ALZHEIMER'SDISEASEPREDICTION USING DEEP LEARNING MODELS WITH MAGNETIC RESONANCEIMAGES (MRI)

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Abstract*—— Alzheimer`s disorder is a popular neurodegenerative sickness characterized via way of means of revolutionary cognitive decline and reminiscence loss. Since current treatment methods are more effective whenapplied in the early stages of the disorder, early identification of AD is crucial for effective therapy and management. Magnetic Resonance Imaging (MRI) has emerged as a precious device for supporting inside the early analysis of AD via way of means of imparting designated structural data approximately the brain. Recent improvements in deep learning have similarly strengthened the abilities of MRI-primarily based total analysis through computerized picture analysis. EfficientNetB2 and MobileNetV3 are lightweightconvolutional neural network (CNN) architectures their high performance and speed make them suitable for contexts with limited resources and real-time applications. In contrast, InceptionV3 is a widely used CNNstructure recognized for its exceptional overall performance on picture-type tasks. In the use of those deep learning architectures and thorough training on a whole MRI scan dataset. These methodologies have the potential to improve patient outcomes and quality of life by assisting doctors in timely and accurate diagnosis. The remaining goal of this research project is to enhance methods for early Alzheimer's disease detection and intervention. It advances the fields of clinical imaging and deep learning.

Keywords—Alzheimer'sdisease;Deeplearning; EfficientNetB3; MobileNetV2; InceptionV3;

1. INTRODUCTION

Alzheimer's disease is a common neurological illness that causes memory loss and progressive cognitive decline.The timely identification of AD is essential for its efficient treatment and care as current therapies are more useful when the illness is still in its early stages. A useful technique for aiding in the earlyidentification of AD is magnetic resonance imaging (MRI) by provides detailed structural information about the brain. Recent advancements in deep learning have further enhanced the capabilities of MRI-based diagnosis through automated image analysis. EfficientNetB2 and MobileNetV3 are lightweight convolutional neural network (CNN) architectures and they are appropriate for real-time applications and resource-constrained contexts because oftheir efficiency and speed optimizations.

InceptionV3 is a widely used CNN architecture known for its excellent performance on image classification tasks. By leveraging these deep learning architectures and training them on a comprehensive dataset of MRI scans, ourgoal is to develop accurate and efficient models for AD detection. In order to improve Alzheimer's disease early diagnosis and interventiontechniques, this research initiative advances the fields ofmedical imaging and deep learning.

The endeavor is prompted by the critical need for timely intervention to improve patient outcomes and mitigate the substantial societal burden posed by AD. Through the utilization of state-of-the-art deep learning architectures, including EfficientNetB3, MobileNetV2, and InceptionV3, thus enhancing diagnostic accuracy and objectivity. By training and evaluating these models on a diverse dataset encompassing various AD stages, the project aims to discern the most effective model and elucidate its robustness and generalization capabilities through rigorous validation.

2. LITERATUREREVIEW

The aforementioned reviews of the literature focus on the application of deep learning and machine learning techniques to the identification, classification, and diagnosis of Alzheimer's disease. These studies tackle the major obstacles that researchers and farmers encounter in correctly identifying and treating diseases that impact individuals with Alzheimer's disease. These research papers use advanced computational methods to provide dependable and efficient solutions for disease classification and detection, allowing for early intervention and successful disease management tactics.

These research papers use advanced computational techniques to provide effective and reliable solutions for disease diagnosis and classification, providing early intervention and effective disease control strategies.

[1].E.Kaplanal.[2021] developed the LPQ Net model for brain image-based Alzheimer's disease detection, outperforming existing models like InceptionV3 and MobileNetV2.The model generates 1536 featuresandselectsthemostimportant256for classification, demonstrating superior performance and lighter computational load. The model achieved 100% accuracy on the Harvard Brain Atlas and 99.64% on theKaggle Alzheimer's dataset.

[2].T.Prasath and V. Sumathi's[2024]study on Alzheimer's disease detectionutilized PLN architecture, achieving a 99.5% accuracy rate. The system,which used internal and external features from a deep learning architecture and the Local Ternary Pattern method, outperformed other approaches in performance metrics and execution span analysis, demonstrating superior results and efficient computational time.

