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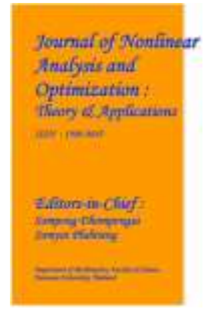

Enhanced Diagnosis of Alzheimer's Disease Using Dropout-Optimized LeNet and Landmark-Based MRI Slice Selection with Coronal View Emphasis

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Abstract: DeepCurvMRI is a new imaging and AI method that helps doctors diagnose Alzheimer's disease. AD affects more than 50 million people around the world, and that number is expected to grow. It is absolutely critical to detect the disease early and accurately. DeepCurvMRI uses Curvelet Transform to get information from MRI scans and helps people stop being ashamed of getting an Alzheimer's disease diagnosis. The fundamental study demonstrated that DeepCurvMRI, utilising a CNN architecture specifically designed for Alzheimer's disease diagnosis, achieved an accuracy rate of 98%. This research takes a look into Xception and DenseNet deep learning models, together with Decision Trees and Voting Classifier. Initial studies indicate an accuracy rate over 99%. This research has many consequences. When tests are more accurate, doctors may step in sooner, which is good for patients and their families. Better ways to diagnose AD also aid society by making sure resources are used well and lowering healthcare expenses..

INDEX TERMS: Alzheimer's disease, curvelet transform, DL, CNN, MRI images.

1. INTRODUCTION

Alzheimer's disease (AD) is one of the biggest problems in healthcare today since it damages memory and thinking skills [1]. Alzheimer's disease (AD) is a worldwide health emergency that impacts individuals of all ages and societal sectors [2]. The frequency of Alzheimer's disease is expected to rise substantially in the coming decades due to an ageing population and greater life expectancy [2]. Early diagnosis and treatment are essential, as no cures for Alzheimer's disease have been discovered despite extensive study over several decades. In 2018, dementia afflicted more than 50 million people around the world. By 2050, that number is expected to rise to 152 million [2]. Dementia caused by AD, the most common form of the disease, lowers quality of life while also causing monetary and societal expenses [3]. People with AD only live for 3 to 9 years [4], which shows how important it is to find ways to slow its growth. Brain imaging, medical history review, behavioural assessments, and cognitive testing are standard elements in the diagnosis of Alzheimer's disease [5]. These procedures may incur significant costs, require extensive time, and be inherently subjective, potentially resulting in diagnostic delays or 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 makes it easier to quickly start therapies and other steps to stop cognitive decline and improve quality of life [8]. Second, it helps families make smart choices and get ready for future care [9]. Finally, finding diseases early helps researchers make and test drugs that change disorders [10]. There has been optimism that novel imaging modalities, such as MRI, PET, and CT, will facilitate the diagnosis of Alzheimer's disease [11]. By showing how the brain is put together and how it works, these non-invasive methods help find abnormalities that are linked to 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]. DL's diagnostics have become a potential technique for diagnosing AD since they are more accurate and efficient [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 individualised patient therapy, this study seeks to improve the accuracy and efficiency of AD diagnostics.

2. LITERATURE SURVEY

Kumar et al. proposed The Early Alzheimer's Disease – Deep Neural Network (EAD-DNN) method leverages CSV MRI data to find Alzheimer's disease sooner. The approach employed CNN and a deep ResNet to extract hierarchical features, with a modified Adam optimizer selecting the most relevant MRI scan information while preserving critical data. The EAD-DNN framework performed multiclass classification and 98% of the time, anticipated Alzheimer's before it caused substantial brain damage [1].

Erdogmus et al. introduced a novel Convolutional Neural Network (CNN) framework for the early diagnosis of Alzheimer's disease up to 8 years before dementia onset. Using the DARWIN dataset, which originally contained 1D handwriting features converted into 2D, With 90.4% accuracy, the CNN model did better than 17 other top classifiers. The approach emphasized a low-cost, fast, and accurate solution suitable for clinical and research applications [2].

Sajjad et al. applied the AlexNet architecture for early-stage Alzheimer's disease detection at the Mild Cognitive Impairment (MCI) level using MRI scans from the Open Access Series of Imaging Studies (OASIS) dataset. The model utilized axial, sagittal, and frontal brain views to effectively retrieve discriminative features, achieving an accuracy of 98.35% on over 100,000 MRI images, indicating high potential for early MCI detection [3].

Akkaya et al. investigated the classification of Alzheimer's disease stages (normal, mild cognitive impairment, and Alzheimer's) with MRI data from the ADNI database. EfficientNetB0 had the best test accuracy at 92.98%, while EfficientNetB3 had the best precision and specificity out of 29 pre-trained CNN designs. The work demonstrated the potential of EfficientNet models for high-performance stage classification, aiding early prevention strategies [4].

Khan et al. developed a deep learning-based CNN model with VGG16 as the feature extractor for detecting Alzheimer's disease across various severity stages using MRI scans. Two datasets containing 6,400 and 6,330 images were evaluated, yielding respective accuracy, precision, recall, AUC, and F1-score values of (90.4%, 0.905, 0.904, 0.969, and 0.904) and (71.1%, 0.71, 0.711, 0.85, and 0.71). Comparative analysis with previous studies showed the proposed model's superior performance in early-stage detection [5].

