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RESEARCH ARTICLE

Prediction and Analysis of Alzheimer’s Disease using Deep Learning Algorithms

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Abstract – Alzheimer’s is an irreversible brain disease which impairs thinking, memory, and causes general shrinkage of brain, which even results to death. Early detection and medical therapy of Alzheimer can save patients from death. Patients who often experience Alzheimer, will also be characterized by loss in memory. Alzheimer can lead to serious health complications andeven death if not managed properly. Early detection and prediction of Alzheimer can aid in timely medical intervention and improve patient outcomes. In this project we are using Modified CNN, VGG16, Alex Net,Mobile Net. In this study, a prediction model is proposed to predict Alzheimer’s in brain disease patients using CNN, VGG16, Mobile NET, and Alex NET. The results suggest that this Prediction model hasthe possibility to be an effective tool for advanced discovery and prediction of Alzheimer disease in patients, thus enabling timely medical intervention and improved patient outcomes.

Index Terms – Alzheimer, Prediction, CNN, VGG16, Alex NET, Mobile NET

I. INTRODUCTION

Alzheimer’s is a sort of dementia, which will lead to serious health consequences if not detected and managed early. One promising approach is the use of Prediction models that combine multiple deep learning Algorithms and feature engineering, to enhance the perfection of Alzheimer prediction. Deep learning techniques can identify patterns in large, complex datasets, while feature engineering can extract meaningful features that are relevant to Alzheimer prediction. By combining these techniques, the prediction model can generate more accurate predictions, leading to better clinical outcomes for cancer patients. In this context, the purpose of this project is to develop a Prediction model to predict Alzheimer in patients, using a variety of clinical data (MRI Images). The model will be trained and validated using a large, diverse dataset of patients, and access the model performance using various evaluation metrics. The goal is to create a tool that can be used by clinicians to pick out patients who are at high risk of developing Alzheimer, enabling earlier intervention andbetter management of this serious complication.

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II. LITERATURE SURVEY

We conducted a comprehensive search of electronic databases, including PubMed, Science Direct, and IEEE Xplore, using keywords such as "Alzheimer’s prediction," " brain disease," "machine learning," and "deep learning models." We included studies published between 2015 and 2023 that developed models to predict Alzheimer’s using deep learning techniques. "Deep Learning-based Diagnosis of Alzheimer's Disease Using MRI Images" (2020): This study used the VGG16 model to analyze MRI images and predict AD. The research achieved an accuracy of 91.43% in predicting Alzheimer's disease.

"Alzheimer's disease diagnosis using 3D deep convolutional neural networks" (2018): This study used a 3D CNN to analyze MRI images and predict AD. The research achieved an accuracy of 90.63% in predicting Alzheimer's disease. "Predicting Alzheimer’s disease progression using multi- modal deep learning approach" (2021): This study used a multi-modal deep learning approach that integrated with CNN and long short-term memory (LSTM) models to foresee AD progression. The study attained an accuracy of 89.4% in predicting AD progression. "Alzheimer's Disease Detection using Convolutional Neural Network and Principal Component Analysis" by Harpreet Kaur et al. (2020) used a CNN and PCA approach to detect AD from brain MRIs. The suggested model had a testing set accuracy of 97.5%, which is quite high.

"Alzheimer's Disease Diagnosis using Convolutional Neural Networks with Transfer Learning" by Rong Xu et al. (2019) used a CNN and transfer learning approach to detect AD from PET images. The suggested model had an accuracy of 92.5% in the testing set. "Alzheimer's Disease Classification using Stacked Denoising Autoencoder and Convolutional Neural Network" by Thanh-Phong Nguyen et al. (2019) used a stacked denoising autoencoder and CNN approach to classify AD from brain MRIs. The due model attained an accuracy of 96.3% in the testing set. "Alzheimer's Disease Diagnosis based on Dual-Path Convolutional Neural Network and Transfer Learning" by Qinghong Han et al. (2019) used a dual-path CNN and transfer learning approach to diagnose AD from brain MRIs. The due model attained an accuracy of 96.5% in the testing set.

