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ALZHEIMER'S DISEASE PREDICTION USING CONVEX FUZZY INDUCED RESNET152V2 ALGORITHM

Jegatheeswari.S[1], Rajesh Kumar.S[4], Selva Rathinam.P[2], Dheenathayalan.S[3]

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Abstract

Memory, behaviour, and thought are all impacted by Alzheimer's disease (AD). Millions of adults in their middle 60s battle the illness each year. Medication cannot totally treat Alzheimer's disease. It is still unclear who among those with moderate cognitive impairment (MCI) will eventually develop AD dementia and when. Early AD detection has never been simple, but the required computer professionals are always researching it. The examination of medical imaging is increasingly commonplace, which has increased awareness of the AD diagnosis. Early AD detection has never been simple, but the required computer professionals are always researching it. The examination of medical imaging is increasingly commonplace, which has increased awareness of the AD diagnosis. The findings demonstrate that AD can be detected using deep learning technologies. The model is trained using the publicly accessible ADNI dataset. A longitudinal collection of information, biospecimens, and images from completely phenotyped patients makes up the intricate and distinctive ADNI. It might greatly advance our knowledge of Alzheimer's disease. The detailed and distinctive data, biospecimens, and photos from completely phenotyped patients are gradually gathered by ADNI. It might greatly advance our knowledge of Alzheimer's disease. The goal of this project is to develop a model for the precise and impartial prediction of Alzheimer's disease using Convex fuzzy and ResNet152V2 techniques. The best achievable accuracy for the proposed model is 99%.

Keywords—*Alzheimer's disease Classification, ResNet152V2, Convex Fuzzy, Deep Learning, ADNI dataset, OASIS dataset, AIBL dataset*

[1]*Computer Science Engineering, National Engineering College,* Kovilpatti
2151010@nec.edu.in

[4]*Computer Science Engineering, National Engineering College,* Kovilpatti
rajeshkumar_cse@nec.edu.in

[2]*Computer Science Engineering, National Engineering College,* Kovilpatti
2151003@nec.edu.in

[3]*Computer Science Engineering, National Engineering College,* Kovilpatti
ddhayalan@nec.edu.in

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I. INTRODUCTION (*HEADING 1*)

Alzheimer's disease is a progressive brain disorder. It is characterised by brain changes that result in protein buildup. The brain contracts as a result of Alzheimer's disease, and over time, brain cells begin to degrade. The most prevalent kind of dementia, Alzheimer's disease, is characterised by a progressive loss of memory, thinking, behaviour, and social skills. One's ability to function is impacted by these changes. The primary sign of Alzheimer's disease is memory loss. Having trouble recalling previous conversations or incidents is a red flag. But as the condition gets worse, memory loss and new symptoms start to appear. A person with the illness may already be exhibiting memory loss and mental clarity issues when they are first identified. A friend or family member may become more aware of the problems as the symptoms increase. To increase forecast accuracy, research is being done continuously. The dataset that is best at predicting Alzheimer's disease contains both MRI and PET images. S denotes a real-valued vector space, an affine space, or an ordered field. This includes affine spaces such as Euclidean spaces. A subset C of S is referred to as convex if the line segment bridging each pair of x and y in the subset C of S is present. This proves that C is the site of the affine combination (1 t)x + ty for any x, y, and t in the range [0, 1]. This illustrates that convexity—the property of being convex—is invariant under affine transformations. This implies that in a real or complex topological vector space, a convex set is connected by path connections. If, excluding the endpoints, every point on the line segment between x and y is located inside the topological interior of C, then the set C is strictly convex. A closed convex subset is said to be strictly convex if and only if each of its boundary points is an extreme point. A set C is unquestionably convex if it is both balanced and convex. The convex subsets of R are the intervals and the points. Convex subsets of the Euclidean plane include solid regular polygons, solid triangles, and crossings of solid triangles. Two examples of convex subsets of a Euclidean three-dimensional space are the Platonic solids and the Archimedean solids. The polyhedra produced by Kepler and Poinsot are a non-convex set. One of the so-called residual networks, ResNet152v2, features many high-performance layers. The residual neural network (ResNet152V2) is a 152-layer convolutional neural network. ResNet can fix the disappearing gradient issue by employing skip connections to modify the output from one layer to the next. It won the 2015 ImageNet competition. It is employed to assess the suggested model's accuracy. In this pre-trained model, there are numerous convolutional layers and layers with maximum pooling. Among the arguments for the ResNet function are top, weights, input tensor, input shape, pooling, classes, and classifier activation. To alter the image, 152 convolutional layers were employed. After relocating the image there for additional processing, the output is then gathered from the concealed layer.

