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Deep Learning – Based Classification of Various Stages of Alzheimer Disease

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Abstract— ***Alzheimer's complaint is a incorrigible, progressive neurological brain complaint. Alzheimer's complaint causes the brain to shrink and brain cells to die. Beforehand discovery of Alzheimer's complaint can help case with proper treatment and help severe brain damage. In this paper a deep convolutional neural network model by assaying MRI reviews for opinion of Alzheimer complaint at early stage. Performed on Models and MRI images member to achieve better training set. Res Net excerpts features and gives significant information about Alzheimer's complaint and Mild Cognitive Impairment. This has ultimately help croakers to prognosticate the stage of complaint and case is in proper treatment consequently our system uses deep learning algorithms to prognosticate the Alzheimer complaint. Different convolutional configurations have proposed to capture information attained by a segmentation network. In addition, a generative inimical network grounded on Pixel 2 Pixel has proposed. The creator is a codec structure combining a residual network and an attention medium to capture detailed information. The discriminator used a convolutional neural network to distinguish the segmentation results of the generated model and that of the expert. Through the continuously transmitted losses of the creator and discriminator, the creator reached the optimal state of hippocampus segmentation classification.***

Keyword: Alzheimer, Generator, MRI, Discriminator, SE block, Residual Network

I INTRODUCTION

Over the years, deep learning has evolved causing a massive disruption into industries and business domains. Deep learning is a branch of machine learning that deploys algorithms for data processing and imitates the thinking process and even develops abstractions. Deep learning uses layers of algorithms for data processing, understands human speech and recognizes objects visually. In deep learning, Information is passed through each layer, and the output of the previous layer acts as the input for the next layer. The first layer in a network is referred as the input layer, while the last is the output layer the middle layers are referred to as hidden layers where each layer is a simple, uniform algorithm consisting of one kind of activation function. Another aspect of deep learning is featuring extraction which uses an algorithm to automatically construct meaningful features of the data for learning, training and understanding. Deep learning is used practically everywhere, In recent years, deep learning methods have been widely used in computer vision, and convolutional neural networks have made some progress in medical image processing. a proposed a method based on machine learning to classify tumors. IT used the fully convolutional network for the first time to perform pixel-level segmentation of natural images. The fully connected layers are converted into convolution operations, and the global information and the local information are taken into account by combination of shallow and deep features. It also supports arbitrary size image training and segmentation, and has made a breakthrough in semantic segmentation. The hippocampus is located between the thalamus and the medial temporal lobe of the brain, and it is a part of the limbic system. It is mainly responsible for the storage, conversion, and orientation of long term memory. The hippocampus is closely related to many neurological diseases, such as Alzheimer's disease, schizophrenia, and dementia. However, the shape of the hippocampus is irregular, its volume is small, its edges have no clear boundaries, and individual differences are large. At present, manual segmentation results are still considered to be the gold standard for hippocampal morphological analysis. The study of the volume and shape of the hippocampus is a necessary condition for the diagnosis of these diseases. Therefore, automatic and accurate segmentation of the hippocampus using magnetic resonance imaging (MRI) images and its analysis and research are of great practical relevance for the correct diagnosis of these diseases. At present, the following methods are used for brain MRI hippocampus segmentation: manual, semiautomatic, and automatic segmentation methods. The manual segmentation method is performed by experts to mark and segment the countours of

the hippocampus on each slice. All through the result of manual segmentation is still considered to be the gold standard, the process is time consuming and subjective. Semiautomatic segmentation uses the threshold method and the image boundary tracking method to introduce initial image contour information and achieve hippocampus segmentation. This process requires precise control of the prior parameters and the parameter adjustment process is too time consuming. Automatic segmentation methods are divided into traditional automatic and deep learning based segmentation methods. Traditional segmentation methods include graph and deformation-based methods. These methods often rely excessively on auxiliary technologies, such as classifiers and optimizers, which are difficult to rely on when using simple registration methods. An accurate segmentation of different hippocampi with large differences is difficult to achieve through simple registration methods. In recent years, deep learning methods have been widely used in computer vision, and convolutional neural networks have made some progress in medical image processing.