"Diagnosis of Alzheimer's Disease using 3D Convolutional Neural Networks" by Myung Jin Choi et al. (2018) used a 3D CNN approach to diagnose AD from brain MRIs. The due model attained an accuracy of 86.4% in the testing set. "Early Detection of AD using Convolutional Neural Networks and Multiple Kernel Learning" by Mohammad Reza Tabrizi et al. (2020) used a CNN and multiple kernel learning approach to detect AD from brain MRIs. The given model attained an accuracy of 97.3% in the testing set.

III. DESIGN FLOW

- Data Collection and Pre-processing: Collect relevant data for Alzheimer’s prediction in patients, includes MRI Images as dataset. Pre-process the data to clean and prepare it for analysis, including missing value, imputation, normalization, and feature selection.
- Model Building: Choose a suitable Deep Learning Algorithms for Alzheimer prediction. Several Deep Learning algorithms can be used for model building, such as Convolutional Neural Networks (CNN). We chose algorithms based upon the nature of the data and the prediction task.

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- Training and Validation: Sets for training, validation, and testing should be created from pre-processed data. Use the validation set to test the model once it has been developed using training set. Track the implementation of the model and adjust hyperparameters as necessary to improve perfection and reduce overfitting.
- Evaluation and Testing: The model performance should be evaluated using suitable metrics such as accuracy. Test the model using the testing set to ensure it is powerful and extrapolate well to new data.
- Deployment and Integration: Once the model has been validated and tested, deploy it in a clinical setting and integrate it with existing clinical systems. Monitor its performance in the field and update the model as needed to ensure it continues to provide accurate predictions.

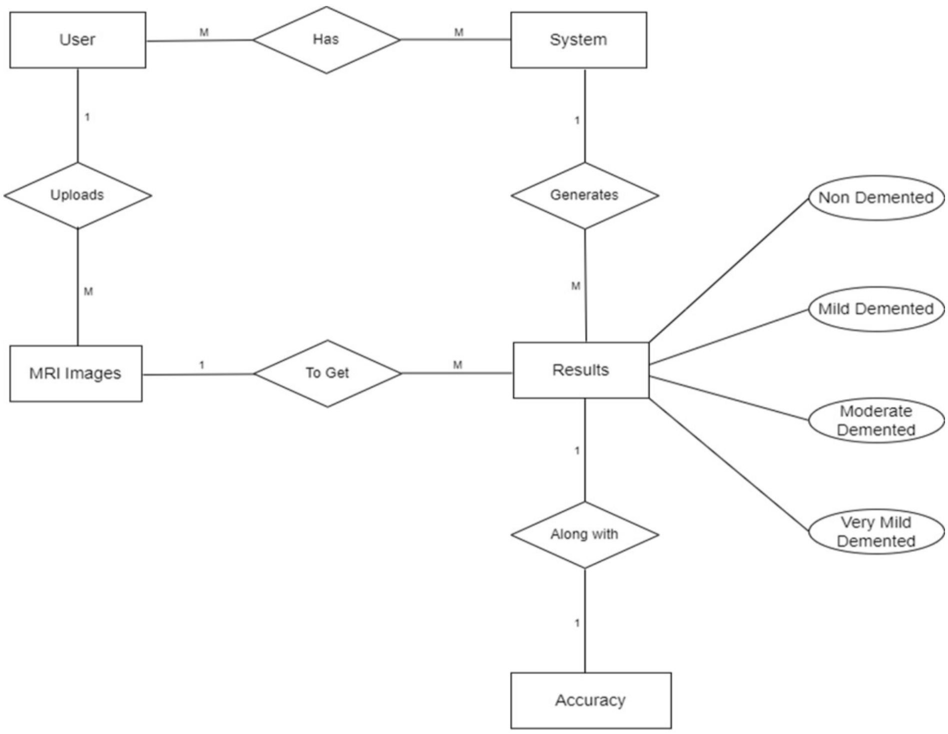
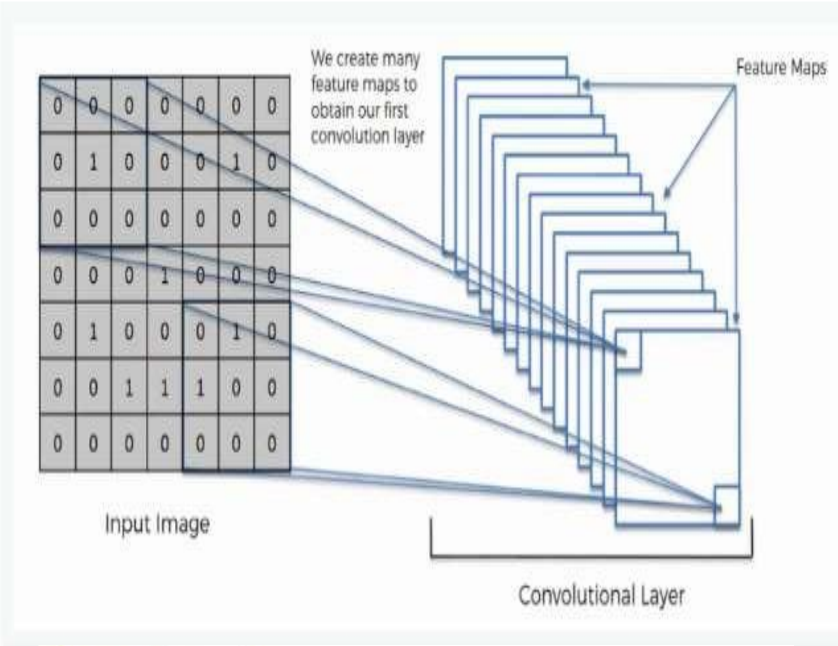