[3].Y. Cabrera-LeonYlermi's research high lights the advancement of machine learning in AD diagnosis, focusing on complex neural computation-based techniques. These methods help identify cases of AD and MCI. The integration of genetic data, speech analysis, bio specimens and neuro psychological scales aids in evaluating alterations linked to AD.

[4]. YusiChenal…[2024]study presentsa groupdeeplearningmodelthatintegratesSoft-NMSinto theFasterR–CNNarchitecturetoclassifyAlzheimer's illness. The ResNet50 network and the Bidirectional Gated Recurrent Unit (Bi-GRU) are used by the model to extract richer image features. In the ADvs.CN challenge, the model obtains a high accuracy of 98.91% and shows effectiveness in distinguishing between stages of cognitive decline. Notwithstanding issues with data accessibility and manual annotation, the excellent accuracy indicates that itmay be utilized for early AD diagnosis and individualized treatment.

[5]. Pradnya Borkar al….[2023] and her team are developing a deep learning-based model to detect Alzheimer's disease in healthy individuals. The model uses MRI scans to identify brain features and is trained using collected data. The proposed model, which combines CNNand LSTM models with Adam's optimization, can achieve 99.7%accuracy,making it a non-invasive and cost- effective alternative to current diagnostic methods. Early detection is crucial for preventing the development of Alzheimer'sdisease.

[6].ELGMarwa's research introduces a deep learning-based method for accurately diagnosing and categorizing Alzheimer's disease stages, using CNN and 2D T1-weighted MR brain images. The method offers fast,precise diagnosis and classification of mild cognitive impairment, with demonstrated the potential of deep learning in early AD diagnosis with an overall testingaccuracy of 99.68%.

[7]. M Eslami al[2023] and colleagues have developed a color-coded visualization method called MachineLearningfor VisualizingAD(ML4VisAD) topredict Alzheimer's disease progression over a 2-year period. The method uses baseline measurements and convolutional neural networks, incorporatingneuroimagingdata, neuropsychologicaltestscores,CSFbiomarkers,andotherrisk factors. The ML model aids in diagnosis and prognosis, providing a comprehensive understanding of Alzheimer's Disease.

[8].W Wang al…[2023] and colleagues isolated curculigoside (CCG) from Curculigo orchioidesGaertn root and studied its neuro protective effect APPswe/PSEN1dE9 transgenic(APP/PS1)mice and L-glutamate (L-Glu)-damaged hippocampus neuron cell line (HT22) were used. CCG prevented excessive calcium intake, stabilized the potential of the mitochondrial membrane, reduced the buildup of reactive oxygen species, and inhibited apoptosis. It also improved memory,behavioralimpairments,cholinergicsystemfunction,and suppressed oxidative stress in the mice's brains.

[9]. Alejandro Puente-Castro'sal…[2020] research aims to detect Alzheimer's disease (AD) early, utilizing sagittal magnetic resonanceimages(MRIs)fromtheADNIandOASISdata sets. Transfer Learning (TL) techniques were used to obtain accurate results. The study found that sagittal MRI can distinguish between AD damage and its stages, and that DL modelswithsagittalMRIsarecomparabletohorizontal- plane MRIs. This could open new avenues for investigation, despitethehighcostofdatasets.

[10]. NasirRahim's al….[2023]researchonAlzheimer'sdisease(AD)focuses on a hybrid multimodal deep learning framework that uses a bidirectional recurrent neural network (BRNN)after a 3D CNN to identify inter- sequence patterns causing AD. To enhance accuracy, precision, recall, and area under the receiver operating characteristic curve, the framework makes use of longitudinal 3D MRI volumes and cross-sectional biomarkers. The explain ability module enhances the progression claim by accurately pin pointing brain areas commonly reported by domain experts. Early diagnosis is crucial for timely therapy delivery.

3. PROBLEMSTATEMENT

The project aims to develop accurate and efficient deep- learning models using MRI images to detect early Alzheimer's disease(AD).Utilizing deep learning architectures like EfficientNetB2, MobileNetV3, and InceptionV3, the project automates the classificationof MRI images into different stages of AD progression. Through rigorous validation, the project aims to identify the most effective model and provide insights into interpretability and feature importance. This research aims to advance automated AD diagnosis, contributing to earlier detection and intervention strategies.

