NeuroPredict: A Comprehensive Approach for Alzheimer's Disease Prediction and Development of a Medical Assisting Kit

Annangi Saikiran Babu
Electronics and Communication
The National Institute of Engineering Mysuru
4ni19me024_a@nie.ac.in

K P Yashika
Electronics and Communication
The National Institute of Engineering Mysuru
4ni19me064_a@nie.ac.in

K S Nishaan Kushalappa
Electronics and Communication
The National Institute of Engineering Mysuru
4ni19ec044_a@nie.ac.in

Aniruddh Adiga
Electronics and Communication
The National Institute of Engineering Mysuru
4ni19ec014_a@nie.ac.in

Shreya B Raj
Electronics and Communication
The National Institute of Engineering Mysuru
2020ec_shreyabraj_b@nie.ac.in

Mrudula N
Electronics and Communication
The National Institute of Engineering Mysuru
2020ec_mrudulan_b@nie.ac.in

Meghana S
Electronics and Communication
The National Institute of Engineering Mysuru
2020ec_meghanas_b@nie.ac.in

Chandhana K B
Electronics and Communication
The National Institute of Engineering Mysuru
2020ec_chandanakb_b@nie.ac.in

Remya Jayachandran
Electronics and Communication
The National Institute of Engineering Mysuru
remyajayachandran@nie.ac.in

***Abstract*—The "NeuroPredict" system aims to address Alzheimer's disease (AD) by providing early prediction and diagnosis using a Convolutional Neural Network (CNN) model on MRI images. With an 80% accuracy rate, the proposed NeuroPredict system offers a robust solution. Exploratory Data Analysis (EDA) is emphasized to uncover patterns and trends within the AD dataset, contributing to research advancements. Additionally, the system introduces "MemorEyes," a low-cost hardware kit to assist AD individuals. It includes smart spectacles displaying pictures of loved ones with details, reminders for exercise and medication, and a smart wristband for live location tracking. Caretakers receive alerts, promoting proactive prevention and personalized support for early-stage AD patients. To ensure accessibility, NeuroPredict offers a user-friendly web application for clinicians and researchers. The user can easily upload MRI images, run predictions using the CNN model, and access detailed reports and visualizations, even without technical expertise. The proposed NeuroPredict focuses on early prediction, proactive prevention, and personalized care and aims to significantly impact AD patients' lives and help in neurodegenerative disease research.**

***Index Terms*—Alzheimer's disease; CNN; wearable device; Exploratory Data Analysis**

I. Introduction

Alzheimer's disease (AD) is a global health concern that significantly impacts individuals, families, and healthcare systems worldwide. Early prediction and diagnosis are crucial for timely interventions and better patient outcomes, as there is currently no cure for AD. Still, the onset and progression of the disease can be potentially reduced with early detection and appropriate management. Accurate and efficient prediction models have the potential to improve the lives of those affected by AD significantly. The literature survey reveals a growing interest in utilizing Convolutional Neural Networks (CNNs) for early prediction and diagnosis of Alzheimer's disease. Studies have highlighted the limitations of traditional diagnostic methods and emphasized CNNs as a promising approach in AD diagnosis [1]. One such study explored the use of CNNs for AD prediction from mild cognitive impairment (MCI) using MRI images, demonstrating the superiority of CNNs over traditional machine learning algorithms [2]. Another research focused on leveraging pre-existing CNN architectures and transfer learning to enhance prediction accuracy for AD [3]. Moreover, a study investigated the application of CNNs for Alzheimer's disease detection on MRI images, achieving high accuracy in classifying AD and healthy control subjects [4]. In addition to prediction and diagnosis, there are various assisting aids available in the market to support individuals with AD. These aids range from wearable devices to mobile applications and smart home technology. For instance, wearable devices can monitor vital signs and detect anomalies, while mobile applications provide reminders for medication and daily tasks. Smart home technology offers an environment that can be adapted to the individual's needs, enhancing safety and independence [5].