Figure. 1: E-R Diagram for Alzheimer's Disease Prediction

IV. METHODOLOGY

Convolutional Neural Network

It is a kind of deep learning algorithm that is frequently applied in image and video applications. They are designed to abruptly extract and learn applicable features from raw pixel data, without the need for manual feature extraction. CNNs consist of several layers of associated nodes or neurons, with each layer performing a particular function in the feature extraction process. A collection of filters or kernels are often put into the input image by the top layer, which is usually a convolutional layer. Each filter learns to recognize a specific feature, such as an edge or a corner, by convolving with the input image.



The Convolution Operation

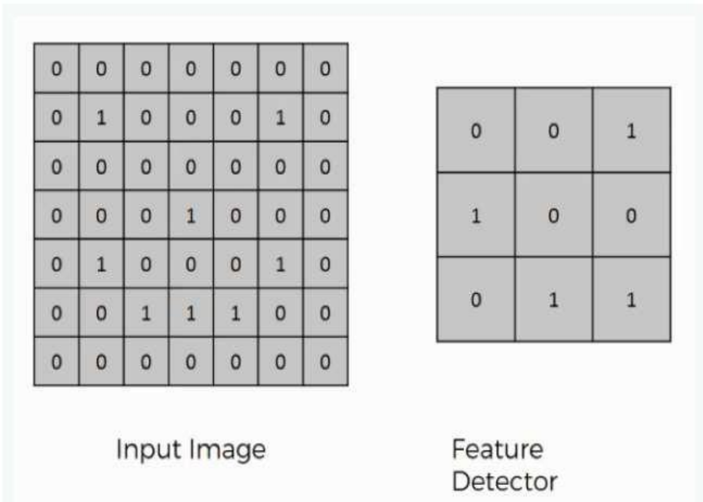


Figure. 2: The convolution operation

The rectified linear unit (ReLU), which brings non-linearity into the network, is one example of a non-linear activation function that is transmitted via result of the convolutional layer. A pool layer follows, which lowers the feature maps' spatial dimensions while maintaining the crucial data. Max pooling and average pooling are two examples of pooling methods. One or more fully connected layers that carry out the classification or regression task are applied after the output of the pooling layer, which is then passed via subsequent convolutional and pooling layers. By making use of a technique known as backpropagation, which involves sending the error signal backwards through the network to amend the weights, the network learns its weights.