II. LITERATURE SURVEY

GülceTurhan et al.(2021). It was hypothesised that MRI could be used to distinguish between mild cognitive impairment (MCI) and Alzheimer's disease (AD). The Alzheimer's Disease Neuroimaging Initiative (ADNI) database made the MRI scans of the people with AD and MCI available. For the computational experiments, 507 scans from 204 MCI patients and 223 AD patients were gathered. The efficiency and resilience of (2+1)D, 3D, and 2D convolutions were assessed. Depending on the design, the CNN algorithms used two to six convolutional layers, followed by four pooling layers and three totally linked layers. The best classification performance (85% AUC score) was attained by a (2+1)D convolutional neural network model, which also had an approximately two-fold faster

convergence rate than traditional 3D CNN techniques. The architecture of the (2+1)D CNN technique, which handles pictures in the spatial and temporal dimensions separately, can provide a considerable speed improvement when utilised with huge datasets and more intricate neural network models.[1]

SreelakshmiShaji et al.(2022). Two sub-anatomical brain structures, the Corpus Callosum (CC) and Lateral Ventricles (LV), are segmented and given morphometric features. ELM, online sequential ELM, and Self-adaptive Differential Evolution ELM (SaDE-ELM) classifiers receive significant features from these regions to aid in the differentiation between HC and AD. The hidden neuron count and activation functions of ELM classifiers are modified by evaluating the classifiers' performance using recognised metrics. Results demonstrate that employing morphometric characteristics from CC and LV, ELM and its variant classifiers successfully identify AD. ELM classifiers are more accurate than 90% when the sigmoid activation function is used to activate both sections. By employing LV and CC features, SaDE-ELM, the ELM variation with the fewest hidden neurons, achieves a maximum sensitivity of 97% and 94%, respectively. The restored LV characteristics have a greater potential for discriminating in the classification of AD as compared to CC. In contrast, ELM exhibits a specificity for CC traits above 95%. The work is clinically significant for discriminating between HC and AD because the suggested method can characterise and identify the morphometric alterations brought on by AD in CC and LV.[2]

AndreaLoddo et al.(2021). By carefully analysing binary classification (determining whether a person has Alzheimer's disease or not) and multiclass type (identifying various levels of dementia), the proposed approach can outperform state-of-the-art in both tasks, achieving an accuracy of 98.51% in the binary case and 98.67% in the multiclass case averaged over the four different data sets. The addition of the suggested deep-ensemble technique would result in robust and dependable CAD systems in light of the vast cross-dataset testing. Our approach has been tested on structural and functional MRIs, and it is easily scalable to other imaging modalities. Finally, our deep-ensemble approach can be used to complete this project, which has enormous potential benefits for patient care.[3]

Alejandro Puente-Castro et al.(2020). T.he creation of a method for the quick and accurate diagnosis of illness in atypical sagittal magnetic resonance imaging (MRI) scans. We used sagittal MRI data sets from OASIS and ADNI. To get more accurate results, experiments were done using Transfer Learning (TL) methods. Experiments using Transfer Learning (TL) approaches were conducted to get more accurate findings. Sagittal MRI can initially differentiate between the stages of deterioration brought on by AD. The results of DL models and sagittal MRIs are also comparable to those of horizontal-plane MRI. These are our study's two most significant implications. This study showed that, despite their rarity, sagittal-plane MRIs could detect early-stage AD at least as well as those from other planes. It could be possible to carry out more study at this time. Not to mention that in some areas, gathering examples for a data set could be expensive. This study showed that DL models may be built in these industries instead of TL, which is an important method for finishing tasks with fewer instances.[4]

