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DIAGNOSIS OF ALZHEIMER'S DISEASE THROUGH CONVOLUTIONAL NEURAL NETWORK ANALYSIS OF SELECTED HIPPOCAMPAL SLICES IN MRI IMAGES

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ABSTRACT

Novel imaging and AI approach, DeepCurvMRI, enhances AD diagnosis. Over 50 million individuals globally are impacted by AD, and that number is projected to increase. It is absolutely critical to detect the disease early and accurately. De-stigmatizing Alzheimer's disease diagnosis, DeepCurvMRI employs Curvelet Transform to extract characteristics from MRI scans. The basic study showed that DeepCurvMRI, which employs a CNN architecture specifically built for AD detection, attained an accuracy rate of 98%. This research takes a look into Xception and DenseNet deep learning models, together with Decision Trees and Voting Classifier. Preliminary research suggests a 99%+ accuracy rate. Numerous implications stem from this research. Doctors are able to intervene earlier when diagnostics are more precise, which benefits patients and their families. Improvements in AD diagnosis also help society with optimal resource allocation and reduced healthcare costs.

INTRODUCTION

The cognitive and memory impairments caused by Alzheimer's disease (AD) make it one of the most significant obstacles in healthcare today [1]. Alzheimer's disease (AD) is a global health crisis that affects people of all ages and all parts of society [2]. Due to an ageing population and increased life expectancy, the prevalence of AD is projected to increase significantly in the next decades [2]. Since no treatments for Alzheimer's disease have been identified despite decades of research, early diagnosis and treatment are crucial.
Dementia affected more than 50 million individuals globally in 2018, and it is projected to reach 152 million by 2050 [2]. Dementia caused by AD, the most common form of the disease, lowers quality of life while also causing monetary and societal expenses [3]. AD patients have a 3- to 9-year life expectancy [4], underscoring the necessity for therapies to slow its progression. Brain imaging, medical history analysis, behavioural evaluations, and cognitive testing are common components of Alzheimer's disease diagnoses [5]. These processes can be costly, time-consuming, and subjective, which can lead to diagnostic delays or even misdiagnosis [6]. The absence of biomarkers, particularly in the early stages of AD, makes diagnosis more difficult [7]. There are numerous reasons why it is crucial to detect AD early. This paves the way for the prompt implementation of treatments and measures to halt cognitive loss and enhance quality of life [8]. Secondly, it aids families in making informed decisions and planning for future care [9]. Finally, early detection aids in the development and testing of medications that change diseases [10].
There has been hope that new imaging techniques, like as MRI, PET, and CT, would make AD diagnosis easier [11]. By illuminating brain structure and function, these non-invasive techniques aid in the detection of changes associated with AD [12]. Thanks to advancements in AI and ML, medical imaging analysis can now detect illnesses automatically and with high accuracy [13].
For the purpose of disease classification, deep learning (DL) models, particularly convolutional neural networks (CNNs), can extract discriminative characteristics from medical images [14]. Unlike traditional ML models, DL ones don't need feature extraction to process raw image data [15]. The improved efficiency and accuracy of DL's diagnostics has made it a promising tool for the diagnosis of AD [16].
Early Alzheimer's disease detection using DL models, namely CNNs, is evaluated using MRI imaging. Our goal is to develop an accurate method for diagnosing AD from imaging data using the hierarchical representation learning capabilities of convolutional neural networks (CNNs). When it comes to AD classification tasks, standard ML techniques like SVM will be pitted against CNN-based models. In order to facilitate early intervention and individualized patient therapy, this study seeks to improve the accuracy and efficiency of AD diagnostics.

2. LITERATURE SURVEY

2.1 Survival in Alzheimer's disease and vascular dementias:

https://n.neurology.org/content/35/6/834

ABSTRACT: After 199 individuals with Alzheimer's disease, 69 with multiple infarctions, and 43 with mixed dementia were followed for 5 years. Similar cognitive and behavioural impairments necessitating either home care or institutionalisation were observed at follow-up in all three diagnostic groups. In contrast to DAT's 3.4-year survival rate, MID and MIX achieved 50% at 2.6 and 2.5 years, respectively, after diagnosis. Longer than anticipated 50% survivals from onset were seen with DAT (8.1 years), MID (6.7 years), and MIX (6.2 years). While both types of dementia cause cognitive and behavioural decline, vascular dementias are more deadly than DAT.