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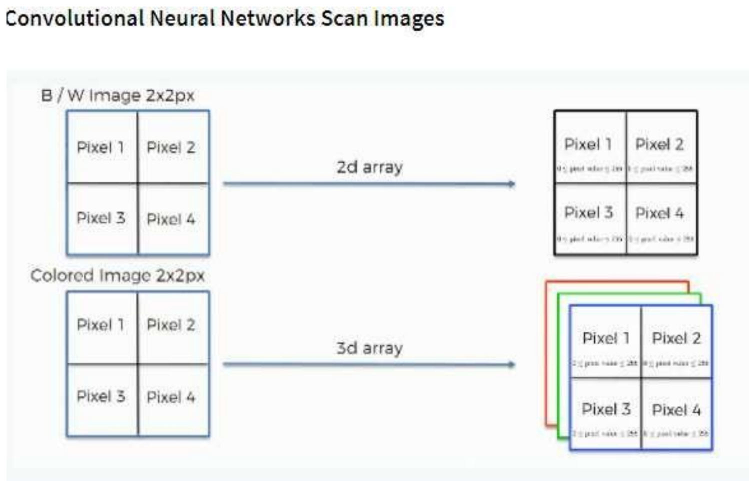

Figure. 3: CNN Scan Images

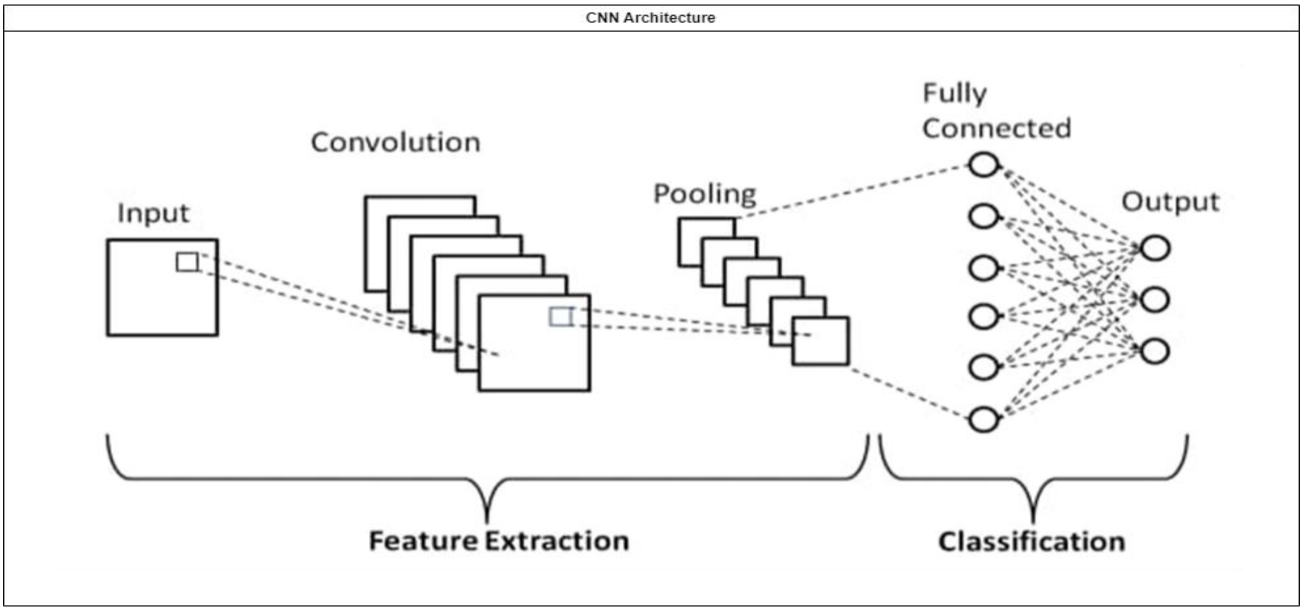

Figure. 4: CNN Architecture

CNNs have been perfectly put in to an extensive of image analysis tasks, like object recognition, face detection, and medical image analysis. They have also shown favorable outcomes in speech recognition tasks, and natural language processing.