This research article introduces the "NeuroPredict" system, which utilizes a Convolutional Neural Network (CNN) model

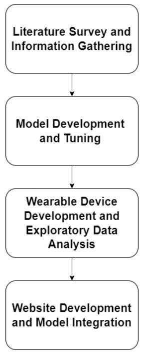

Fig. 1. Flowchart of the proposed methodology.

to predict AD based on MRI images, offering a reliable solution for early diagnosis with an 80% accuracy rate. The study emphasizes Exploratory Data Analysis (EDA) to uncover patterns and relationships within the AD patient's dataset, contributing valuable insights to neurodegenerative disease research and interventions. The proposed system also introduces "MemorEyes," a low-cost hardware kit designed to assist individuals in the early stages of AD. MemorEyes, consisting of smart spectacles and a wristband, provides personalized support, including displaying pictures of loved ones, reminders, and live location tracking for caregivers, thus improving AD patients' quality of life. The Neuropredict system aims to democratize access to early AD detection, accommodating individuals without technical expertise. By combining CNN models, EDA insights, and innovative hardware and web applications, NeuroPredict addresses the critical need for early prediction and personalized care in AD. The primary goal is to make a significant impact on the lives of AD-affected individuals and contribute to broader neurodegenerative disease research conclusion. The NeuroPredict system, with its high accuracy and user-friendly interface, holds promise for early detection and intervention. MemorEyes and the accessible web application further contribute to improving healthcare. By focusing on early prediction, proactive prevention, and personalized care, this research aims to enhance patient outcomes and advance neurodegenerative disease research.

II. Methodology

This paper presents a comprehensive approach to predicting AD using MRI images. The methodology for developing an Alzheimer's disease (AD) detection system is briefly mentioned in Fig.1. Firstly it involves a comprehensive literature survey and information gathering phase. During this stage, CNN models used for AD detection are extensively researched, and relevant information on AD diagnosis using MRI images is collected. This serves as the foundation for the subsequent steps in the process. The next phase focuses on model development and tuning. A dataset of MRI images of the brain is collected and pre-processed to ensure data quality and consistency. Subsequently, a Convolutional Neural Network (CNN) model is trained on the pre-processed data to perform AD detection. The model is carefully tuned to achieve optimal performance and accuracy in predicting AD based on the provided MRI images. Additionally, an exploratory data analysis is conducted on the collected data, which aids in gaining insights and understanding potential patterns or trends relevant to AD detection. Furthermore, this methodology includes the design and development of a wearable device specifically tailored for AD patients, enabling continuous monitoring and data collection. The final phase revolves around website development and model integration. A user-friendly website interface is designed and developed to facilitate easy interaction with the AD detection system. The trained CNN model is then seamlessly integrated into the website to allow users to upload MRI images for AD detection and receive prediction results. This integrated system creates a user-centric platform, providing valuable insights and support for early AD diagnosis and management.

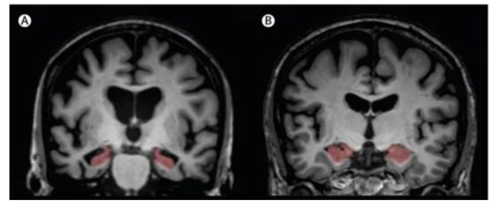

Fig. 2. Differences between MRI of AD patient and healthy control. (a) Patient diagnosed with Alzheimer's disease; (b) Healthy individual [6]

III. Differences between MRI scans of a healthy individual and AD patient

MRI images of individuals with Alzheimer's disease (AD) differ from those of healthy individuals in several ways, a sample MRI image of a healthy individual and a person diagnosed with AD is as shown in Fig.2. AD patients exhibit significant hippocampal atrophy, reduced cortical thickness in specific brain regions, and enlarged ventricles with increased cerebrospinal fluid volume. White matter lesions, indicated by hyperintensities, are common in AD. Advanced MRI techniques indirectly provide information about the presence and distribution of amyloid plaques and neurofibrillary tangles. Expert interpretation is crucial due to individual variations. These MRI differences contribute to understanding AD's structural alterations and aid in early detection and diagnosis [6].

IV. Exploratory data analysis on Alzheimer's dataset

A. Objective

Exploratory Data Analysis (EDA) is important for the development of a medical kit for Alzheimer's disease (AD) as it helps uncover patterns and relationships within the AD patient dataset, providing insights for research and interventions. EDA can also identify the most probable group of people who are at a higher risk of developing AD, enabling targeted preventive measures and personalized care strategies.