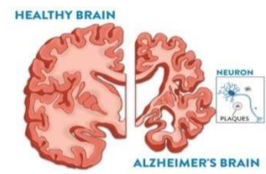


Fig1.1 Human Brain

4. METHODOLOGY

Methodology is the systematic and theoretical examination of practices used in a particular subject or area of study.Theexamination and elucidation of the procedures, techniques, and instruments used in the gathering and processing of data associated with research.

4.1 DatasetDescription

Alzheimer's disease-related Kaggle features include a varietyofdata,includingindividualgeneticinformation, evaluations,and demographics.These datasets frequently seek to support researchersincomprehending the course of Alzheimer's disease, pinpointing risk factors, and creating predictivemodelsforanearly diagnosis. They usually comprise a combination of organized and unorganized data,suchaspatienthistories,MRI scans, and results from cognitive tests. To improve Alzheimer's disease diagnosis, treatment, and care approaches for afflicted individuals, researchers use these datasets to investigate patterns, correlations, and possible biomarkers. The disorders associated withthevariousforms ofADaredepictedinthebelow graphics, and they include non-dementia, moderate dementia, very mild dementia,andmilddementia.Ithas6400photostotal whichthe tests and validation datasets are separated out.

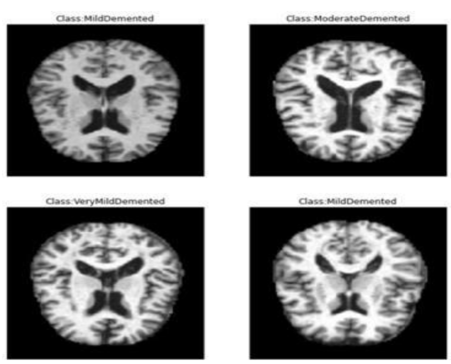


Fig 1.2 MRI Datasets

4.2 *Pre-processing*

Data preprocessing, sometimes referred to as data cleaning or data preparation, is the process of transformingraw data into a format that can be analyzed.It involves cleaning, organizing, and enhancing the data to improve its quality, consistency, and usability. Data preprocessing is an essential step in the data analysis process because Errors, inconsistencies, missing values, outliers, and irrelevant information can all be found in raw data. By preprocessing the data, researchers and analysts can ensure that the data is reliable, accurate, and properly formatted before conducting further analysis or building predictive models.

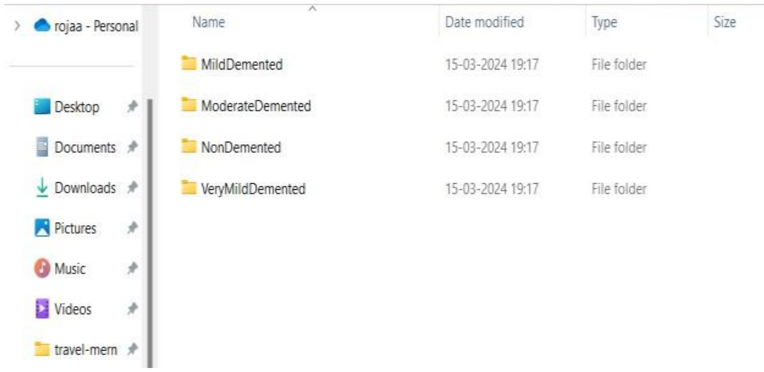
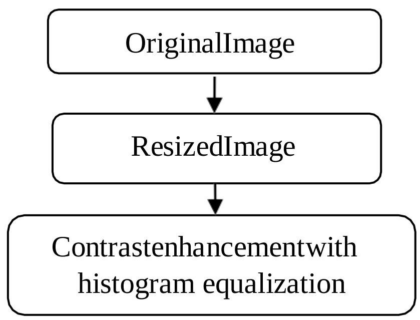


Fig 1.3 Dataset stored

The program loads the dataset from Google Drive and resizes all the imagestothe size of [224, 224]pixels. After that, it configures the Image Data Generator to import the photos from the dataset and uses several data augmentation methods—such as rescaling, shearing, zooming, andflipping—on the training data.Following flowchart is the Workflow of Data Preprocessing



#re-sizealltheimagestothis:

```
IMAGE_SIZE=[224,224]
train_path='/content/drive/MyDrive/Alzheimer_sDataset/train'
test_path='/content/drive/MyDrive/Alzheimer_sDataset/test'
```

4.3 FeatureSelection

The process of selecting a more manageable subset of relevant features (variables, characteristics) from a larger, easily accessible body of data is known as feature selection. in relation to data analysis and machine learning. It is an essential step in the machine learning process because it appears to be the most helpful and discriminating feature while eliminating superfluous or undertones. Feature selection attempts to improve machine learning model performance by lowering dimensionality, increasing computational efficiency, fortifying model interpretability, and lowering over fitting.

