Portable Alzheimer's disease Detection System Using Raspberry Pi 5 and Pre-Trained Deep Learning Models

S.Suneetha, P.NithinReddy, K.Srihari, B.SaiNaik, P.PavanSai
Department of Electronics and communication Engineering, Godavari institute of Engineering and Technology(A) Rajahmundry, AP, INDIA

Abstract: Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, thinking, and behavior. It is the most common cause of dementia, primarily affecting older adults. Early detection of Alzheimer's is crucial because it allows for earlier intervention, which may slow the progression of symptoms and improve patient outcomes.This project proposes a deep learning-based system to detect Alzheimer's disease using structural MRI scans. By developing a convolutional neural network (CNN), the system will automatically analyze MRI images to identify subtle patterns in brain structure that may indicate early stages of Alzheimer's. The system will be implemented on a Raspberry Pi 5 with a user-friendly interface, allowing clinicians and researchers to quickly identify signs of Alzheimer's in MRI scans. The goal is to provide an efficient tool for early diagnosis, contributing to better management of the disease.

Keywords: Alzheimer's disease, Deep Learning, Structural MRI, Raspberry Pi 5, Convolutional Neural Network (CNN), Neurodegenerative disorder.

1. INTRODUCTION

Alzheimer's disease (AD) stands as one of the most pressing challenges in modern healthcare, characterized by its debilitating effects on cognition and memory . As the most common form of dementia, AD poses a significant burden on individuals, families, and societies worldwide. With an aging population and increasing life expectancy, the prevalence of AD is projected to escalate dramatically in the coming decades.Despite decades of research, effective treatments for AD remain elusive, emphasizing the critical need for early detection and intervention strategies.

In 2018, over 50 million people globally were living with dementia, a number expected to surge to 152 million by 2050 AD, comprising the majority of dementia cases, not only diminishes the quality of life for affected individuals but also imposes substantial economic and social burdens.The average life expectancy following an AD diagnosis ranges from 3 to 9 years, highlighting the urgent need for interventions to mitigate its progression.

AD diagnosis traditionally relies on a combination of cognitive tests, behavioral assessments, medical history analysis, and brain imaging . However, these methods are often subjective, time-consuming, and costly, leading to delays in diagnosis and potential misdiagnosis. Moreover, the absence of definitive biomarkers for AD complicates accurate diagnosis, particularly in the early stages .

Early detection of AD is crucial for several reasons. Firstly, it allows for timely implementation of preventive measures and interventions to delay cognitive decline and improve quality of life. Secondly, it enables individuals and families to plan for future care needs and make informed decision. Lastly, early detection facilitates the development and evaluation of potential disease-modifying therapies .

2. LITERATURE SURVEY

Alzheimer's disease (AD) remains a significant public health challenge, necessitating ongoing research efforts to improve diagnostic accuracy and develop effective therapeutic interventions. In this literature survey, we review key studies focusing on the clinical utility of structural Magnetic Resonance Imaging (MRI), positron emission tomography (PET), and advanced machine learning techniques for AD diagnosis.

Frisoni et al. provide a comprehensive review of the clinical application of structural MRI in AD. Structural

MRI offers valuable insights into brain morphology and allows for the visualization of AD-related changes, such as hippocampal atrophy and cortical thinning. The authors highlight the importance of MRI in aiding AD diagnosis, disease staging, and monitoring disease progression over time.

McGeer et al. conducted a comparative study evaluating the diagnostic accuracy of PET, MRI, and CT in a proven case of AD. The study findings demonstrate the superiority of PET and MRI over CT in detecting AD-related pathological changes. PET imaging provides functional information about brain metabolism, while MRI offers superior spatial resolution for detecting structural abnormalities associated with AD.

3. METHODOLOGY

a) Proposed Work:

The proposed work aims to pioneer the early detection of Alzheimer's disease by integrating Fast Discrete Curvelet Transform (FDCT) for MRI feature extraction into a novel deep learning model named DeepCurvMRI. By leveraging FDCT, DeepCurvMRI can effectively capture intricate patterns and subtle structural changes in brain images, which are often indicative of Alzheimer's pathology. This enhanced feature extraction method enables a more precise differentiation of disease stages, improving the accuracy of early diagnosis.