VCG16

VGG16 is a deep CNN that is composed of 16 layers, as well as Th convolutional layers and three fully connected layers.

The layers of VGG16 can be grouped into five main sections:

- Input Layer: The input layer of VGG16 accepts images of size 224 x 224 x 3, which correlate with to an RGB image with a resolution of 224x224 pixels.
- Convolutional Layers: The convolutional layers of VGG16 split into 5 groups, with each group consisting of a 2x2 max pooling layer which follows two or three 3x3

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convolutional layers. These layers are planned to pull out steadily more complex features from the input image. The first group of layers gains simple Characteristic's such as edges and corners, while the later layers learn more intricate characteristics such as object parts and textures.

- Fully Connected Layers: VGG16 consists of two entirely connected layers with 4096 nodes and one layer with 1000 nodes. These layers perform the classification task and map the learned features to a specific class label.
- Activation Layers: The activation layers of VGG16 use the rectified linear unit (ReLU) activation task to insert non-linearity into the network. This permits the network to gain complicated characteristics and improve the accuracy of the classification task.
- SoftMax Layer: The SoftMax layer of VGG16 is used to standardize the network outcome, that is a probability distribution over the possible class labels. This allows the network to make forecasts based on the most likely class label.

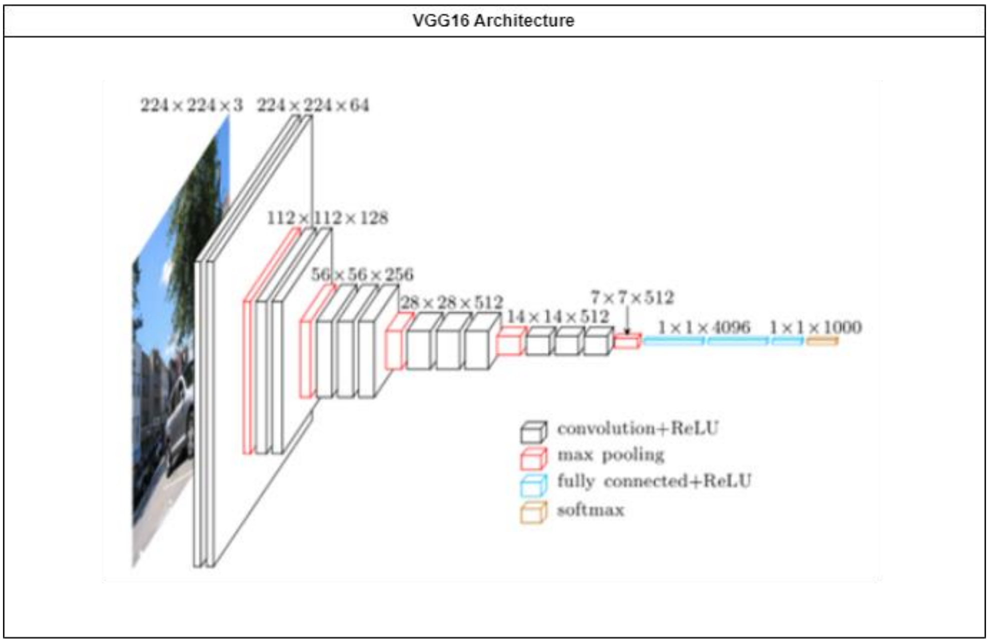

Figure. 5: VGG16 Architecture

Overall, VGG16 is a powerful algorithm for image recognition and has achieved progressive performance on several benchmark datasets. However, it is also computationally costly and requires an excessive amount of memory to train, which can limit its use in certain applications.