B. Dataset

The dataset includes longitudinal data from 150 subjects (aged 60-96) with 3-4 T1-weighted MRI scans taken during multiple visits. Among them, 72 subjects remained nondemented, while 64 were initially and continuously demented (51 with mild to moderate Alzheimer's disease). Another 14 subjects transitioned from nondemented to demented. This comprehensive dataset allows for studying disease progression over time in individuals with varying dementia statuses. The dataset includes information on Alzheimer's patients and normal individuals, covering demographics, clinical data, and derived anatomic volumes. It contains unique IDs for subjects and MRI scans, and groups them as Converted, Demented, or Nondemented based on dementia status. The dataset captures gender, age, education, socioeconomic status, MMSE scores, CDR ratings, eTIV, nWBV, and ASF. These parameters provide insights into Alzheimer's progression and cognitive decline.

C. Methodology

EDA is performed in four stages: data cleaning, univariate analysis, bivariate analysis, and key insights. Missing values are treated in the data cleaning stage to ensure data completeness. Univariate analysis examines individual variables using histograms, box plots, and summary statistics. Bivariate analysis explores relationships between variables through scatter plots, correlation matrices, and cross-tabulations. Key insights summarize findings, including significant variables, correlations, and patterns observed in the data. This systematic approach to EDA extracts valuable conclusions, guiding subsequent analysis and decision-making processes [7].

D. Observations / conclusions

In our study, we observed that a significant portion, approximately 39%, of the cases in our dataset were classified as demented, indicating a majority of non-demented cases. Furthermore, around 10% of the data represented converted cases. Based on our analysis, the following conclusions can be drawn: Dementia was most commonly observed in the age group of 70-80 years. Men tended to develop dementia at an earlier age, typically before 60 years, while women had a higher tendency to develop dementia at a later age, typically after 60 years. In men, dementia onset occurred at an education level of around 4 years, with the highest prevalence observed at education levels of 12 and 16 years. Dementia cases were also observed in individuals with education levels exceeding 20 years. For women, dementia onset occurred after approximately 5 years of education, with the highest prevalence observed around 12-13 years. The prevalence of dementia decreased as women's education levels increased. Men with both the highest and lowest socioeconomic status had higher rates of dementia, while women with medium socioeconomic status experienced higher dementia cases. Lower values of the Atlas Scaling Factor (ASF), close to 1, corresponded to severe dementia cases. The diagnosis of severe dementia typically requires a minimum of three visits. These findings provide important insights into the characteristics and trends related to dementia, highlighting the influence of age, gender, education level, socioeconomic status, and the severity of the condition within our study.

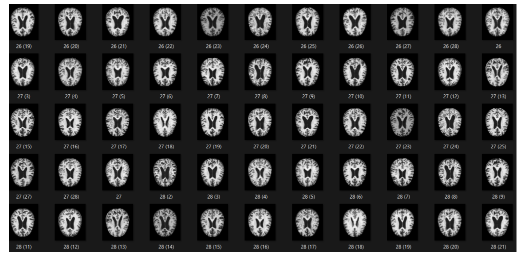

Fig. 3. Sample of dataset used.

V. Development of a Convolutional Neural Network Model for Alzheimer's Disease Detection Using MRI Images

Alzheimer's disease is a prevalent neurodegenerative condition that affects millions worldwide. Early detection plays a crucial role in providing timely care and improving patient outcomes. In this study, we propose the development of a Convolutional Neural Network (CNN) model for Alzheimer's disease detection using MRI images. The dataset comprises four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. We describe the data collection, preprocessing, model building, training, evaluation process, and result analysis. The optimized model demonstrates promising results in accurately detecting Alzheimer's disease from brain images, offering the potential for real-world clinical applications [8], [9].

