ALZHEIMER'S DISEASE PREDICTION USING DEEP LEARNING MODELS WITH MAGNETIC RESONANCE IMAGES (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 when applied 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 mastering have similarly strengthened the abilities of MRI-primarily based total analysis through computerized picture analysis. EfficientNetB2 and MobileNetV3 are lightweight convolutional 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 CNN structure recognized for its exceptional overall performance on picture-type tasks. By leveraging those deep mastering architectures and schooling them on a complete dataset of MRI scans, we intend to expand correct and green fashions for AD detection. These fashions can help clinicians in making well-timed and correct diagnoses, in the end enhancing affected person effects and exceptional of life. This study venture contributes to advancing the sector of clinical imaging and deep mastering, with the remaining purpose of improving early detection and intervention techniques for Alzheimer's disorder.**

Keywords— Alzheimer's disease; Deep learning; EfficientNetB3; MobileNetV2; InceptionV3;

I. 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 early identification 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 of their efficiency and speed optimizations.

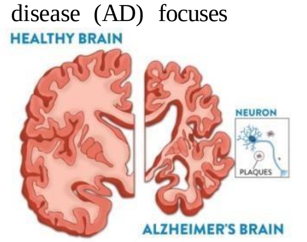
In contrast, InceptionV3 is a widely used CNN architecture known for its excellent performance on image classification tasks. By leveraging these deep learning architectures and training them on a comprehensive dataset of MRI scans, our goal is to develop accurate and efficient models for AD detection. These models have the potential to assist clinicians in making timely and accurate diagnoses, ultimately improving patient outcomes and quality of life. In order to improve Alzheimer's disease early diagnosis and intervention techniques, this research initiative advances the fields of medical imaging and deep learning.

In this discussion, 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, the project seeks to automate the classification of MRI images into different stages of AD progression, 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.

II. LITERATURE REVIEW

The aforementioned literature evaluations concentrate on the use of machine learning and deep learning methods in the diagnosis, categorization, and detection of Alzheimer's disease. These studies address the significant challenges farmers and researchers face in accurately diagnosing and managing diseases that affect tomato plants. By leveraging advanced computational methods, these research papers aim to provide efficient and reliable solutions for disease detection and classification, enabling early intervention and effective disease management strategies.

The above literature review focuses on using deep learning and machine learning to detect, identify, and classify tomato leaf diseases. These studies highlight a major challenge for farmers and scientists in correctly diagnosing and controlling diseases affecting tomatoes. 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 LPQNet model for brain image-based Alzheimer's disease detection, outperforming existing models like InceptionV3 and MobileNetV2.The model generates 1536 features and selects the most important 256 for classification, demonstrating superior performance and lighter computational load. The model achieved 100% accuracy on the Harvard Brain Atlas and 99.64% on the Kaggle Alzheimer's dataset.[2].T.Prasath and V. Sumathi's[2024]study on Alzheimer's disease detection utilized 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 highlights 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, biospecimens, and neuropsychological scales aids in evaluating alterations linked to AD.[4].Yusi Chenal…[2024] study presents a group deep learning model that integrates Soft-NMS into the Faster R–CNN architecture to classify Alzheimer'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 AD vs. 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 it may 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 CNN and 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's disease. [6].ELG Marwa'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 testing accuracy of 99.68%. [7]. M Eslami al[2023] and colleagues have developed a color-coded visualization method called Machine Learning for Visualizing AD (ML4VisAD) to predict Alzheimer's disease progression over a 2-year period. The method uses baseline measurements and convolutional neural networks, incorporating neuroimaging data, neuropsychological test scores, CSF biomarkers, and other risk 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 curculigo side (CCG) from CurculigoorchioidesGaertn root and studied its neuroprotective 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, behavioral impairments, cholinergic system function, and suppressed oxidative stress in the mice's brains.[9]. Alejandro Puente-Castro's al…[2020] research aims to detect Alzheimer's disease (AD) early, utilizing sagittal magnetic resonance images (MRIs) from the ADNI and OASIS data 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 models with sagittal MRIs are comparable to horizontal- plane MRIs. This could open new avenues for investigation, despite the high cost of data sets.[10].Nasir Rahim's al….[2023] research on Alzheimer's disease (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 explainability module enhances the progression claim by accurately pinpointing brain areas commonly reported by domain experts. Early diagnosis is crucial for timely therapy delivery.