Rahul Sharma et al.(2021). Using the extracted sagittal plane slices from 3D MRI images, a DL model for all-level feature extraction and fuzzy hyperplane-based least square twin support vector machine (FLS-TWSVM) were used to classify the obtained features for early detection of AD (FDN-Adnet). The ADNI dataset, which is

freely accessible online, is used to train the model, and a classification hyperplane is created using the fuzzy triangle function. When compared to other cutting-edge networks, the proposed model achieves the highest Accuracy of 97.15%, 97.29%, and 95% for the classification of CN vs AD, CN vs MCI, and AD vs MCI, respectively.[5]

SadiqAlinsaif et al.(2021). The magnetic resonance imaging (MRI) datasets from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and The Open Access Series of Imaging Studies are used. We classify AD using a variety of shearlet-based descriptors and specific traits. Each MRI sample contains a large number of slices, hence the enormous dimensionality of the feature vectors in these datasets creates a significant classification challenge. Because the MRI data are volumetric, we suggest using the 3D shearlet transform (3D-ST). The average of all the directionalities we find, however, causes the dimensionality to drop. In contrast, we propose to exploit the ability of convolutional neural networks (CNNs) to extract feature maps from stacked MRI slices, which yield a minimal feature vector for each MRI sample. The feature vectors from 3D-ST and CNN are combined for AD categorization. The classifier is then trained using the concatenated feature vectors. Instead, a customised CNN model constructs the classification model by reviewing each descriptor. Our test results show that adding shearlet-based descriptors to in-depth features improves classification performance, especially on the ADNI dataset.[6]

JinwangFeng et al.(2020). In this study, we extract the wavelet transformation energy feature (WTEF) from the sMRI image and propose a novel method (named AD-WTEF) to separate AD and MCI patients from HC controls. The subbands are then separated into multiple energy zones of interest at the same direction and transformation level (ROIs) using a new brain mask that AD-WTEF created based on the automated anatomical labelling (AAL) atlas. Third, energy features from various EROIs are connected to build an energy feature vector that characterises the subbands at the same level of direction and transformation. The coefficients of an EROI for AD-WTEF are averaged to determine the energy characteristics. So, by further concatenating these energy feature vectors, the WTEF of the same image is produced. Then, to identify AD, the closest neighbour (NN) classifier is selected. In contrast to the other seven cutting-edge methods, our AD-WTEF can precisely identify AD patients using the subtle changes in energy distribution in MRI images. Furthermore, experimental results imply that our AD-WTEF can identify important brain ROIs linked to AD.[7]

BaiyingLei et al.(2021). Create a framework using cooperative learning and deep learning to predict AD clinical scores. We study the multi-layer independently recurrent neural network regression to check the intrinsic connectivity between various brain regions and the temporal correlation between longitudinal data. The proposed integrated deep learning network analyses and predicts the clinical score by looking at the correlation between MRI and clinical score. Doctors can quickly diagnose a patient's medical conditions using the expected clinical score values and start treatment.[8]