II LITERATURE SURVEY

E. A. A. Alaoui, S. C. K. Tekouabou, S. Hartini, Z. Rustam, H. Silkan, and S. Agoujil, Improvement in automated diagnosis of soft tissues tumors using machine learning, Big Data Mining and Analytics, vol. 4, no. 1, pp. 33–46, 2021.AUTHORS: E. A. A. Alaoui, S. C. K. Tekouabou, S. Hartini, Z. Rustam, H. Silkan, and S. Agoujil Soft Tissue Tumors (STT) are a form of sarcoma found in tissues that connect, support, and surround body structures. Because of their shallow frequency in the body and their great diversity, they appear to be heterogeneous when observed through Magnetic Resonance Imaging (MRI). They are easily confused with other diseases such as fibroadenoma mammae, lymphadenopathy, and struma nodosa, and these diagnostic errors have a considerable detrimental effect on the medical treatment process of patients. Researchers have proposed several machine learning models to classify tumors, but none have adequately addressed this misdiagnosis problem. Also, similar studies that have proposed models for evaluation of such tumors mostly do not consider the heterogeneity and the size of the data. Therefore, we propose a machine learning-based approach which combines a new technique of preprocessing the data for features transformation, resampling techniques to eliminate the bias and the deviation of instability and performing classifier tests based on the Support Vector Machine (SVM) and Decision Tree (DT) algorithms. The tests carried out on dataset collected in Nur Hidayah Hospital of Yogyakarta in Indonesia show a great improvement compared to previous studies.

Fusion analysis of resting-state networks and its lication to Alzheimer’s disease, Tsinghua Science and Technology, vol.

AUTHORS: S. Pei, J. Guan, and S. Zhou

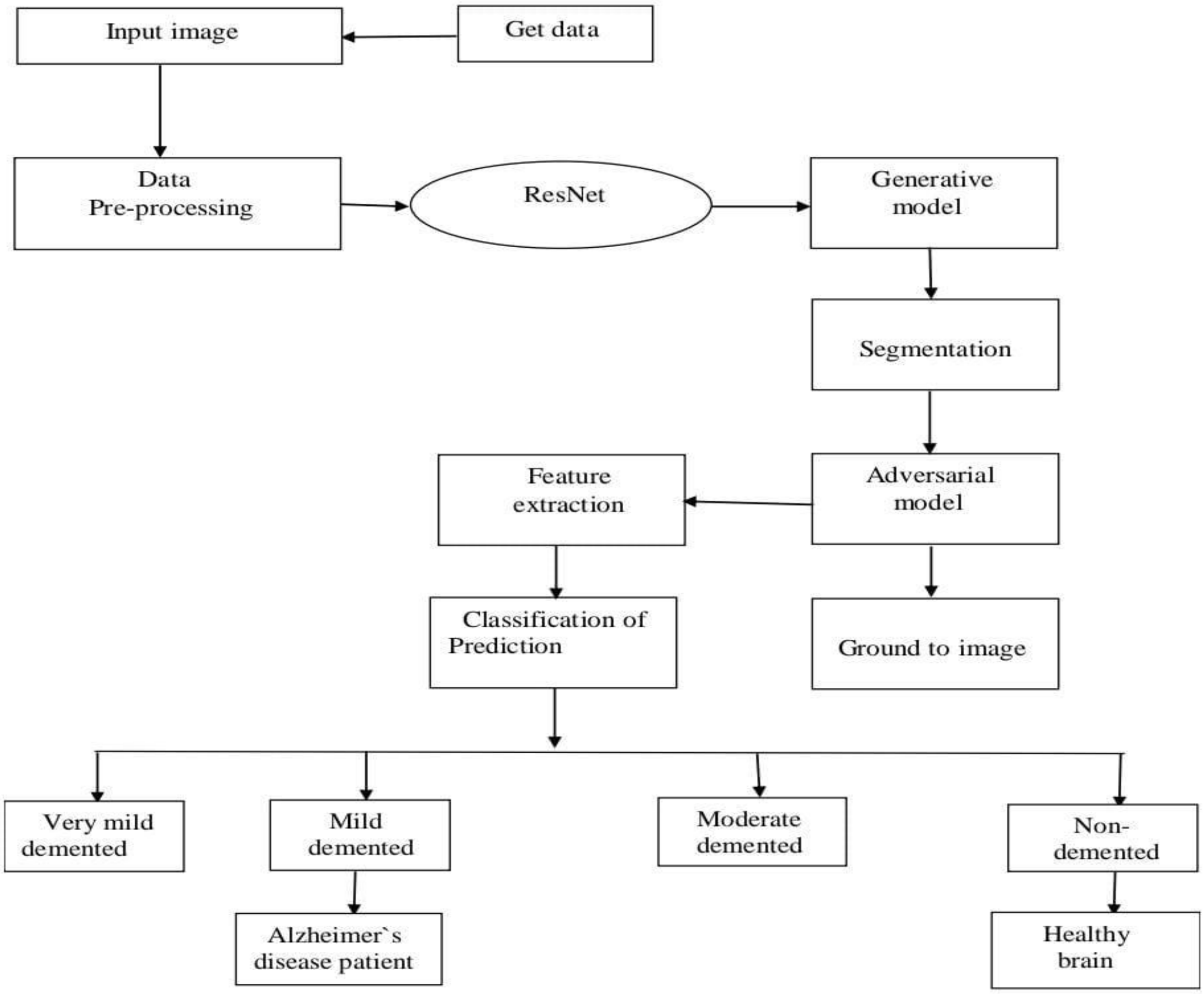
Functional networks are extracted from resting-state functional magnetic resonance imaging data to explore the biomarkers for distinguishing brain disorders in disease diagnosis. Previous works have primarily focused on using a single Resting-State Network (RSN) with various techniques. Here, we apply fusion analysis of RSNs to capturing biomarkers that can combine the complementary information among the RSNs. Experiments are carried out on three groups of subjects, i.e., Cognition Normal (CN), Early Mild Cognitive Impairment (EMCI), and Alzheimer’s Disease (AD) groups, which correspond to the three progressing stages of AD; each group contains 18 subjects. First, we apply group Independent Component Analysis (ICA) to extracting the Default Mode Network (DMN) and Dorsal Attention Network (DAN) for each subject group. Then, by obtaining the common DMN and DAN as templates for each group, we employ the individual ICA to extract the DMN and DAN for each subject. Finally, we fuse the DMNs and DANs to explore the biomarkers. The results show that (1) the templates generated by group ICA can extract the RSN for each subject by individual ICA effectively; (2) the RSNs combined with the fusion analysis can obtain more informative biomarkers than without fusion analysis; (3) the most different regions of DMN and DAN are found between CN and EMCI and between EMCI and AD, which show differences. For the DMN, the difference in the medial prefrontal cortex between the EMCI and AD is smaller than that between CN and EMCI, whereas that in the posterior cingulate between EMCI and AD is larger. As for the DAN, the difference in the intraparietal sulcus is smaller than that between CN and EMCI; (4) extracting DMN and DAN for each subject via the back reconstruction of group ICA is invalid. 2

