechanism to compile comprehensive reports containing: • Patient details. • Results and findings from both the CNN and classifying algorithm models. • Recommendations or further steps based on model outcomes.

IV. RESULTS AND DISCUSSION

The proposed Dementia Detection System was developed using a CNN for MRI scans along with a classifier for patient attributes such as MMSE and CDR. The system achieved good accuracy, with the CNN model reaching about 91% validation accuracy, while the patient attribute classifier achieved around 85%. When combined, the integrated model performed even better with an overall accuracy of about 95%.

The system not only provided predictions but also generated visual explanations using Grad-CAM heatmaps, showing which brain regions influenced the model's decisions. A PDF report was also created for each case, including the prediction, confidence score, and visualization. The web-based interface allowed users to upload MRI scans and patient data easily and receive results within a few seconds.

Compared to traditional methods of dementia diagnosis, which depend heavily on manual interpretation, the proposed system is faster, more consistent, and less error-prone. However, some challenges were noticed when handling low-quality or corrupted MRI scans, which slightly reduced accuracy. This shows the importance of using larger and more diverse datasets to improve performance.

Overall, the results show that the system is accurate, easy to use, and clinically useful. It has strong potential to support healthcare professionals in early detection of dementia and improve decision-making in patient care.

V. CONCLUSION

The Comprehensive Dementia Detection system developed is a significant advancement in the field of healthcare technology. By integrating MRI-based predictive models using Convolutional Neural Networks (CNN) and patient-recorded data predictive models using classification algorithms, the system offers a reliable and efficient way to detect and predict dementia at an early stage.

The user requirements, system requirements, and functional requirements outlined in the report emphasize the importance of user-friendly interfaces for administrators, accurate prediction models, and secure data handling to protect patient confidentiality. The system's design ensures a seamless flow of data, accurate predictions, and timely interventions, reflecting a thoughtful consideration for both accuracy and patient privacy.

The validation mechanism implemented to assess the accuracy and effectiveness of the predictive models, along with the emphasis on data security and confidentiality, further enhance the system's credibility and reliability. The non-functional requirements such as performance, security, usability, reliability, and scalability ensure that the system can deliver accurate predictions under varying conditions while maintaining data integrity and confidentiality.

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