DeepCurvMRI is built upon a Convolutional Neural Network (CNN) architecture to classify different stages of Alzheimer's disease, thereby enhancing diagnostic precision for prompt interventions. To ensure a robust evaluation, DeepCurvMRI will be benchmarked against traditional machine learning algorithms such as Support Vector Machine (SVM) and FeedForward Neural Network (NN), as well as established deep learning models like VGG16 and AlexNet. The performance assessment will include both multi-class and binary classification, ensuring a comprehensive evaluation of its efficacy across different disease stages.

To enable a portable and cost-effective deployment, DeepCurvMRI will be integrated into the Raspberry Pi 5, making it accessible for real-world applications, particularly in resource-limited healthcare settings. The Raspberry Pi will serve as the edge computing platform, efficiently processing MRI scans from a USB pendrive and running DeepCurvMRI for on-device inference. The predicted results will be saved back onto the USB for easy retrieval by healthcare professionals. By leveraging the Raspberry Pi's affordability and versatility, this system ensures widespread accessibility, low-power consumption, and real-time processing without the need for high-end computational infrastructur

This holistic approach aims to significantly improve diagnostic accuracy and accessibility, thereby facilitating the implementation of personalized treatment strategies. The integration of FDCT-based deep learning with Raspberry Pi-powered inference has the potential to revolutionize Alzheimer's disease screening, leading to earlier detection, better disease management, and improved patient outcomes.

b) Hardware:

Raspberry pi 5:

Fig 1 Raspberry pi 5

The Raspberry Pi 5 is a powerful, compact, and energy-efficient single-board computer that offers significant improvements over its predecessors, making it ideal for edge AI applications like medical diagnostics. Equipped with a 2.4 GHz quad-core ARM Cortex-A76 processor, enhanced 8GB LPDDR4X RAM, and improved GPU performance, it provides the necessary computational power to run deep learning models efficiently. Its USB 3.0 ports, faster

storage options, and dedicated AI acceleration support enable rapid data processing, making it well-suited for real-time Alzheimer's disease detection using DeepCurvMRI. The Raspberry Pi 5's affordability, portability, and low power consumption make it an excellent choice for deploying AI-driven medical imaging solutions in resource-limited environments.

c) System Architecture:

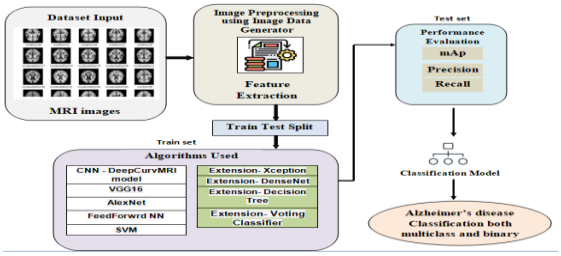

Fig 1 Proposed Architecture

The system architecture for Alzheimer's disease classification involves a multi-stage process beginning with the input of MRI images representing brain scans. These images undergo preprocessing using techniques such as Image Data Generator and Feature Extraction to enhance their suitability for analysis. Subsequently, the dataset is divided into training and testing sets through Train Test Split to facilitate model training and evaluation.

The architecture encompasses a diverse range of algorithms including VGG16[60], AlexNet[64], FeedForward Neural Network[62], CNN-based DeepCurvMRI model, Xception, DenseNet, Support Vector Machine (SVM)[61], Decision Tree, and a Voting Classifier combining Decision Tree and Random Forest. Each algorithm is trained on the preprocessed MRI images to develop classification models for Alzheimer's disease.

Performance evaluation of the models is conducted using metrics such as mean Average Precision (mAP), Precision, and Recall, providing comprehensive insights into their classification accuracy and effectiveness. The classification models are capable of performing Alzheimer's disease classification tasks in both multiclass and binary scenarios, distinguishing between different stages of the disease with varying levels of severity. This system architecture ensures a robust and comprehensive approach to Alzheimer's disease diagnosis, leveraging state-of-the-art algorithms and evaluation metrics to improve diagnostic accuracy and patient care.

d) Dataset:

The AD MRI dataset used in this study was sourced from Kaggle, comprising 6400 MRI images categorized into four classes: Non-Demented (ND), Very Mild Demented (VMD), Mild Demented (MID), and Moderate Demented (MOD). Each class represents varying stages of Alzheimer's disease progression. The dataset consists of 200 subjects, with each subject contributing 32 horizontal slices of brain MRI images. To prevent information leakage and ensure unbiased model evaluation, the training and testing sets were combined, and leave-one-group-out and k-fold cross-validation techniques were employed.