III. PROBLEMSTATEMENT

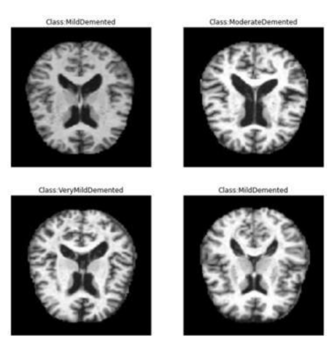
The project aims to develop accurate and efficient deep-learning models using MRI images to detect early Alzheimer's disease (AD). Utilizing deep learning architectures like EfficientNetB2, MobileNetV3, and InceptionV3, the project automates the classification of MRI images into different stages of AD 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 in combating AD.

IV. METHODOLOGY

The systematic and theoretical analysis of procedures used within a specific subject or field of study is referred to as methodology. It is the study and explanation of how research is carried out, including the guiding concepts, methods, and tools for data collection and analysis.

A. Dataset Description

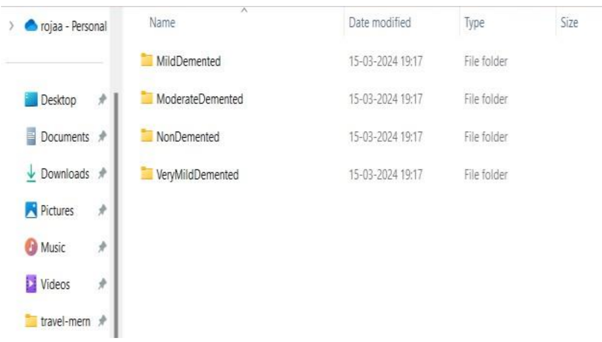
Alzheimer's disease-related Kaggle features include a variety of data, including individual genetic information, clinical



evaluations, and demographics. These datasets frequently seek to support researchers in comprehending the course of Alzheimer's disease, pinpointing risk factors, and creating predictive models for an early diagnosis. They usually comprise a combination of organized and unorganized data, such as patient histories, 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 with the various forms of AD are depicted in the above graphics, and they include non-dementia, moderate dementia, very mild dementia, and mild dementia. It has 6400 photos total which the test and validation datasets are separated out.

B. *Pre-processing*

Data preprocessing, sometimes referred to as data cleaning or data preparation, is the process of transforming raw 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.



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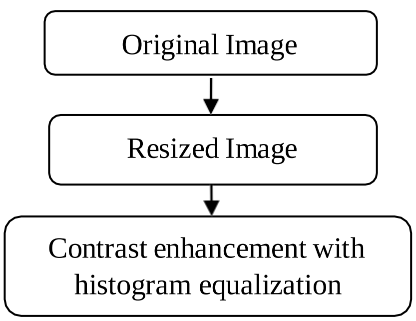
Following Figure 1 is the Workflow of Data Preprocessing



#re-sizealltheimages to this:
IMAGE_SIZE =[224, 224]
train_path='/content/drive/MyDrive/Alzheimer_sDataset/tra in'
test_path='/content/drive/MyDrive/ Alzheimer_sDataset/test'

The program loads the dataset from Google Drive and resizes all the images to the 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, and flipping—on the training data.

C. Feature Selection

Feature selection is the process of choosing a more manageable subset of pertinent features (variables, characteristics) from a larger collection of information that is readily available. in the context of machine learning and data analysis. Since it looks the most helpful and discriminating traits while deleting un needed or undertones, it is a crucial step in the machine learning process. By reducing dimensionality, strengthening model interpretability, decreasing overfitting, and boosting computing efficiency, feature selection aims to enhance the performance of machine learning models.