A. Data Collection

The dataset used in the project is collected from various reliable sources, including ADNI - The Alzheimer's Disease Neuroimaging Initiative and Kaggle. This dataset is divided into two sets: a training set and a testing set. The training set comprises a substantial number of images, including 717 mild demented, 52 moderate demented, 2560 non-demented, and 1792 very mild demented images. On the other hand, the testing set consists of 179 mild demented, 12 moderate demented, 640 non-demented, and 448 very mild demented images. A sample of the dataset used in this work is shown in Fig.3. The inclusion of data from reputable sources like The Alzheimer's Disease Neuroimaging Initiative (ADNI)and Kaggle ensures the dataset's quality and reliability, as these sources are widely recognized and utilized in the research community for Alzheimer's disease prediction and neuroimaging studies. With a diverse set of images and a thorough training-testing set division, the model can learn from a broad range of cases while effectively evaluating its performance on unseen data.

B. Data Preprocessing

To ensure the quality and suitability of neuroimaging data for CNN-based AD classification, several preprocessing steps

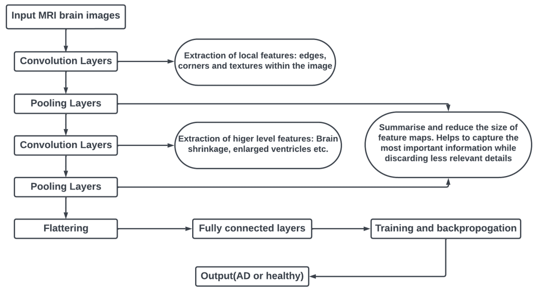

Fig. 4. CNN architecture.

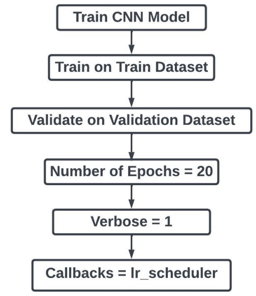

Fig. 5. Training of CNN model.

are employed: Neuroimaging data often comes from different sources and scanners, leading to spatial inconsistencies. Image registration techniques are utilized to align images to a common coordinate system, reducing spatial variations across subjects and facilitating meaningful feature extraction. The removal of non-brain tissues from neuroimaging scans is crucial to focus analysis on the brain regions. Skull stripping techniques, such as thresholding, morphological operations, and atlas-based methods, are applied to isolate the brain from the surrounding tissues. Variations in image intensity can arise due to acquisition parameters, scanner differences, and subject-related factors. Intensity normalization methods, like histogram matching and z-score scaling, are employed to standardize the intensity values across images, ensuring comparability during model training. Neuroimaging scans often have varying resolutions, affecting the network's ability to learn meaningful features. Voxel resampling is performed to achieve a consistent voxel size across all images, improving model generalization and reducing computational complexity.

C. Model Building

Convolutional layers are responsible for extracting local features from input images. These layers as shown in Fig.4 use learnable filters to perform spatial convolutions, capturing meaningful patterns and textures within the neuroimaging data. Pooling layers reduce spatial dimensions while retaining important features. Common pooling operations, such as max pooling, help to down-sample the feature maps, enabling the network to focus on the most relevant information. Fully connected layers receive flattened feature maps from the convolutional and pooling layers. They learn high-level representations and perform the final classification based on the extracted features. Dropout regularization is often incorporated to prevent overfitting. The output layer consists of one or more neurons, representing the classes to be predicted (e.g., AD or non-AD). Binary cross-entropy or categorical cross-entropy loss functions are commonly used for training the CNN, measuring the dissimilarity between predicted and ground truth labels.

D. Model Parameters

Effective model parameterization is crucial for achieving optimal performance in CNN-based AD classification. The following parameters are essential to consider: The number and size of filters, as well as the choice of activation functions and padding schemes, are critical parameters for capturing meaningful spatial features within neuroimaging data. Tuning these parameters based on the dataset characteristics can significantly impact model performance. The choice of pooling operations (e.g., max pooling) and their respective sizes directly affect the down-sampling process, enabling the network to focus on salient features while reducing computational complexity. Incorporating dropout regularization within the fully connected layers helps prevent overfitting by randomly deactivating neurons during training, enhancing the model's generalization capability.