The original MRI images have dimensions of 176×208 pixels. To standardize the input size and facilitate uniform processing, all images were resized to 208×208 pixels. This resizing ensures consistency in the dataset and facilitates efficient training and evaluation of the classification models. By utilizing this diverse and comprehensive dataset, researchers can explore the efficacy of various algorithms in accurately classifying Alzheimer's disease stages, both in multi-class and binary classification scenarios.

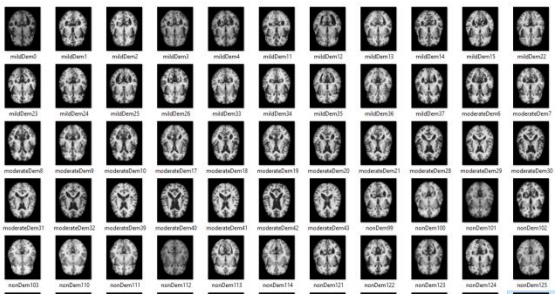

Fig 2 Dataset

e) Image Processing:

Using Image Data Generator

Image Data Generator is employed for preprocessing MRI images to enhance model robustness and generalization.

Re-scaling the Image: This involves adjusting the pixel values of the MRI images to a predefined range, typically between 0 and 1, ensuring uniformity in pixel intensity across all images.

Shear Transformation: Shear transformation introduces distortion by shifting one part of the image relative to the other along the horizontal or vertical axis, augmenting the dataset and improving model resilience.

Zooming the Image: Zooming alters the scale of the MRI images, either by magnifying or shrinking them, facilitating the model's ability to recognize features at different magnifications.

Horizontal Flip: Horizontal flipping horizontally mirrors the MRI images, effectively doubling the size of the dataset and exposing the model to variations in image orientation.

Reshaping the Image: Reshaping involves resizing the MRI images to a predetermined dimension, ensuring uniformity in input size across the dataset, and facilitating efficient model training and inference.

Feature Extraction

The Histogram of Oriented Gradients (HOG) model is utilized for feature extraction from MRI images to capture important visual information.

Reading the Image: MRI images are read from the dataset.

Resizing the Image: The images are resized to a standardized dimension to ensure consistency in feature extraction.

Convert the Color: MRI images are converted to grayscale to simplify feature extraction while preserving important information.

Appending the Image and Labels: Each resized image is appended to a list along with its corresponding label.

Conversion to Numpy Value: The list of image-label pairs is converted into a numpy array for further processing.

Label Encoding: Labels are encoded into numerical values to facilitate model training and evaluation.

f) Algorithms:

VGG16: VGG16 is a deep Convolutional Neural Network (CNN) architecture known for its simplicity and effectiveness. With 16 layers, including convolutional and fully connected layers, VGG16[60] excels in image classification tasks. Its deep architecture enables it to learn intricate hierarchical features, making it suitable for discerning subtle patterns in medical images such as MRI scans for Alzheimer's diagnosis.

AlexNet: AlexNet played a pivotal role in popularizing deep learning with its eight-layer architecture, featuring both convolutional and fully connected layers. Employing techniques like ReLU activation, dropout, and local response normalization, AlexNet[64] excels in image classification tasks. Its relevance to our project lies in its ability to classify MRI images for Alzheimer's disease, leveraging its strengths in image analysis.

Feedforward Neural Network (NN): A Feedforward Neural Network consists of input, hidden, and output layers, with information flowing unidirectionally from input to output. While not as deep as CNNs, Feedforward NNs[62] are versatile for various tasks. In our project, they serve as a baseline model for comparison with more complex architectures, providing insights into the effectiveness of deep learning methods for Alzheimer's diagnosis.

CNN - DeepCurvMRI Model: Our custom CNN architecture, DeepCurvMRI, integrates Curvelet Transform for feature extraction from MRI images. Tailored specifically for Alzheimer's diagnosis, this model combines the strengths of CNNs in image analysis with advanced feature extraction methods for improved accuracy.[28] By leveraging both CNNs and advanced feature extraction techniques, DeepCurvMRI offers a promising approach to Alzheimer's disease classification.