JunhaoWen et al.(2020). to contribute three crucial things in order to overcome these limitations. We started by carefully examining the literature. Our techniques were grouped into four groups: 3D patch-level, 2D slice-level, ROI-based, and 3D subject-level The four different forms of CNN. In addition, we discovered that more than 50% of the study's papers would have had data leakage, resulting in their reporting of skewed results. Our second contribution involves expanding our open-source method for categorising AD using CNN and T1-weighted MRI. In addition to previously created tools that automatically

transform ADNI, AIBL, and OASIS data into the BIDS standard, the system also includes a modular group of picture preparation, classification, and assessment techniques designed specifically for deep learning. Finally, we carefully compared various CNN designs using this framework. Only the training and validation sets were used for model selection after the data had been split into training, validation, and test sets. The test sets were only changed after peer review in order to prevent overfitting. Overall, the 3D strategies (3D-subject, 3D-ROI, and 3D-patch) performed similarly, however the 2D slice technique performed worse. Notably, an SVM with voxel-based features outperformed the different CNN techniques. Instead of datasets with variable inclusion criteria or demographic characteristics, the various methodologies may have more effectively generalised to populations with comparable traits.[9]

FarzanehSalami et al.(2022). A clinical decision support system (CDSS) based on DL methods may be able to recognise AD using 3D-MRI data. To establish which model would serve as the most reliable basis for our CDSS, we ran a number of tests. To do this, models such as convolutional neural network (CNN), ResNet, DenseNet, and Inception-v3 are now available. Using the most recent Open Access Series of Imaging Studies (OASIS-3) part 3 data set, we evaluated the models. After reviewing the results, we recommend a special network that performed better than the tried-and-true models. When it comes to categorising AD, the suggested model fared better than the prior described networks. By include clinical variables and 3D image inputs in our suggested ensemble design, the model's performance was enhanced. The suggested model's trained version, which features a graphical user interface, is intended to support doctors as a CDSS. We used person-disjoint portions of the data to prevent biassed reporting of the study effort's findings. Conclusions: Our results demonstrate that the suggested approach enhances the accuracy and reliability of clinical tests. This CDSS might be able to recognise AD patients with high confidence. This detailed examination of the OASIS-3 data set yields important insights for the first time.[10]

MaysamOrouskhani et al.(2022).We employ a tailored deep triplet network as a metric learning approach for the study of brain MRIs and the diagnosis of Alzheimer's disease. The suggested deep triplet network incorporates a conditional loss function to boost the model's accuracy because there isn't enough data. The complete network of this model was affected by VGG16, and OASIS (open access imaging research) studies were used to conduct the research. The study's conclusions demonstrate that the proposed model performs better in terms of accuracy than more current models.[11]

Tiantai et al.(2022). The brain slice generative adversarial network for ADD detection, or BSGAN-ADD, is a novel three-component adversarial network-based Alzheimer's disease (AD) detection method that avoids this bottleneck. BSGAN-ADD combines brain slice image enhancement using generative adversarial networks (GAN) with deep convolutional neural network (CNN)-based AD diagnosis. Under the constraints of the discriminator, the generator in BSGAN-ADD learns to use the illness category feedback from the classifier in the 2D-brain slice image reconstruction process for image enhancement in the training phase. Using the stacked CNN layers in the generator, high-level brain characteristics are extracted from category-enhanced 2D-brain slice images in the prediction phase. The classifier also gets the returned brain properties (Normal, AD, and MCI) in order to output the posterior probability of disease states. Experimental results on two real-world datasets (Alzheimer's disease neuroimaging initiative, ANDI, and Open Access Series of Imaging Studies, OASIS) show that the new feature extraction process used in BAGAN-ADD can extract

more representative high-level brain features to achieve a significant diagnosis performance gain when compared with several conventional methods.[12]

Samaneh AbolpourMofrad et al.(2021). a method for using long-term MRI images to create mixed effects models and machine learning predictions of cognitive deterioration. A sizable subject pool from the Australian Imaging, Biomarkers and Lifestyle Flagship Study of Ageing and the Alzheimer's Disease Neuroimaging Initiative (ADNI) is used to identify the conversion of cognitively normal (CN) to mild cognitive impairment (MCI) and from MCI to Alzheimer's disease (AD) (AIBL). Using linked T1-weighted images and FreeSurfer v.6.0, we separate bilateral 3D regions of interest related to neurodegeneration/dementia into subcortical segmentation and cortical parcellation. Then, we forecasted their longitudinal volume trajectories using linear mixed-effects models. An ensemble of machine learning classifiers is then trained to identify stable CN from converters to MCI and stable MCI from converters to AD utilising attributes characterising these model-based trajectories. Routine T1-weighted MRI acquisitions may be used to discover imaging-based biomarkers for diagnostic prediction, as shown by the models' average accuracy, precision, and recall scores of 69/73/60% for MCI and 75/74/77% for AD on various test sets.[13]