E. Training

The training process involves optimizing model parameters using labeled training data to minimize classification loss. The following steps as mentioned in Fig.5 are typically undertaken: The available dataset is divided into training, validation, and testing sets. The training set is used to update the model's parameters, the validation set helps monitor performance during training and perform hyperparameter tuning, while the testing set serves as an independent benchmark for evaluating the final model. Training is performed using mini-batches, where a subset of training samples is processed at each iteration. Stochastic Gradient Descent (SGD) algorithms, such as Adam or RMSprop, are commonly employed to update the model parameters based on the computed loss and gradients. Gradients are propagated backward through the network using the chain rule to calculate the gradients with respect to each parameter. These gradients are then used to update the model weights, iteratively improving the model's ability to classify AD accurately [10]. Hyperparameter tuning was performed to fine-tune the model and improve its performance. This process involved adjusting learning rates, batch sizes, and other parameters to achieve optimal results.

VI. Website

The website developed for Alzheimer's disease detection using MRI images aims to provide a user-friendly and accessible platform for analyzing MRI scans and predicting the probability of Alzheimer's disease in patients. Alzheimer's disease is a neurodegenerative disorder that affects millions of people worldwide, and early detection plays a crucial role in effective management and treatment. Our aim is to make this kind of technology a valuable tool for medical professionals, researchers, and individuals concerned about their cognitive health.The website provides a clean and well-organized layout with the incorporation of grids and distinct sections, ensuring effortless navigation and structured presentation of information. It starts with a concise overview of Alzheimer's disease and provides an input field for users to upload MRI images. The prediction percentages for each of the four Alzheimer's disease classes are showcased, with the class having the highest prediction highlighted.

A. Website architecture and technologies

The website follows a client-server architecture, with the frontend developed using HTML, CSS, and JavaScript, and the backend powered by Flask [11], a lightweight Python web framework. The user interacts with the client, a web browser, to request data and upload an MRI image. Upon submission, an HTTP POST request is sent to the Flask backend [12], where the image is processed and forwarded to a machine-learning model, developed with TensorFlow for prediction. The Flask backend manages routing, HTTP request handling, and communication with the machine learning model. Once the prediction is generated, the backend prepares the results data to be sent back to the client. The user is then directed to a results webpage, where JavaScript code utilizes Chart [13] to display the prediction probabilities in the form of a bar graph.

VII. MemorEyes: A Wearable Medical Assisting Kit for Alzheimer's Patients

Wearable devices have revolutionized various aspects of our lives, and their potential extends far beyond mere convenience or fitness tracking. One area where wearable technology shows great promise is in assisting Alzheimer's patients [14]. MemorEyes is a smart wearable device designed to support early and mild-stage Alzheimer's patients and their caregivers. It consists of smart spectacles and a wristband, offering features such as displaying pictures of loved ones, medication reminders, GPS tracking, and safe zone monitoring. This paper presents the device's architecture, functionality, and advantages while exploring potential future enhancements. It also discusses the integration of Convolutional Neural Network (CNN) data analysis to personalize care and enable remote monitoring. MemorEyes aims to improve patient well-being and caregiver support through innovative technology. Smart spectacles is the core of MemorEyes, equipped with an Arduino Nano microcontroller and a 3.5-inch TFT LCD display. The patient's cherished memories are stored on a 4GB Micro SD card, and with the aid of a 1.5x magnifying lens, the images are vividly displayed. Moreover, a small mirror, positioned at a 60-degree inclination, reflects the displayed image onto the spectacle lens for optimal visualization. The wristband is driven by an ESP32 microcontroller, acts as an advanced GPS tracker. The smart spectacles and the wrist band is shown in Fig. 6 (a) and (b) respectively. The wristband's GPS tracking and safe zone monitoring capabilities provide a comprehensive safety

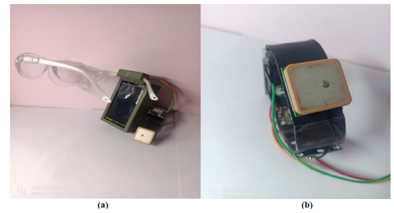

Fig. 6. Prototype of designed (a) Smart spectacles (b) Wristband

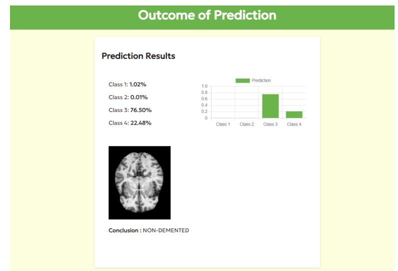

Fig. 7. Output shown for the MRI image uploaded.

net for Alzheimer's patients [16]. By notifying caregivers of any deviation from the designated safe zones, MemorEyes significantly reduces the risk of wandering incidents and enhances patient security. It benefits patients and caregivers by reducing caregiver stress, improving cognitive function, and enhancing patient independence. Future enhancements may include navigation features, mental exercises, health monitoring sensors, and battery life improvements [17].