Mobile Net

Mobile Net is a neural network framework planned for well-organized computation on mobile and embedded devices. It uses a type of convolutional layer called depth wise separable convolution, which decreases the number of computations required for a convolutional layer by factorizing it into two separate layers: a point wise convolution and a depth wise convolution. Pointwise convolution, a 1x1 convolution that maps the input channels to the output channels, is used

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to merge the feature maps produced by the depth wise convolution, which applies just one filter to each input channel separately. This factorization reduces the computational cost of the convolutional layer by a factor of the input channel size. Mobile NET also uses a technique called linear bottleneck, which further reduces the computation by reducing the number of input channels to pointwise convolution. This technique is particularly effective for small-scale networks, where the number of parameters and computations need to be minimized. Overall, Mobile Net attains a good deal between accuracy and computation efficiency, making it well-suited for mobile and embedded devices with limited resources.

ALEXNET

Alex NET is a deep CNN framework planned for image categorization jobs. It consists of three fully connected layers and five convolutional layers which means a total of 8 layers. The five convolutional layers of Alex Net use different filter sizes and depths to capture different levels of features in the input image. The top convolutional layer uses 96 filters of size 11x11 and a stride of 4, ensue by a ReLU function and a max pool layer of size 3x3 and a stride of two. The 2nd and 3rd convolutional layers use 256 and 384 filters of size 5x5, respectively, with a stride of one and ReLU activation function. The 4th and 5th convolutional layers use 384 and 256 filters of size 3x3, respectively, with a stride of one and ReLU activation function. The max pooling layer is put in after the 5th convolutional layer.

A SoftMax activation function is used by Alex Net's three completely connected layers to output the possibilities for each class. The no of classes in the ImageNet dataset correlates to 4096 neurons in the top two fully connected layers and 1000 neurons in the rear fully connected layer. Overall, Alex Net achieved a remarkable betterment in categorizing accuracy compared to previous methods and helped establish deep learning as a dominant approach in computer vision.