Hippocampus segmentation by optimizing the local contribution of image and prior terms, throughgraph cuts and multi-atlas, in Proc. 9th Int. Symp. Biomedical Imaging (ISBI), Barcelona, Spain, 2012, pp. 1168–1171.

AUTHORS: D. Zarpalas, P. Gkontra, P. Daras, and N. Maglaveras

This paper presents a new method for segmentation of ambiguously defined structures, such as the hippocampus, by exploiting prior knowledge from another perspective. An expert's experience of where to use prior knowledge and where image information, is captured as a local weighting map. This map can be used to locally guide the evolution in a level set evolution framework. Such a map is produced for every training image using Graph-cuts to calculate the most suited balance of current and prior information. Training maps are optimally adapted on the test image, through non-rigid registration, producing the Optimum Local Weighting map, which is anatomically the most suitable to this test image.Experimental results demonstrate the efficacy and accuracy of the proposed method.

III METHODOLOGY



BLOCK DIAGRAM OF SYSTEM

This system implementation MRI images are used as a input. Data pre processing is primary and important step while giving input to Resnet mode Here image rescaling, naming image sion is done. Next part a feature extraction. In deep learning and image processing arcture are created from the initial dataset. Which is used for the training process. The selected stures include information about the input data Feature extraction layer of resnet layers of convolution activation, max pooling and future extraction, the images are classified in the fally connected layers of classification age activation function Rela is used to avoid overfitting as this is non-linear function.

There are following steps involved in our methodology:

I) First, we will collect the data.

ii) Then we will process the data.

iii) Then we will get the data as input from patient and process it model.

iv) After that classification the model predicts the disease.

v) Then the system will show the output.