Most pertinent characteristic should be chosen since they can result in simpler more effective models, quicker training and inference durations, and better generalization on untried data.

D. Classification

Classification is a machine learning task that involves categorizing input data into predefined classes or categories based on their features. It is a supervised learning approach where labeled training, the algorithm gains knowledge data to forecast or assign to new, unseen data.

E. 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.

F. 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 measures how well the model performed on the training 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.

V. MODELS

A. 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 for an 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 training and 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.

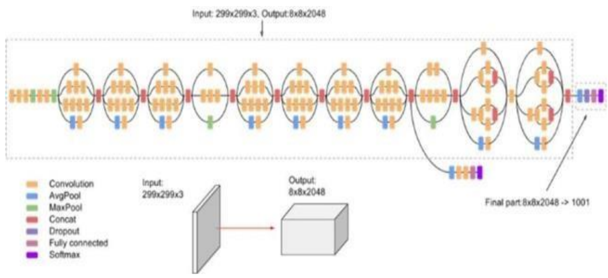
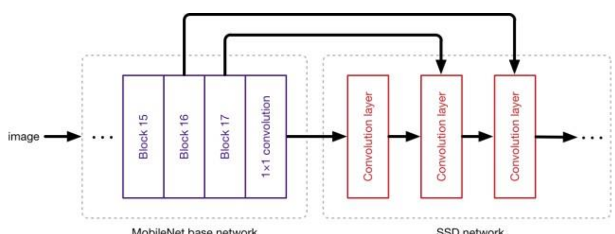


Figure 2 InceptionV3 Architecture

B.MOBILENETV2

A convolutional neural network (CNN) that is lightweight architecture called MobileNetV2 was unveiled by Sandler et al. for use in embedded and mobile vision applications. It is composed of inverted residuals and depthwise separable convolutions. Reputable for its effectiveness, MobileNetV2 is suitable since it finds a good balance between speed and accuracy. for a range of computer vision tasks such as semantic segmentation, object detection, and image classification. For MobileNetV2, pre-trained weights are available, which facilitates ease of use and fine- tuning on particular tasks with smaller datasets.

Convenient to use and fine-tune on particular tasks with smaller datasets, thanks to its compatibility with MobileNetV2. Because of this, even with constrained computational resources, faster convergence and good performance are possible.



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.

C. EFFICIENTNETB3

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).

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

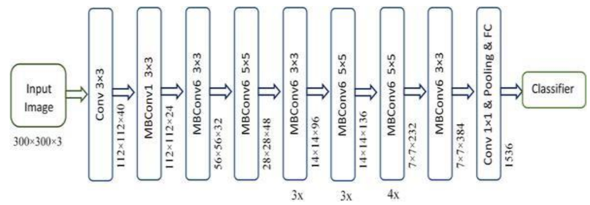


Figure 4 EfficientnetB3 Architecture

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 that show 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)

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

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

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

$$\text{F1 score} = \frac{\sum 2TP}{\sum(2TP + TN + FP + FN)}$$

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

VI. 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.

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

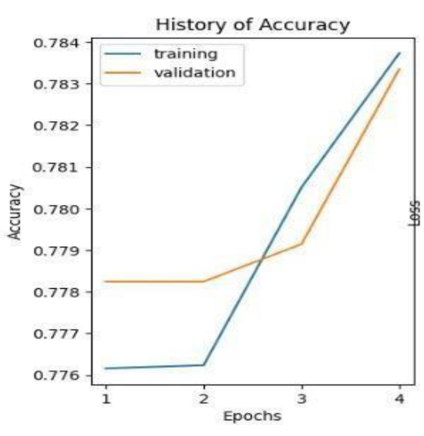


Figure 5 Graph Representation Of Inception V3 Result

For applications where computational resources are limited, MobileNetV2 is the ideal option; nevertheless, InceptionV3 is still a good choice since it strikes a balance between performance and efficiency.