The most relevant characteristics should be selected because they can lead to more straightforward and efficient models, faster training and inference times, and improved generalization on untested data.

A. Classification

The task of classifying input data into predefined classes or categories based on their features is known as classification in machine learning. This method of supervised learning uses labeled training to give the algorithm knowledge about data to forecast or assign to new, unseen data.

B. Prediction

Using the trained model, the prediction was made following the training phase.The prediction code is as follows:
#Perform prediction on the test set :

y_pred = model.Predict(test_set)

In this code, the ‘model.predict’ function is used to generate predictions for the test set (test_set). The test_set is passed as an argument to the predict function, and the model outputs the predicted class probabilities for each sample in the test set.

C. Result

The main result generated is the training and evaluation metrics of the model. These metrics include:

- **Training loss**: The training phase's loss value, which shows how well the model fits the training set of data.
- **Training accuracy**: The proportion of samples in the training set that were properly classified, which measureshow well themodel performed onthetraining data.
- **Validation loss**: The loss value during the validation phase, indicates how well the model is generalizing to unseen data.
- **Validation accuracy**: The accuracy of data on the validation model.

5. MODELS

5.1 INCEPTIONV3

InceptionV3 uses its first layers as a high-level image feature extractor. To improve generalization and training stability, more layers are added to the model to fine- tune it from Alzheimer's disease classification task. The final dense layer uses softmax activation to produce class probabilities.

The architecture of InceptionV3 consists of multiple Inception modules, each capturing features at various scales including many parallel convolutional layers of varied sizes to the modules including 1x1 convolutions for dimensionality reduction and factorized convolutions to reduce parameters and computation.

Batch normalization is employed for faster trainingand reduced overfitting, while auxiliary classifiers aid in mitigating the vanishing gradient problem. InceptionV3 is well suited for applications including image classification, object identification, and picture segmentation because it successfully combines local and global data to obtain high accuracy.

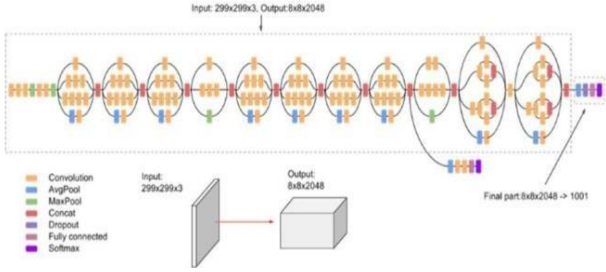


Fig 1.4 InceptionV3 Architecture

5.2 MOBILENETV2

Sandler et al. introduced MobileNetV2, a lightweight convolutional neural network (CNN) designed for embedded and mobile vision applications. It consists of depthwise separable convolutions and inverted residuals. MobileNetV2, which is reputable for its efficacy, is appropriate because it strikes a good balance between accuracy and speed. for a variety of computer vision applications, including object identification, semantic segmentation, and picture classification. Pre-trained weights are available for MobileNetV2, which makes it easier to use and fine-tune on specific tasks with smaller datasets. Easy to use and adjust for specific tasks using smaller datasets because it is compatible with MobileNetV2. This makes it possible to achieve faster convergence and good performance even with limited computational resources..

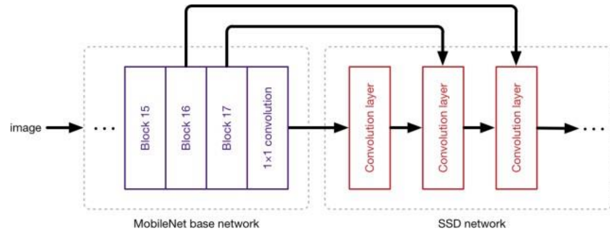


Fig 1.5 MobileNetV2 Architecture

MobileNetV2 extensively uses depth-wise separable convolutions, which consist of a depth-wise convolution followed by a pointwise convolution. This factorization reduces the computational cost while maintaining representational capacity.