INPUT IMAGE

The Radiological imaging technique, Magnetic Resonance imaging (MRI) was developed during abandonment of ultra sound was widely used for brain tumors detection through imaging MRI is used to create a detailed image of the human body organ It is also known as magnetic resonance imaging Radio waves and strong magnetic fields is used to observe the part of the body that were earlier not possible X-rays, CT-Scan or Ultra sound. Doctors can now observe inside tendons, ligament, muscles, cartilage and Joints.

PRE-PROCESSING IMAGE

Pre-Processing of MRI Images In this Phase the MRI is processed by using necessary image segmentation techniques. This image segmentation technique is used to improve the feature of the image at lowest level. This need not add some extra feature but remove undesirable features from image. Image resizing image conversion, and intensity adjustments of image are done.

RESNET:

Residual Network (ResNet) is a deep learning model used for computer vision applications. It is a Convolutional Neural Network (CNN) architecture designed to support hundreds or thousands of convolutional layers. Previous CNN architectures were not able to scale to a large number of layers, which resulted in limited performance. However, when adding more layers, researchers faced the “vanishing gradient” problem. Neural networks are trained through a backpropagation process that relies on gradient descent, shifting down the loss function and finding the weights that minimize it. If there are too many layers, repeated multiplications will eventually reduce the gradient until it “disappears”, and performance saturates or deteriorates with each layer added. ResNet provides an innovative solution to the vanishing gradient problem, known as “skip connections”. ResNet stacks multiple identity mappings (convolutional layers that do nothing at first), skips those layers, and reuses the activations of the previous layer. Skipping speeds up initial training by compressing the network into fewer layers. Then, when the network is retrained, all layers are expanded and the remaining parts of the network—known as the residual parts—are allowed to explore more of the feature space of the input image. Most ResNet models skip two or three layers at a time with nonlinearity and batch normalization in between.

GENERATIVE MODEL

The generative model is designed the principle of semantic segmentation, this design is achieved by combining the codec structure of the residual network and the attention mechanism. It obtained encoding part and Inception layer. Senet 34 can strengthen the characteristics of important channels. IT also models the relationship in the feature map channel in an efficient computing manner and is designed to enhance the network module`s expressive ability in the network. First, we require a dataset consisting of many examples of the entity we are trying to generate. This is known as the training data, and one such data point is called an observation. The generative model is designed the principle of semantic segmentation, this design is achieved by combining the codec structure of the residual network and the attention mechanism. It obtained encoding part and Inception layer. Senet 34 can strengthen the characteristics of important channels. IT also models the relationship in the feature map channel in an efficient computing manner and is designed to enhance the network module`s expressive ability in the network.

IMAGE SEGMENTATION

A deep learning-based image segmenting approach is experimented in detecting the delicate features of brain morphological changes due to AD that benefits classification performance for cognitive normal, mild cognitive impairment and AD, and thus provides an easy automatic diagnosis of Alzheimer's diseases. Or It is a commonly used technique in digital image processing and analysis to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image. Segmentation of MRI image

Why segment brain images?

Anatomical brain image segmentation has a variety of uses: Quantitative anatomy: to describe anatomical phenotypes and individual variations in an intersubjective, reproducible manner Brain morphometry: to measure how diseases/conditions affect the shape and size of the structures that compose the brain Biomarker discovery: to obtain morphometric biomarkers for diagnosis, prognosis, and disease monitoring Intervention trials / drug testing: to monitor imaging biomarkers as surrogates for treatment response or disease progression Functional imaging support: to assign anatomical locations to functional activations in PET and fMRI.

ADVERSARIAL MODEL

The adversarial model takes the hippocampus image and the corresponding level image as the input. The corresponding level diagram is the result of expert segmentation and the segmentation result of the generative model. They are input into the model through a series of convolution layers and maximum pooling layers, and a probability is generated to judge whether the level map is close to the expert segmentation standard. The closer it is to 1, the more realistic the segmentation result of the generative model is and the closer it is to the expert segmentation result. The adversarial model then transfers the loss to the generative model; after many iterations of confrontation, when the discriminator cannot distinguish between the generator`s segmentation result and the expert segmentation result, the network reaches the state of optimal segmentation effect.