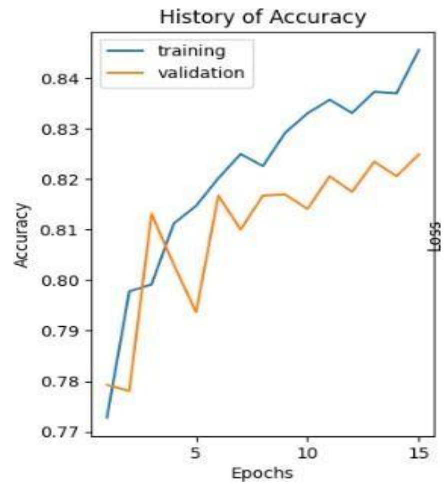


Figure 6 Graph Representation of MobileNetV2 Result

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.

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 mobile vision applications and provides a great balance between speed and accuracy.

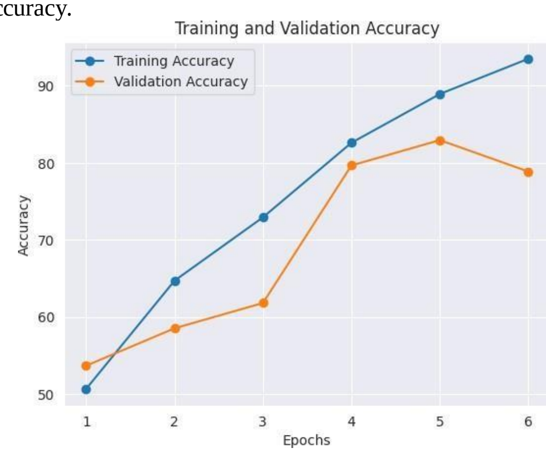


Figure 7 Graph Representation of EfficientNetB3 Result

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

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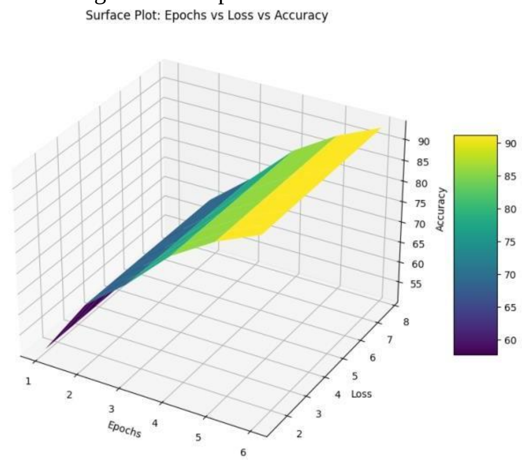
VII. 3D PLOTTING

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.

Figure 8 3D Representation of EfficientNetB3



VIII. COMPARATIVE GRAPH

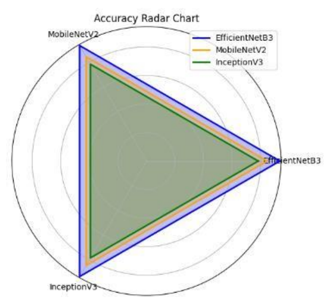


Figure 8 Comparative Radar graph

This radar graph in Figure 5.8 visualizes the accuracy of three different models (EfficientNetB3, MobileNetV2, and InceptionV3) across multiple evaluation metrics. Each model is represented as a line plot within a polar coordinate system, with the distance from the center indicating the accuracy score.

XI. CONCLUSION AND FUTURE WORK

Early diagnosis and treatment outcomes can be greatly impacted by the project Enhancing Diseases Identification in Alzheimer's disease using deep learning models, such as EfficientNetB3, MobileNetV2, and InceptionV3.

These models can accurately When trained on 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 dataset 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 awareness of one's surroundings and ability to converse. starting with mild memory loss. The brain regions that regulate language, memory, and thought are affected by Alzheimer's disease.

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