2.2 FDA position statement 'early Alzheimer's disease: Developing drugs for treatment, guidance for industry: https://www.fda.gov/regulatory-information/search-fda-guidance-documents/alzheimers-disease-developing-drugs-treatment-guidance-industy

ABSTRACT: Drug developers can use these recommendations to target the pre-dementia stages of sporadic Alzheimer's disease (AD). The purpose of this guidance is to initiate conversations among pharmaceutical sponsors, members of the scientific community, the general public, and representatives from the appropriate divisions within the Centres for Drug Evaluation and Research and the Centres for Biologics Evaluation and Research, as applicable, regarding the Division of Neurology Products and other related topics. The design of clinical trials for Alzheimer's disease patients with overt dementia or autosomal dominant AD is not specifically addressed in this guidance, although some of its ideas might be applicable.

2.3 Early diagnosis of Alzheimers disease: Is MCI too late?: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3098139/

ABSTRACT: Researchers in the fields of ageing and dementia are making great strides towards the goal of early clinical symptom diagnosis. Identifying at-risk patients who are asymptomatic is a goal of clinicians. Modern medicine currently classifies mild cognitive impairment (MCI) as a clinical stage halfway between normal ageing and the earliest signs of Alzheimer's disease. Epidemiologic research are defining the frequency of MCI in the general population, and the disease has been studied intensively in recent years. These studies identify risk factors for an accelerated transition from mild cognitive impairment to Alzheimer's disease and provide methods to tailor clinical trials of treatments. Alzheimer's disease and ageing are the two main neuropathologies that comprise MCI. The scope and analysis of MCI research will be broadened.

3. METHODOLOGY

a) Proposed Work:

Hippocampus magnetic resonance imaging (MRI) slices provide the basis of the novel Alzheimer's disease (AD) classification system. The LeNet model shows promise for AD categorisation in the project because of its improved accuracy across views. Due to the use of the publicly available Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset for both training and validation, the results and implications are rock solid.

b) System Architecture:

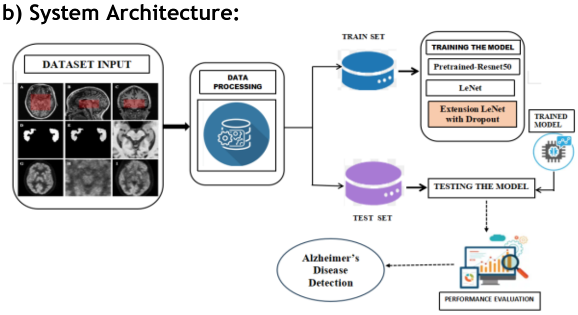

Fig 1 Proposed Architecture

Neuroimaging scans of the brain are the first step in the multi-stage process of Alzheimer's disease categorization. Before these images are ready for study, they are processed using Image Data Generator and Feature Extraction. In order to train and evaluate models, Train Test Split partitions the dataset into two parts: one for testing and one for training. Included in the design are the following: VGG16[60], AlexNet[64], FeedForward Neural Network[62], Xception, DenseNet, SVM[61], Decision Tree, and a Decision Tree-Random Forest Voting Classifier based on CNN-based DeepCurvMRI. Every algorithm uses preprocessed MRI data to train a model for Alzheimer's disease categorisation. Indicators of model performance that show how well categorisation is done include Precision, Recall, and mean Average Precision (mAP). The models are able to distinguish between stages of Alzheimer's disease with varying degrees of severity and classify the disease in both multiclass and binary contexts. Modern algorithms and measurements are incorporated into this system architecture to enhance patient care and diagnose Alzheimer's disease.

c) Dataset:

The 6400 adolescent magnetic resonance imaging (MRI) scans used in this research were sorted into four categories: non-demented (ND), mildly demented (MID), moderately demented (MD), and very mildly demented (VMD). Each class stands for a distinct stage of Alzheimer's disease. A total of 200 patients' 32 MRI horizontal slices were included in the analysis. To keep information from escaping and make sure the models were evaluated fairly, we employed k-fold cross-validation and leave-one-group-out on both the training and testing sets. The initial MRI images had a resolution of 176 x 208 pixels. To ensure consistency and uniformity, all images were downsized to 208x208 pixels. Training and evaluating classification models is made easier with this scaling, which also guarantees consistency in the dataset. This comprehensive dataset allows researchers to evaluate algorithms' performance in classifying Alzheimer's disease stages using both multi-class and binary criteria.

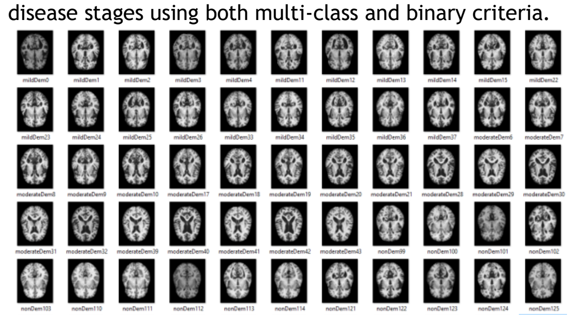

Fig 2 Dataset

d) Image Processing:

Using Image Data Generator

Image Data Generator is used to preprocess MRI data in order to make the model more generalizable and resilient.