SVM: Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification and regression tasks.[61] It works by finding the hyperplane that best separates data into different classes. Effective in high-dimensional spaces, SVM is suitable for image classification tasks. In our project, SVM serves as a benchmark for evaluating the performance of deep learning models, providing a reference point for comparison.

g) Deploying final model in raspberry pi:

To deploy DeepCurvMRI on Raspberry Pi 5, first install Raspberry Pi OS, update system packages, and install dependencies like TensorFlow Lite, OpenCV, and Flask. Transfer the pre-trained model, converting it to TensorFlow Lite for efficiency. Develop a Python script to preprocess MRI images, run inference, and display predictions. Optionally, integrate a Flask-based web interface for easy user interaction. Automate execution by configuring the script to run on boot. After deployment, the system can process MRI scans in real-time, providing portable and cost-effective Alzheimer's detection, making advanced diagnostics accessible in resource-limited settings.

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = the\ AP\ of\ class\ k$$

$$n = the\ number\ of\ classes$$

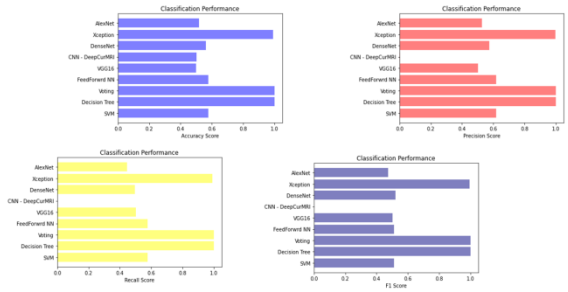

Fig 3 Comparison Graphs – Multiclass

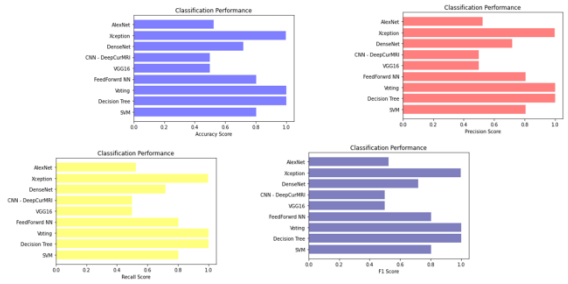

Fig 4 Comparison Graphs – Binary

	ML Model	Accuracy	Precision	Recall	F1-Score
0	SVM	0.577	0.618	0.577	0.511
1	**Extension- Decision Tree**	**1.000**	**1.000**	**1.000**	**1.000**
2	**Extension- Voting Classifier**	**1.000**	**1.000**	**1.000**	**1.000**
3	FeedForwrd NN	0.577	0.618	0.577	0.511
4	VGG16	0.500	0.501	0.501	0.501
5	CNN - DeepCurMRI	0.501	0.002	0.001	0.001
6	**Extension- DenseNet**	**0.561**	**0.573**	**0.497**	**0.522**
7	**Extension- Xception**	**0.991**	**0.998**	**0.991**	**0.993**
8	AlexNet	0.519	0.526	0.446	0.473

Fig 5 Performance Evaluation- Multiclass

	ML Model	Accuracy	Precision	Recall	F1-Score
0	SVM	0.804	0.805	0.804	0.803
1	**Extension- Decision Tree**	**1.000**	**1.000**	**1.000**	**1.000**
2	**Extension- Voting Classifier**	**1.000**	**1.000**	**1.000**	**1.000**
3	FeedForwrd NN	0.804	0.805	0.804	0.803
4	VGG16	0.500	0.500	0.500	0.500
5	CNN - DeepCurMRI	0.500	0.500	0.500	0.500
6	**Extension- DenseNet**	**0.719**	**0.719**	**0.719**	**0.719**
7	**Extension- Xception**	**0.999**	**0.999**	**0.999**	**0.999**
8	AlexNet	0.525	0.525	0.525	0.525