WORKING

Adversarial machine learning is a machine learning\deep learning method that aims to trick machine learning models by providing deceptive input. Hence, it includes both the generation and detection of adversarial examples, which are inputs specially created to deceive classifiers. There are a large variety of different adversarial attacks that can be used against machine learning\deep learning systems. Many of these work on deep learning systems and traditional machine learning models such as Support Vector Machines (SVMs) and linear regression. Most adversarial attacks usually aim to deteriorate the performance of classifiers on specific tasks, essentially to "fool" the machine learning\deep learning algorithm. Adversarial machine learning is the field that studies a class of attacks that aims to deteriorate the performance of classifiers on specific tasks. Adversarial attacks can be mainly classified into the

following categories:

Poisoning Attacks

Evasion Attacks

Model Extraction Attacks

FEATURE EXTRACTION

Feature Extraction is done after applying model operations Mapping the image pixels into the feature space is known as feature extraction In feature extraction the data is divided and reduced to more manageable groups and wall help to reduce redundant data from dataset Feature extraction that help to build model with less machine's effort and increase is speed of execution of machine learning process.

CLASSIFICATION OR PREDICATION

It is a process of categorizing data into classes. The classes are often referred a target, labels of categories. The objective is in which class the data will fall into. And after end of all process, we can detect or categorize the final prediction between Alzheimer`s disease present or healthy brain.

IV IMPLEMENTATION

The experimental dataset comes from the database. A total of 130 sets of baseline T1-weighted whole brain MRIs from different subjects and their corresponding label images were downloaded, and data were all from the normal control group.it is a visualization of the fusion of data of whole brain MRI images and corresponding hippocampal tags. Considering that the hippocampus occupies a small volume in the entire brain and its position in the entire brain is relatively fixed, we roughly cropped the data and used it as
input.. The accuracy rate is the highest when set to 300. When set to 350, the accuracy rate is not improved but decreased. The loss of the computer is large, and the effect is not ideal; thus, the epoch is set to 300.

Proposed system

The system is designed to detect diseases such as Alzheimer's disease, breast cancer,brain tumours, heart disease and Covid-19. Each disease has different signs and symptoms for patients. Various datasets are pulled from Kaggle's machine learning database to implement the disease detection system. The classification computation uses a random forest classifier algorithm in a disease detection system to detect diseases. It is a machine learning algorithm that leads to epidemic identification in
disease detection with maximum accuracy, precision and recall. The Disease Detection Web App is built with Flask Framework support as a screening tool for doctors and medical professionals to easily identify patients with disease.