5.3 EFFICIENTNET B3

The EfficientNetB3 family of convolutional neural network architectures, which includes EfficientNetB3, was put forth by Quoc V. Le and Mingxing Tan in their paper "EfficientNetB3: Rethinking Model Scaling for Convolutional Neural Networks." B3 is one of the larger versions of the scaled-down version of the EfficientNetB3 model. EfficientNetB3 is appropriate for a variety of computer vision tasks because it achieves a balance between model size and accuracy.

Compound scaling is used in the EfficientNetB3 architecture employing fixed scaling coefficients to scale network width, depth, and resolution uniformly: resolution factor(γ), depth factor(β), and width factor(α).

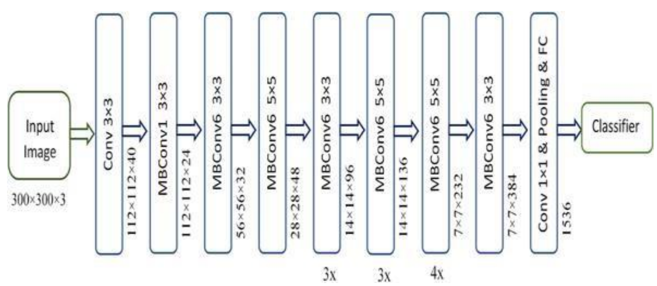


Fig 1.6 EfficientnetB3 Architecture

Neural Architecture Search (NAS) is used to find the best network architecture, which is how EfficientNetB3 is created.

Performance Matrices

A machine learning model's performance is evaluated using performance metrics, sometimes referred to as performance measures or evaluation metrics. In terms of accuracy, precision, recall, F1 score, and other evaluation criteria, these metrics offer quantitative measurements thatshow how well the model is doing.

		Predicted Class Lable	
		Positive	Negative
Actual Class Label	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

$$\text{Accuracy} = \frac{\sum TP+TN}{\sum(TP+TN+FP+FN)}$$

$$\text{Precision} = \frac{\sum TP}{\sum(TP+FP)}$$

$$\text{Recall} = \frac{\sum TP}{\sum(TP+FN)}$$

$$\text{F1score} = \frac{\sum 2TP}{\sum(2TP+TN+FP+ FN)}$$

6. MODEL COMPARISON

InceptionV3 performs significantly better than EfficientB3 and MobileNetV2 in terms of overall F1 score, recall, accuracy, and precision. It obtains a 0.983 accuracy. indicating that it accurately predicts the classes for the test dataset.

Model	**Overall**	**Weighted**		
	Accuracy	***Precision***	***Recall***	***F1-Score***
Inceptionv3	0.783	0.677	0.257	0.373
MobileNetV2	0.84	0.734	0.597	0.43
EfficientNetB3	0.93	0.64	0.54	0.75

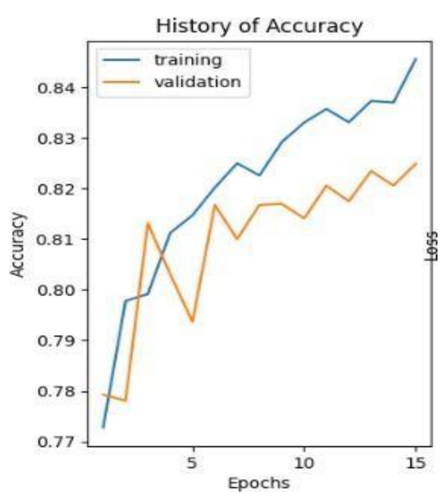


Fig 1.7 Graph Representation of MobileNetV2 Result

The accuracy values are the focus of the y-axis, while the x-axis explains the number of epochs. Our model is constructed over a period of 15 epochs, as shown in the above graph. It provides an accuracy of 84% using 15 epochs. Both trained and validated accuracy are explained by the graph.