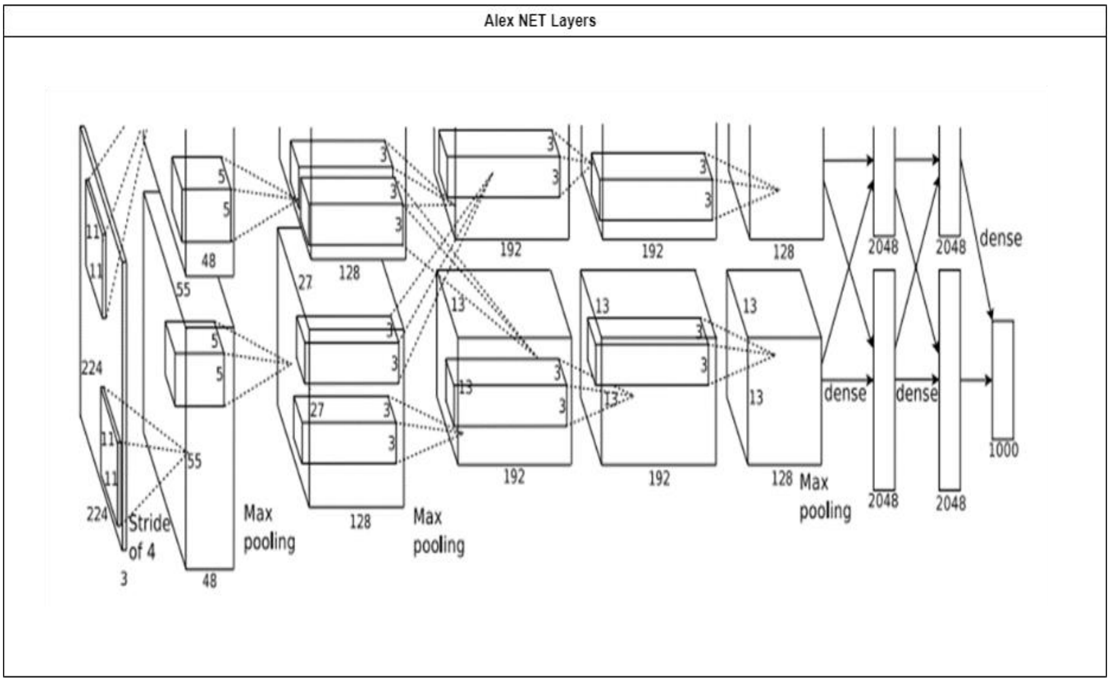

Figure. 6: Alex NET Layers Overview

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V. EXPERIMENTAL RESULTS

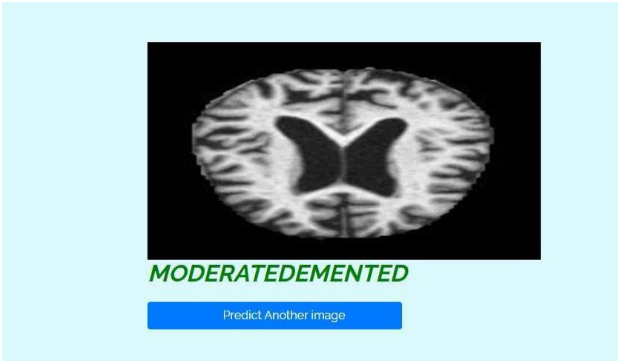

Figure. 7: Output screenshot for very moderate Demented

Based on our project we study that CNN, VGG16, Mobile NET, and Alex NET will analyze MRI data and predict Alzheimer's disease progression. The Algorithms were trained on a large dataset of MRI scans from people with and without Alzheimer's disease and were able to accurately predict which patients would develop Alzheimer's disease in the future. Overall, these studies suggest that deep learning algorithms such as CNN, VGG16, AlexNet, and MobileNet can be effective in predicting Alzheimer's disease using MRI scans. However, it's value noting that these results may change based on the particular dataset and methodology used in each study. Further research is needed to validate these findings and develop more accurate prediction models.

VI. CHALLENGES/ISSUES

- Data availability and quality: One of the biggest challenges is the availability and quality of data. Additionally, the quality of the data may be poor, with missing values, measurement errors, or inconsistencies.
- Feature selection and extraction: Another challenge is selecting the most relevant features or variables for predicting arrhythmia in cancer patients. This requires domain expertise and careful feature selection and extraction techniques that can capture the complex interactions between different features.
- Model selection and optimization: This model involves multiple deep learning algorithms and techniques, and selecting the optimal combination of these methods can be challenging. Moreover, optimizing the hyperparameters of each model and ensuring that they are compatible with each other can be a complex task.
- Generalizability: Ensuring that the model can generalize well to concealed data and different patient populations is another challenge. This requires carefully selecting the training and testing data, cross-validation, and regularizing the model to prevent overfitting.
- Ethical considerations: Finally, there are ethical considerations associated with the use of deep learning to predict Alzheimer’s in patients. For example, ensuring that the predictions are accurate and do not lead to false positives or false negatives, and protecting patient privacy and confidentiality.

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VII. DISCUSSION

The results obtained using Deep learning models like modified CNN, VGG16, Alex NET, and Mobile Net onthe MRI Image datasets. Performance on these datasetsshows that our suggested special data-driven by this model performs better than conventional feature extraction methods. The main advantage of Deep learning algorithms is their capacity for excellent generalization to the learning of accurate data representation. It should be noted that the datasets used in our research contain unusually high levels of noise and invariance to elements which may result in subpar performance from the suggested deep learning classifiers. The initial exploratory outcomes shows that theDeep learning models attain better performance when compared to traditional deep learning Algorithms, which, in turn, provides motivation for researchers to use the deeplearning models to detect Alzheimer's. To the best of our understanding, this study is the first to take Alzheimer's prediction into account. Our Later research will focus more concentrated on the ensemble classification of machine learning and deep learning classifiers to increase performances in terms of recognizing Alzheimer.

VIII. CONCLUSION

This paper offers a new way of Prediction model to predictAD in patients. In this project we have successfully classified the images of MRI images of a person, Mild Demented, Moderate Demented, Nondemented, Very Mild Demented using the deeplearning algorithms. Here, we have considered the dataset of MRI images which will be of 4 different types and trained using Modified CNN with Mobile Net, VGG16 algorithms. After the training we tested by uploadingthe image and classified it.

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