Ashraf Haroon Rashid et al.(2022). A special and portable architecture called "Biceph-net" that duplicates both intra-slice and inter-slice information is used to diagnose AD using 2D MRI data. Through testing, it has been established that "Biceph-net" outperforms Spatio-temporal neural networks while consuming less processing power. Biceph-net outperforms 2D convolutional neural networks (CNN) in the diagnosis of AD using 2D MRI slices. The internal neighborhood-based model interpretation feature of Biceph-net may also be utilised to better understand the classification decision made by the network. We also give theoretical assurances regarding the generalisation of the Biceps-ability net. When comparing cognitively normal (CN) vs. AD tasks, MCI vs. AD tasks, and CN vs. MCI vs. AD tasks, Biceps-net completes tests with accuracy of 100 percent, 98.16%, and 97.80%, respectively.[14]

Shakila Basheer et al.(2021). To create a unique strategy by suggesting changes to the capsule network's design that would improve prediction accuracy and increase processing speed. According to this study, the design of the capsule network should be changed in order to increase model processing efficiency and prediction accuracy. The 373 x 15 OASIS dataset makes a distinction between classifications for patients who are demented and those who are not. Exploratory data analysis is a technique used to examine all available data points in a hierarchical manner in order to assess the importance of features, correlate factors, and establish the density of data that best reflects the state of factors. This approach is distinctive since it completes a whole research. To expedite and improve the model's correctness, the variables are put through a variety of optimisation techniques and feature selection is carried out. The claims have been proven true by demonstrating the correlation accuracy at various levels and iterations with a respectable accuracy of 92.39%. Using a range of performance metrics, the model is contrasted with benchmark state-of-the-art deep learning classifiers. An ablation study is carried out to validate the model's predictions using the OASIS dataset.[15]

Esther E.Bron et al.(2021). The categorization of AD patients and controls (CN) based on MRI findings may be extended to external data sets, and this study (MCI) demonstrates that it is difficult to predict when moderate cognitive impairment would progress to Alzheimer's disease. We employed a traditional support

vector machine (SVM) and a deep convolutional neural network (CNN) technique based on structural MRI images that either underwent little preprocessing or more thorough preparation into modulated grey matter (GM) maps. This attempt at external validation will be advantageous to the use of machine learning in healthcare settings.[16]

JinwangFeng et al.(2022). In this study, a novel approach is used to construct the shearlet subband energy feature-based individual network (SSBIN) for AD detection. The SSBIN, which uses directional subbands and can record correlations between ROIs, can accurately represent the ROI. Before building a network, this method permits accurate ROI characterisation in the frequency domain. To create the SSBIN, the preprocessed fMRI image was segmented into 90 ROIs using the automated anatomical labelling atlas. The directional subband-based energy feature vectors (SVs), which are utilised to represent the ROIs, are energy features obtained from the directional subbands of the 90 ROIs. The node feature vector (NV) is formed by averaging the 90 SVs, and the low-dimensional edge feature vector (LV) is generated using kernel principal component analysis after two network characteristics have been retrieved from the SSBIN (KPCA). An SSBIN-based feature for the same picture is then created using the concatenation of NV and LV. Finally, we classify 680 participants chosen from the AD Neuroimaging Initiative (ADNI) database using a support vector machine (SVM) and radial basis function kernel. Experimental studies have shown that the NV can differentiate the ROI with ease, and that the LV's ability to recognise AD depends on the correlations between the ROIs it has acquired. Currently, the SSBIN method surpasses four other cutting-edge methods for detecting AD.[17]