The precision of 0.96 and recall of 0.921 show that it has a high degree of accuracy in classifying positive examples and retrieve relevant instances, respectively. However, the F1- score of 0.157 suggests that there may be some imbalance between precision and recall, possibly due to the trade-off between them and is a widely used and effective model for tasks involving image recognition. Inception V3 is renowned for its superior performance and economical use of computing power.

Inception V3 is less efficient than MobileNetV2. All of the architectures may be the best option depending on the particular needs. EfficientNetB3, however, would be the recommended choice for tasks where computational resources are not a constraint and performance is crucial.

EfficientNetB3 outperforms MobileNetV2 and is more effective than Inception V3. EfficientNetB3 strikes a balance between model size and accuracy to attain cutting-edge outcomes in a range of computer vision applications. MobileNetV2, on the other hand, is designed for embedded and mobilevisionapplicationsandprovidesagreat balance between speed and accuracy.

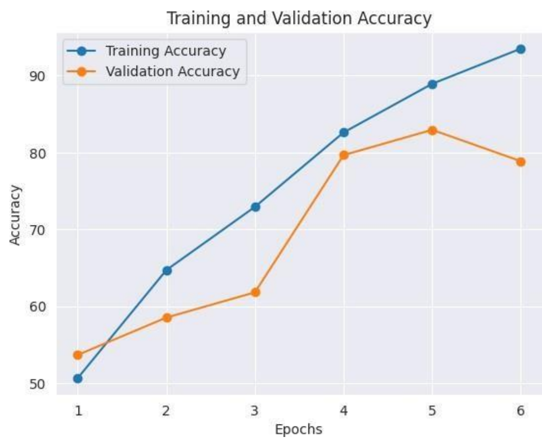


Fig 1.8 Graph Representation of EfficientNetB3 Result

The accuracy values are the focus of the y-axis, while the x-axis explains the number of epochs. Our model is constructed over sixe pochs, as shown in the above graph. Six epochs are used, yielding a 93% accuracy. The classification of each class is explained by the graph.

7. 3D PLOTTING

3D plotting for Alzheimer's disease, using the EfficientNetB3 plotting shows the relationship between the Epochs, Accuracy, and Loss. Created a 3D CNN relevance map interactive visualization that makes model inspection simple.

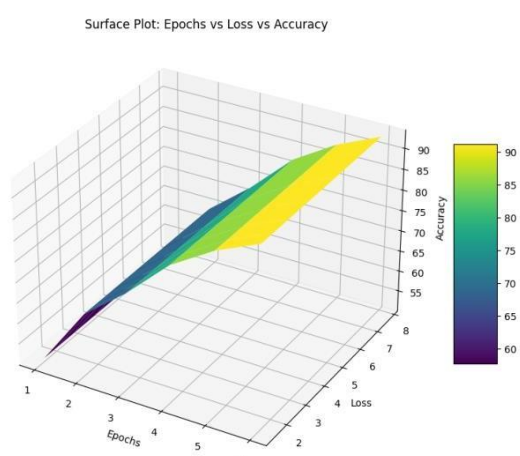


Fig 1.9 3D plotting

The radar graph in Figure5.8 visualizes the accuracy of three different models (EfficientNetB3, MobileNetV2, and InceptionV3)a cross multiple evaluation metrics. Each model is represented as a line plot with in a polar coordinate system, with the distance from the center indicating the accuracy score.

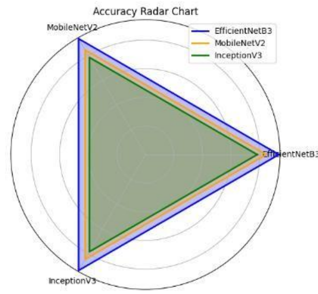


Fig 1.10 Comparative Radar graph

8. CONCLUSION ANDFUTUREWORK

Early diagnosis and treatment outcomes can begreatly impacted by the project Enhancing Diseases Identification in Alzheimer's disease using deep learning models, such as EfficientNetB3, MobileNetV2, and InceptionV3. Thesemodelscan accuratelyWhen trainedon clinical data, predict the onset and course of Alzheimer's disease such as cognitive test results and genetic information, as well as medical imaging data, such as MRI scans.