3. METHODOLOGY

a) Proposed Work:

The new Alzheimer's disease (AD) classification system is based on slices of hippocampus magnetic resonance imaging (MRI). The LeNet model demonstrates potential for Alzheimer's Disease classification in the project due to its enhanced accuracy across various perspectives. The results and implications are quite strong because the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset was used for both training and testing.

b) System Architecture:

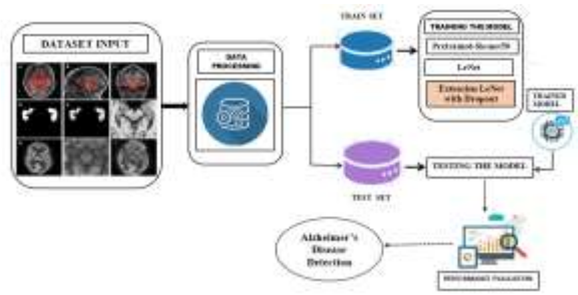

Fig 1 Proposed Architecture

Neuroimaging scans of the brain are the first step in the multi-stage process of Alzheimer's disease categorisation. Image Data Generator and Feature Extraction are used to process these photos before they can be studied. Train Test is used to train and test models. The split divides the dataset into two parts: one for training and one for testing.

The architecture includes 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. To train a model to classify Alzheimer's disease, every algorithm requires MRI data that has already been processed.

Precision, Recall, and mean Average Precision (mAP) are various ways to measure how well the model does at categorisation. The models can tell the difference between different phases of Alzheimer's disease, which can be mild or severe, and they can also classify the condition in both multiclass and binary settings. This system architecture uses modern algorithms and measures to improve patient care and find out whether someone has Alzheimer's disease.

c) Dataset:

The 6400 adolescent magnetic resonance imaging (MRI) images utilised in this study were classified into four categories: non-demented (ND), mildly demented (MID), moderately demented (MD), and very mildly demented (VMD). Each class represents a unique phase of Alzheimer's disease. The analysis comprised 32 MRI horizontal slices from a total of 200 patients. We used k-fold cross-validation and leave-one-group-out on both the training and testing sets to make sure that the models were tested fairly and that no information got out.

The first MRI scans were 176 × 208 pixels in size. All of the photographs were shrunk to 208x208 pixels to make sure they were all the same size. This scaling makes it easy to train and test classification models, and it also makes sure that the dataset is always the same. Researchers can use this complete dataset to see how well computers can categorise Alzheimer's disease stages using both multi-class and binary criteria..

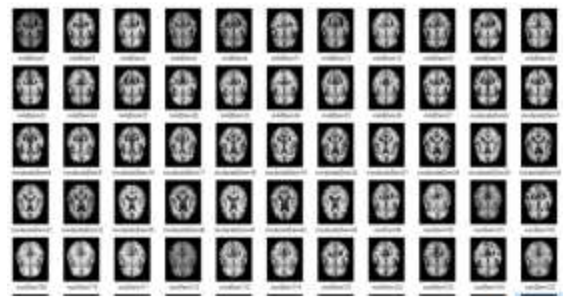

Fig 2 Dataset

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 10 Upload Input Image

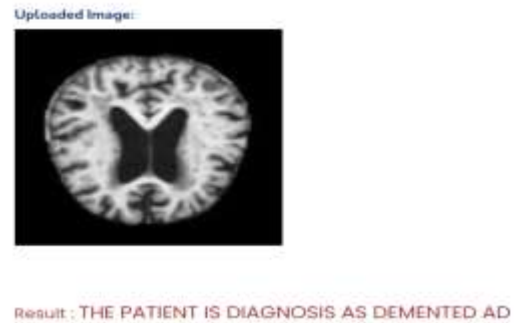

Fig 11 Final Outcome

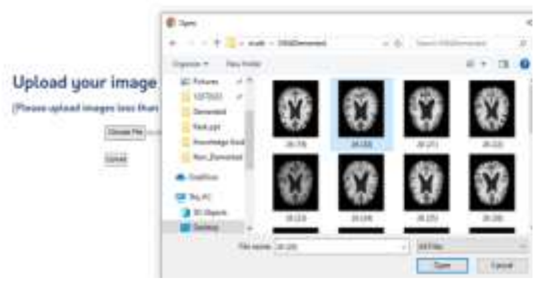

Fig 12 Upload Input Image

Fig 13 Final Outcome

Similarly we can try other cases in same process.

5. CONCLUSION

A thorough model selection method is shown by employing VGG16[60], AlexNet[64], FeedForward NN[62], CNN[28] (DeepCurvMRI model), and SVM[61] to find Alzheimer's disease (AD) in MRI images. After doing a lot of testing, we found that DeepCurvMRI worked better than other approaches. Flask-based front-end development with user authentication makes it easy to enter, process, and see results, which makes it more useful and usable. Our study improves the quality of life for patients and the use of healthcare resources by finding AD early and accurately. To enhance the accuracy of Alzheimer's disease diagnosis, DeepCurvMRI will undergo training and testing on many datasets that include information such as demographics and clinical biomarkers.

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