Kwok Tai Chui et al.(2022). creating an AD detection model utilising a convolutional neural network (CNN) and common MRI images as inputs. Transfer learning (TL), which incorporates the domain knowledge from several datasets, is used to improve the fine-tuning of hyperparameters and, therefore, the detection accuracy. Generative adversarial networks (GAN) are used to enhance the minority classes' training data from the benchmark datasets. Performance evaluation and analysis using three benchmark (OASIS-series) datasets were used to show the effectiveness of the proposed method, which increases the accuracy of the detection model by 2.85-3.88%, 2.43-2.66%, and 1.8-40.1% in the ablation study of GAN and TL as well as the comparison with existing works.[18]

DiedreCarmo et al.(2021). It takes use of enhanced 2D multi-orientation technology and automates preprocessing and orientation alignment. The public HarP dataset, a hippocampus segmentation dataset for Alzheimer's disease, was used to develop and test the approach. In two different domains—the HarP test set and the HCUnicamp internal epilepsy dataset with hippocampal resections—we compare our approach to existing deep learning approaches. The outcomes of exercising and testing on HCUnicamp volumes are also shown individually, along with comparisons between training and testing in data related to epilepsy and Alzheimer's illness and the contrary.All tested methods, including ours, produced false positives in HCUnicamp resection regions, demonstrating that there is still room for improvement for hippocampus segmentation methods when resection is involved, even though the most recent state-of-the-art methods, including ours, achieve upwards of 0.9 Dice in HarP.[19]

Mahjabeen Tamanna Abedi et al.(2020). High dimensional Deep Neural Network (DNN) models that have been trained and combined with transfer learning have been utilised to diagnose AD using fMRI images. The Alzheimer's Disease Neuroimaging Initiative (ADNI) assembled

the fMRI picture bank. To categorise people as having AD, MCI, or cognitively normal (CN), we employed three distinct DNN models: VGG19, Inception v3, and ResNet50. We initially separated the pictures into training, testing, and validation sets after applying various preprocessing techniques. Second, we initialised new DNN models with weights from pre-existing models built using the ImageNet dataset. Finally, all DNN models underwent training and evaluation. After only 15 training epochs, we were able to obtain 90%, 85%, and 70% accuracy using VGG19, Inception v3, and ResNet50. As a result, our research produced great classification accuracy in a brief amount of time. Contribution: Accurately classifying early-stage and late-stage AD may be made achievable through transfer learning.[20]

III. DATASET ANALYSIS

Although AD detection is difficult, researchers do not need to work alone and can use different online datasets and software packages to help. Matlab, Keras, Tensorflow, Torch and other software packages can be used to realize the depth model. ADNI, OASIS, AIBL, and other datasets provide publicly available biomarkers.

A. ADNI Dataset

The premier database for Alzheimer's research is now ADNI. It is the most often used dataset in our articles, and 90% of research either utilise it alone or in conjunction with other studies. The National Institute on Ageing and the National Institutes of Health established this organisation in 2004 to gather and organise data on individuals with Alzheimer's disease, follow their pathogenesis, discover changes and reasons in their pathogenesis, uncover the pathogenesis of AD, and find a treatment. According to Dimitriadis, Liparis, Tsolaki, and Initiative (2018), ADNI data is now separated into four stages: ADNI-GO, ADNI-1, ADNI-2, and ADNI-3. While ADNI-GO and ADNI-1 are baseline data, ADNI-2 and ADNI-3 primarily consist of follow-up data and newly added modal data, respectively. The genetic component is the main cause of Alzheimer's disease. As a result, one of the key objectives of ADNI is to give researchers the chance to integrate genetics with imaging and clinical data to help in the study of illness aetiology. The main goal of ADNI is to determine if biological samples, continuous MRI, and PET scans can track the development of MCI and early AD.