The expansion of the data set and improved coding of Alzheimer's disease prediction projects can be the main areas of future improvement. The most prevalent form of dementia is Alzheimer's disease. It is a progressive illness that may finally result in loss of a wareness of one's surroundings and ability to converse. Starting with mild memory loss and the brain regions that regulate language,memory, and thought are affected by Alzheimer's disease.

9. REFERENCES

[1] Kaplan, Ela,etal."Feed-forward LPQ Net based automatic alzheimer's disease detection model."Computers in Biology and Medicine 137 (2021): 104828.

[2] Prasath, T., and V. Sumathi. "Pipelined deep learning architecture for the detection of Alzheimer’s disease." Biomedical Signal Processing and Control 87 (2024): 105442 [3]Cabrera-León, Ylermi, et al. "Neural Computation-Based Methods for the Early Diagnosis and Prognosis of Alzheimer’s Disease Not Using Neuro imaging Biomarkers: ASystematic Review. "Journal of Alzheimer's Disease Preprint (2024): 1-31.

[4]Chen, Yusi, etal."Automated Alzheimer's disease Classification using deep learning models with Soft NMS and improved ResNet50 integration."Journal of Radiation Research and Applied Sciences17.1 (2024): 100782.

[5]Borkar, Pradnya, etal. "Deep learning and Image processing –based early detection of Alzheimer disease in cognitively normal individuals. "Soft Computing(2023):1- 23.

[6]Marwa, EL-Geneedy, et al. "An MRI-based deep learning approach for accurate detection of Alzheimer’sdisease." Alexandria Engineering Journal63(2023):211-221. [7]Eslami, Mohammad, SolaleTabarestani, and MalekAdjouadi. "Aunique color-coded visualization System with multi modal information fusion and deep learning in a longitudinal study of Alzheimer's disease."Artificial Intelligence in Medicine 140 (2023): 102543.

[8] Wang, Wenqi, et al. "Neuroprotective effects ofcurculigoside against Alzheimer’s disease via regulation oxidative stress mediated mitochondrialdys functionin L- Glu-exposedHT22cellsandAPP/PS1mice." Food Science and Human Wellness 12.4 (2023): 1265-1278.

[9] Puente-Castro, Alejandro, et al. "Automatic assessment of Alzheimer’s disease diagnosis based on deep learning techniques." Computers in biology and medicine 120 (2020): 103764.

[10] Rahim, Nasir, et al. "Prediction of Alzheimer's progression based on multimodal deep- learning-based fusion and visual explainability of time-series data." InformationFusion 92 (2023): 363-388.

[11] Huang, Yadong, and Lenna Sorour, Shaymaa E., et al. "Classification of Alzheimer's disease usingMRI data based on Deep Learning Techniques." Journal of King Saud University- Computer and Information Sciences 36.2 (2024): 101940rt Mucke. "Alzheimer mechanisms and therapeutic strategies." Cell 148.6 (2012):1204-1222.

[12] Tanveer,M.,Richhariya,B.,Khan,R.U.,Rashid,A.H., Khanna, P., Prasad, M. and Lin, C.T., 2020. Machine learning techniques for the diagnosis of Alzheimer's disease: A review. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM).

[13] Akomolafe, Abimbola, et al. "Diabetes mellitus and risk of developing Alzheimer disease: results from the Framingham Study." Archives of neurology 63.11 (2006): 1551-1555.Salehi, A. W., Baglat, P., Sharma, B. B., Gupta, G., & Upadhya,A.(2020,September).ACNN model:earlier diagnosis and classification of Alzheimer disease using MRI. In 2020 International Conference on Smart Electronics and Communication (ICOSEC) (pp. 156-161)IEEE.

[14] Scheltens, P., Blennow, K., Breteler, M.M.,De Strooper,B., Frisoni, G.B., Salloway, S. and Van der Alzheimer's disease. The Lancet, 388(10043), pp.505-517

[15] Sorour, Shaymaa E., et al. "Classification of Alzheimer's disease using MRI data based on Deep Learning Techniques." Journal of King Saud University- Computer and Information Sciences 36.2 (2024): 101940.

[16] Arafa, D. A., Moustafa, H. E. D., Ali, H. A., Ali-. vM., & Saraya, S. F. (2024). A deep learning framework for early diagnosis of Alzheimer's disease on MRI images. Multimedia Tools and Applications, 83(2), 3767-3799

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