A. Integration with CNN Data Analysis

By integrating CNN data analysis, MemorEyes becomes a powerful tool for early Alzheimer's detection. The personalized care plans generated through data analysis can be adjusted based on the patient's unique requirements, ensuring optimal support and intervention. Continuous monitoring and remote patient assistance enhance caregivers' ability to provide timely and effective care, contributing to improved patient outcomes and well-being. MemorEyes represents a transformative advancement in Alzheimer's care, harnessing technology to empower patients and caregivers alike. By integrating AR, VR, and CNN data analysis, the device redefines patient-centered care, promoting independence, safety, and emotional well-being. The implementation of stringent data security measures ensures that MemorEYEs serves as a reliable and trusted medical assisting kit in clinical settings.

VIII. Result and Discussion

The website has successfully provided a user-friendly platform for individuals and healthcare professionals to upload MRI images and obtain predictions for Alzheimer's disease probability. The integration of machine learning algorithms, image processing techniques, and user interface design has resulted in a powerful tool for early detection and monitoring. The development of the website for Alzheimer's disease detection using MRI images has been a significant milestone

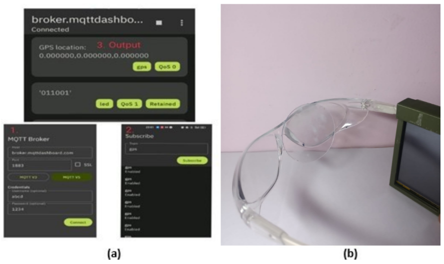

Fig. 8. MemorEyes: (a) GPS data received by the by the wrist band (b) Image displayed by smart spectacles

in the advancement of medical technology. The integration of machine learning, image processing, and user-friendly interfaces has created a powerful tool for early detection and intervention. The website's achievements, effectiveness, and collaboration with healthcare professionals have contributed to its success in aiding the fight against Alzheimer's disease. Figure 7 shows the prediction results obtained from the proposed Neuropredict system. One of the key strengths of NeuroPredict lies in its utilization of Convolutional Neural Networks (CNN), which enables the model to learn effectively even when MRI image datasets are scarce due to privacy concerns and limited data sharing. This ability to make accurate predictions with an accuracy of 80% with fewer data samples makes NeuroPredict highly practical and efficient in real-world scenarios, where privacy is a significant concern and large datasets may not be readily available. Moreover, NeuroPredict provides a comprehensive one-stop platform that covers various aspects of Alzheimer's disease, setting it apart from traditional methods that often focus on singular aspects. Through the integration of Exploratory Data Analysis (EDA), The proposed NeuroPredict system gains valuable insights into demographic and clinical factors associated with Alzheimer's. This deeper understanding of the disease's underlying patterns, progression, risk factors, and preventive measures empowers the development of proactive strategies and personalized support for vulnerable populations and individuals already diagnosed with Alzheimer's. The hardware kit, informed by EDA insights, further reinforces NeuroPredict impact on Alzheimer's detection and personalized care. Hardware model of the proposed low cost wearable device MemorEyes is implemented and tested. Figure 8(a) shows the location data recieved by the caretaker from the wrist band and Fig. 8 (b) is the image displayed using the smart spectacles of MemorEyes.

IX. Conclusions

The proposed "NeuroPredict" is a remarkable advancement in the field of neurodegenerative disease research and healthcare. Its utilization of CNN technology for effective learning from limited data, combined with its one-stop solution covering early prediction, personalized care, and data-driven insights, sets it apart from existing methods. By offering targeted interventions and contributing to research, NeuroPredict stands as a pioneering project that has the potential to improve patient outcomes, revolutionize Alzheimer's diagnosis and management, and shape the future of healthcare in the fight against neurodegenerative diseases.

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