B. OASIS Dataset

OASIS is a project aimed at the free distribution of brain MRI data (Khaki, Lee, Pyun & Kwon, 2019), consisting of two comprehensive datasets. The cross-sectional data set included MRI data from 416 subjects aged 18 to 96 (young, middle-aged, non-dementia, and older adults with dementia). For each MRI, three to four T1-weighted scans with high contrast to noise ratio were performed. Here, estimates of total brain volume and intracranial volume were used to analyze normal ageing and AD (Bachman, Lee, Sidtis & Ardekani, 2014). The dataset also provided data on 20 dementia patients.

C. AIBL Dataset

This includes clinical and cognitive assessment, MRI, biological samples, PET, and lifestyle assessment (Martins et al., 2018). The dataset consists of information on more than 2000 individuals. Different questionnaires and clinical procedures were used to collect data. All information was collected over ten years and enriched 582 regular 142 CE and 220 MCI patient information. In addition, the baseline cohort contained information on 211 CE, 133 MCI, and 786 healthy individuals. Proxy data included age and gender recruitment periods.

IV. PROPOSED WORK ARCHITECTURE

Alzheimer's disease is a brain condition that gradually impairs memory, thinking, learning, and organizational skills. The capacity quickly deteriorates for doing

ordinary tasks. The most frequent cause of dementia documented is Alzheimer's disease (AD). The objective of the multisite research project Alzheimer's Disease Neuroimaging Initiative (ADNI) is to enhance clinical trials for the early detection, management, and prevention of Alzheimer's disease (AD). Participants with AD, those at risk of developing AD, and healthy controls without cognitive impairment are all evaluated in this joint study. Resources and skills are provided by both the public and commercial sectors. Researchers at 63 sites in the US and Canada employ biochemical, genetic, and neuroimaging signs to track the onset of AD in human brain tissue. Designing clinical studies that are more efficient in treating and preventing AD will be made simpler by these findings. the raw structural MRI information. The structural MRI scan data for AD was stored in the ADNI database in NII-format. In order to prepare the data for our experiment, preprocessing was done. The next paragraph will discuss the initial steps. a three-dimensional view of the outside Two different sizes of the first MRI data were provided: 256*256*170 and 256*256*166. We rebuild the data into a three-plane structure with smaller patches in order to standardise it. There are several slices in the MRI data. None of our biomarkers are present in either the first few slices or the last few slices. As a result, we solely take into account inner reference points while taking three plane patches. The 32*32 patch size was chosen. data enhancement Since convolution neural networks need a lot of data to train, we must increase data collection. 1) To create more training data, we employ random translation. 2) Dividing a reference region into three slices of 32*32 pixels. Due to the limited number of AD and NC situations and instances in the training set, this is particularly crucial. the determination of the truth By purposefully sampling inside the picture coordinate range, we establish a reference point. Taking three patches of aircraft photographs with the reference point in the middle comes next. They served as the starting points for the hippocampus offset calculations that we performed. The hippocampus must be found in a specified area of the picture when using this offset. One of the so-called residual networks, ResNet152v2, features several high-performance layers. A 152-layer convolutional neural network called the residual neural network (ResNet152V2) is used. ResNet uses skip connections to address the gradient fading issue and fit the output from one layer to the next. The 2015 ImageNet contest was won by it. It is employed to assess the recommended model's accuracy. This pretrained model has a number of convolutional layers as well as max pooling layers. A few of the parameters for the ResNet function are include_top, weights, input_tensor, input_shape, pooling, classes, and classifier_activation. To alter the image, 152 convolutional layers were employed. After moving the image there for extra processing, the output is then gathered from the concealed layer. Let S denote a real-valued vector space, an ordered field, or an affine space. This includes affine spaces such as Euclidean spaces. A subset C of S is said to be convex if the line segment connecting each pair of x and y in the subset C of S is present. This demonstrates that for every x and y in C and for every t in the range [0, 1], C is the location of the affine combination (1 t)x + ty. This demonstrates that under affine transformations, convexity—the quality of being convex—is invariant. This implies that a convex set in a real or complex topological vector space is path-connected and thus linked. If, excluding the endpoints, every point on the line segment between x and y is located inside the topological interior of C, then the set C is strictly convex. If and only if each of a closed convex subset's border points is an extreme point, the subset is said to be strictly convex.A set C is unquestionably convex if it is both balanced and convex.The convex subsets of R (the set of