Re-scaling the Image: The pixel values are often set to a predetermined range, typically between 0 and 1, in order to ensure that all MRI images have the same pixel intensity.

Shear Transformation: Improving the robustness of datasets and models, shear transformation warps images by translating them horizontally or vertically.

Zooming the Image: The model is able to identify features at various magnifications with the use of zoomed MRI images.

Horizontal Flip: The dataset is doubled and the model is exposed to picture orientation changes when MRI pictures are horizontally flipped, which mimics them.

Reshaping the Image: Model training and inference are both made easier by reshaping MRI images to guarantee input size uniformity.

Feature Extraction

To extract important visual information from MRI images, the Histogram of Orientated Gradients (HOG) model is used.

Reading the Image: The dataset contains MRI pictures.

Resizing the Image: Standardising image size ensures feature extraction consistency.

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.

e) Algorithms:

VGG16: One straightforward and powerful deep convolutional neural network (CNN) architecture is VGG16. The sixteen convolutional and fully linked layers that make up VGG16[60] make it an excellent picture classifier. Because of its deep design, which learns complex hierarchical structures, it is able to detect subtle patterns in medical imaging, such as MRI images of Alzheimer's disease.

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): The three layers of a feedforward neural network—input, hidden, and output—are designed to receive and send data in only one way. Although feedforward NNs aren't as deep as CNNs, they are very adaptable. In order to evaluate deep learning techniques for Alzheimer's diagnosis, our project uses them as a baseline model to compare with more complex structures.

CNN - DeepCurvMRI Model: Using Curvelet Transform, our CNN architecture, DeepCurvMRI, retrieves MRI features. To boost accuracy, our CNN-based system for Alzheimer's diagnosis employs CNN image analysis and enhanced feature extraction.[28] in Using convolutional neural networks (CNNs) and enhanced feature extraction methods, DeepCurvMRI offers a potential approach to classifying Alzheimer's illness.

SVM: Classification and regression are handled by the robust supervised learning method SVM.[61] in It determines the best hyperplane for data classification. When it comes to high-dimensional picture categorisation, SVM shines. In our study, we compare the performance of deep learning models using SVM.

4. EXPERIMENTAL RESULTS

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

Precision = TP/(TP + FP)