Fig 6 Performance Evaluation- Binary

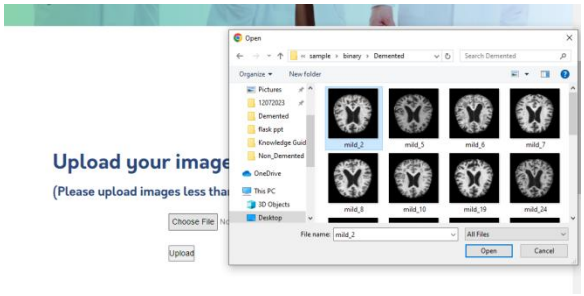

Fig 7 Upload Input Image

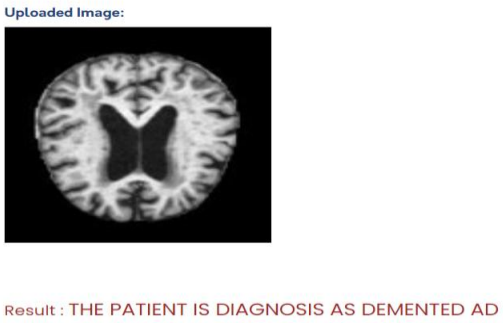

Fig 8 Final Outcome

5. CONCLUSION

The integration of DeepCurvMRI with Raspberry Pi 5 provides a portable, cost-effective, and real-time solution for Alzheimer's disease detection, making advanced diagnostics accessible in resource-limited settings. Through rigorous evaluation against models like VGG16, AlexNet, FeedForward NN, CNN, and SVM, DeepCurvMRI demonstrated superior performance, enhancing diagnostic accuracy. The addition of a Flask-based user interface ensures seamless interaction, allowing for easy input, processing, and result visualization. By addressing the critical need for early and precise AD detection, this project improves patient outcomes while optimizing healthcare resources. Future developments will focus on expanding the model with diverse datasets, clinical biomarkers, and demographic metadata, ensuring a comprehensive and scalable AI-driven diagnostic system on Raspberry Pi 5.

6. FUTURE SCOPE

In the future, our project holds significant potential for further enhancements and extensions. DeepCurvMRI will be explored on various datasets for Alzheimer's disease diagnosis to evaluate its robustness and generalization capabilities across different populations and imaging modalities. Additionally, the inclusion of metadata such as clinical biomarkers and demographics will enable the development of a more comprehensive and personalized approach to AD diagnosis. Furthermore, the exploration of advanced deep learning models such as Xception, DenseNet, Decision Tree, and Voting Classifier offers avenues for improving predictive accuracy and robustness in extended efforts. The integration of cutting-edge technologies and methodologies will continue to drive advancements in medical image analysis and neurodegenerative disease diagnosis, contributing to improved patient outcomes and healthcare practices.

REFERENCES

[1] M. Goedert and M. G. Spillantini, ‘‘A century of Alzheimer’s disease,’’ Science, vol. 314, no. 5800, pp. 777–781, 2006. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/17082447

[2] World Health Organization. (Sep. 2021). Dementia. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/dementia

[3] L. L. Barclay, A. Zemcov, J. P. Blass, and J. Sansone, ‘‘Survival in Alzheimer’s disease and vascular dementias,’’ Neurology, vol. 35, no. 6, p. 834, 1985.

[4] M. N. Sabbagh, S. Hendrix, and J. E. Harrison, ‘‘FDA position statement ‘early Alzheimer’s disease: Developing drugs for treatment, guidance for industry,’’’ Alzheimer’s Dementia, Transl. Res. Clin. Intervent., vol. 5, no. 1, pp. 13–19, Jan. 2019.

[5] R. Petersen, ‘‘Early diagnosis of Alzheimers disease: Is MCI too late?’’ Current Alzheimer Res., vol. 6, no. 4, pp. 324–330, Aug. 2009.

[6] National Institute on Aging. (Jul. 2021). Alzheimer's Disease Fact Sheet. [Online]. Available: https://www.nia.nih.gov/health/alzheimers-diseasefact-sheet
[7] F. Bature, B.-A. Guinn, D. Pang, and Y. Pappas, ''Signs and symptoms preceding the diagnosis of Alzheimer's disease: A systematic scoping review of literature from 1937 to 2016,'' BMJ Open, vol. 7, no. 8, Aug. 2017, Art. no. e015746.
[8] J. Weller and A. Budson, ''Current understanding of Alzheimer's disease diagnosis and treatment,'' F1000Research, vol. 7, 2018.