real numbers) are its intervals and points. Convex subsets of the Euclidean plane include solid regular polygons, solid triangles, and crossings of solid triangles. Two examples of convex subsets of a Euclidean three-dimensional space are the Platonic solids and the Archimedean solids. One sort of non-convex set are the Kepler-Poinsot polyhedra. The goal of this project is to use Convex fuzzy and ResNet152V2 approaches to create a model for the accurate and objective prediction of Alzheimer's disease. The best feasible accuracy is attained by the suggested model, which is 99%.

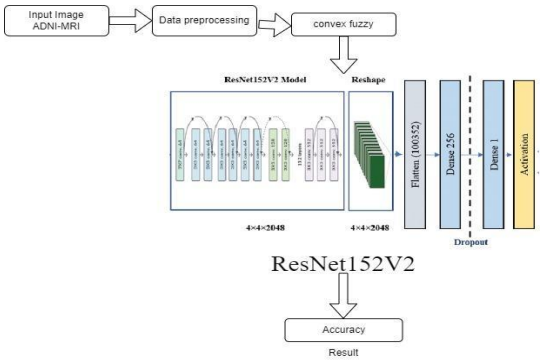

Fig. 1. Architecture Of ResNet152V2

V. RESULTS AND DISCUSSION

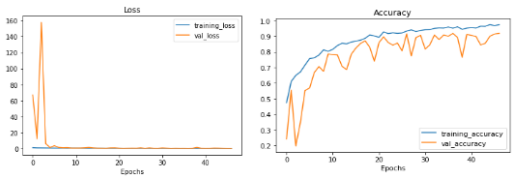

Fig. 2. Training and validation Dataset plot

dividing the dataset into training and test halves. Only 25% and 75% of our time, respectively, is spent testing and training. The training portion of the split dataset comprises 70% of the total data, followed by testing at 20% and validation at 10%. Figure 2 shows how the training and test sets of data were divided, how the ResNet152V2 function was applied to the test set, and how the prediction losses were shown against the epochs. The loss decreases as the time period becomes longer.

	precision	recall	f1-score	support
MildDemented	0.9965	0.9776	0.9870	896.0000
ModerateDemented	1.0000	1.0000	1.0000	64.0000
NonDemented	0.9586	0.9921	0.9751	3200.000
VeryMildDemented	0.9850	0.9433	0.9637	2240.0000
accuracy	0.9931	0.9931	0.9931	0.9931
macro avg	0.9850	0.9782	0.9814	6400.0000
weighted avg	0.9736	0.9731	0.9730	6400.0000

Fig. 3. Performance comparison of metrics of ResNet152V2

In fig.3, The performance metrics are precision,recall,f1 score is calculated for the ResNet152V2 proposed Architecture Model.

VI. CONCLUSIONS

AD is one of, if not the most, debilitating neurological disorders since there is no known treatment for it and because it always worsens to the point that it interferes with daily activities. According to a recent research, AD affects 50 million individuals worldwide. As lifespans increase globally, it is predicted that the prevalence of neurodegenerative illnesses would increase significantly over the next several decades.By 2050, there will probably be 152 million individuals worldwide suffering from AD and other dementias. It is vital to identify AD as soon as possible since doing so has several benefits.In this research, we suggest a deep learning model for early Alzheimer's disease diagnosis based on ResNet152v2. Pre-processing was done initially. Convex fuzzy parameters were suggested for the model to increase output accuracy; resnet152v2 provided the final output. The ResNet152v2 Model allows us to finally reach 99% accuracy. The model's superiority has therefore been demonstrably demonstrated.The outcome was better than anticipated.

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