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

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

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

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

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

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

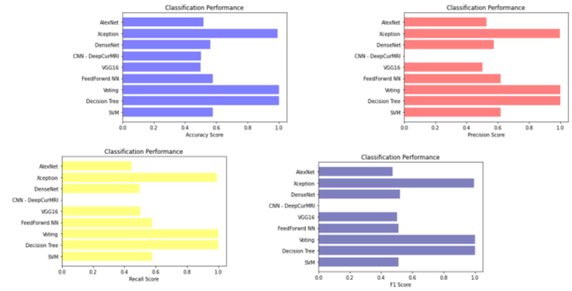

Fig 3 Comparison Graphs – Multiclass

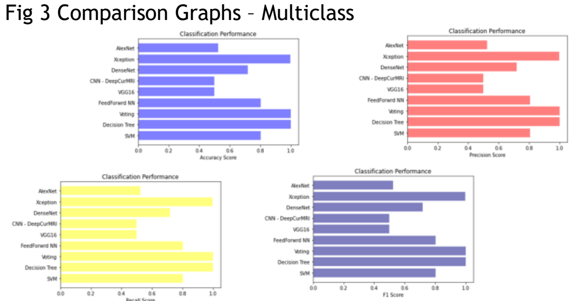

Fig 4 Comparison Graphs – Binary

	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

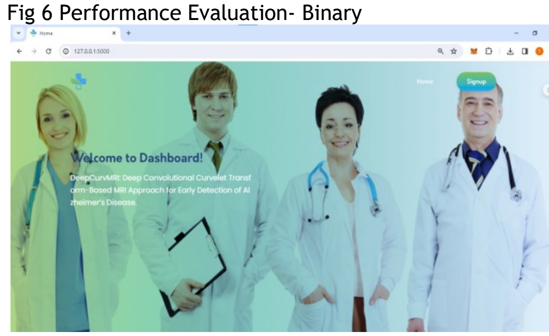

Fig 7 Home Page

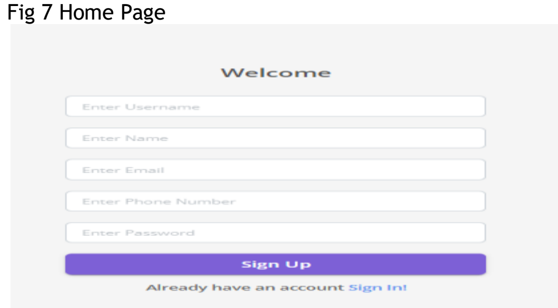

Fig 8 Registration Page

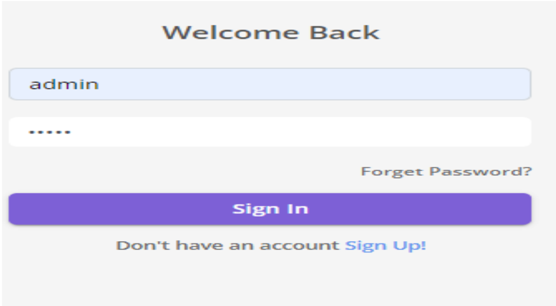

Fig 9 Login Page

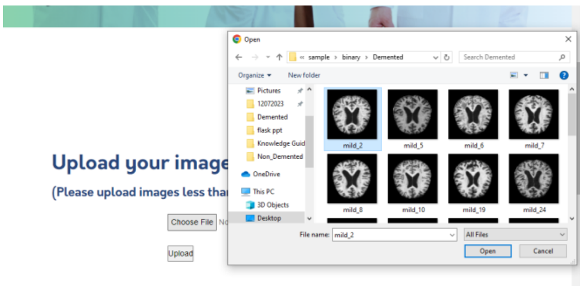

Fig 10 Upload Input Image

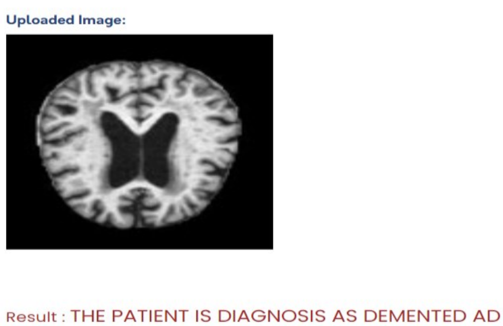

Fig 11 Final Outcome

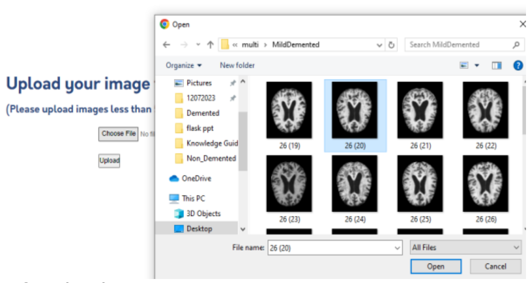

Fig 12 Upload Input Image

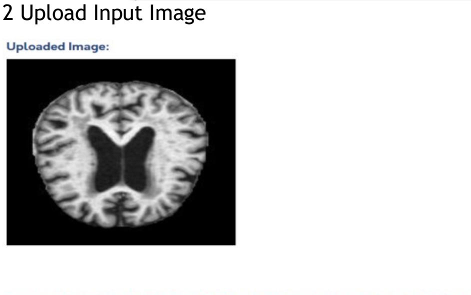

Fig 13 Final Outcome

Similarly we can try other cases in same process.

CONCLUSION

A comprehensive model selection technique is demonstrated by the use of VGG16[60], AlexNet[64], FeedForward NN[62], CNN[28] (DeepCurvMRI model), and SVM[61] for the diagnosis of Alzheimer's disease (AD) using MRI images. After conducting thorough testing, we discovered that DeepCurvMRI performed better than competing methods. Flask-based front-end development with user authentication provides an intuitive interface for input, processing, and visualising results, which increases usability and practicality. By identifying AD at an early and accurate stage, our project enhances both the quality of life for patients and the allocation of healthcare resources. In order to make a more complete diagnosis of Alzheimer's disease, DeepCurvMRI will be trained and tested on several datasets with metadata like as demographics and clinical biomarkers.

6. FUTURE SCOPE

There is room for growth and enhancement in our project moving forward. To gauge DeepCurvMRI's robustness and generalisability across demographics and imaging modalities, it will be evaluated on several Alzheimer's disease datasets. A more thorough and tailored AD diagnosis will be made possible by metadata such as demographics and clinical biomarkers. Xception, DenseNet, Decision Tree, and Voting Classifier are some advanced deep learning models that can enhance the accuracy and robustness of predictions in extended tries. The integration of state-of-the-art methods and technologies into medical image analysis and the diagnosis of neurodegenerative diseases will lead to better patient outcomes and healthcare practices.

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- **Dataset Link:**
- *MultiClass AD:*
- https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images
- *Convert MultiAD to BinaryAD :*
- https://www.kaggle.com/datasets/sachinkumar413/alzheimer-mri-dataset