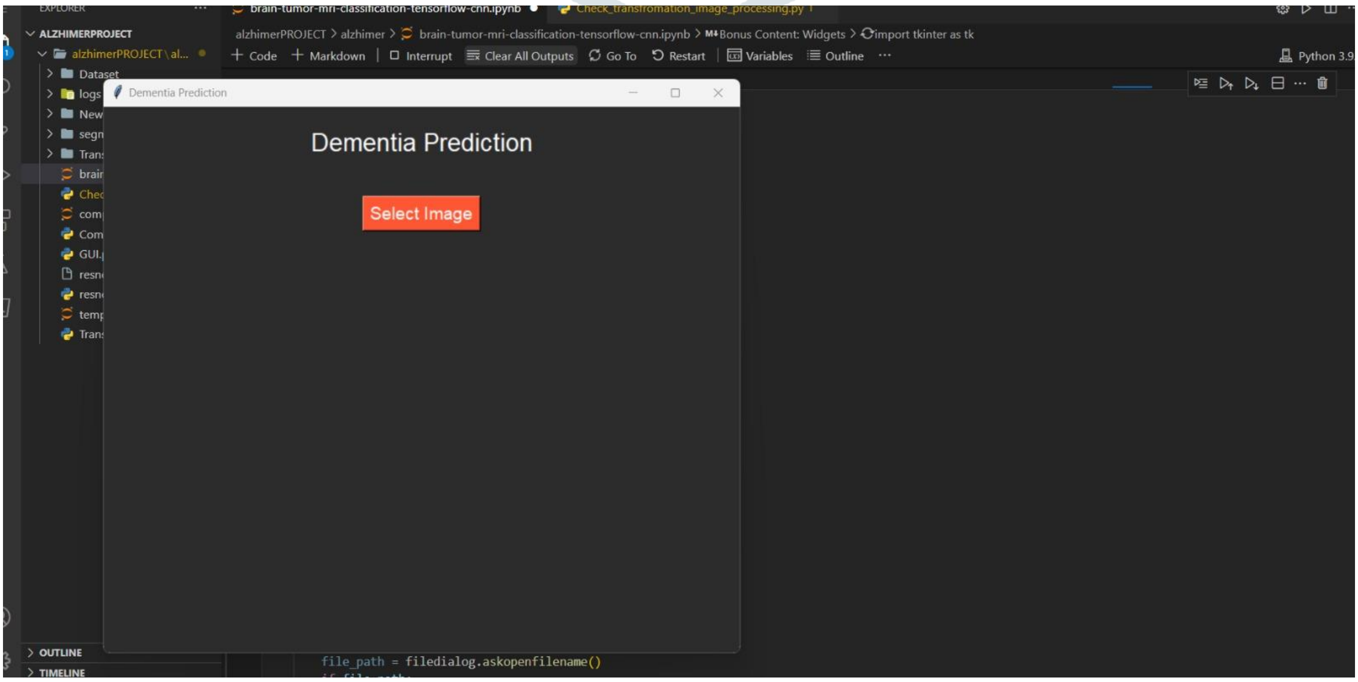
Advantage of proposed system

- One of the primary advantages is the identifications and diagnosis of disease which are otherwise considered to be as hard to detect.
- The main advantage of this project is that we can get the test results immediately at our home with just a few clicks.
- Treatment can be made effective by pairing patient health records with predictive analysis.
- Can be implemented with additional features like if patient is found suffering from any disease then our app will show what precautions needs to take primarily

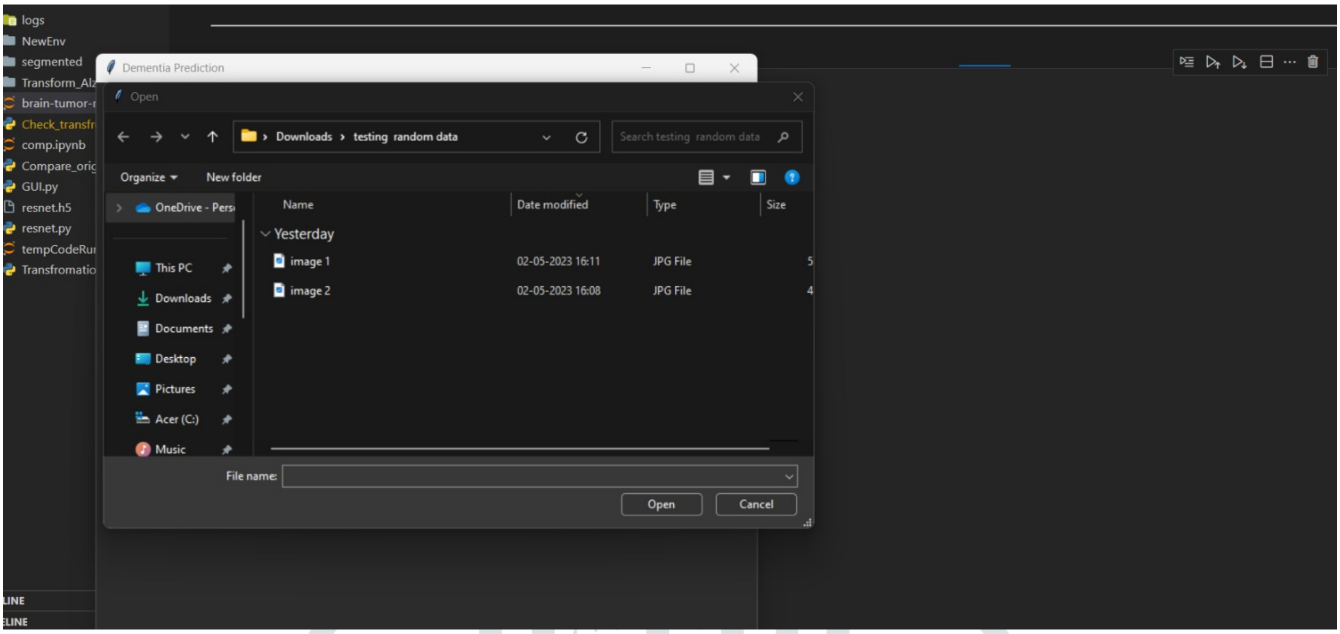
V RESULT

The performance of the proposed network model was quantitatively evaluated using the dataset. To verify the performance of the algorithm proposed in this study, the experiment used ten-fold cross-validation to Analyze the segmentation results. Self-contrast experiments and comparisons with other methods were conducted. Using DSC, SEN, and PPV as evaluation indicators can quantitatively evaluate the accuracy of the segmentation results.

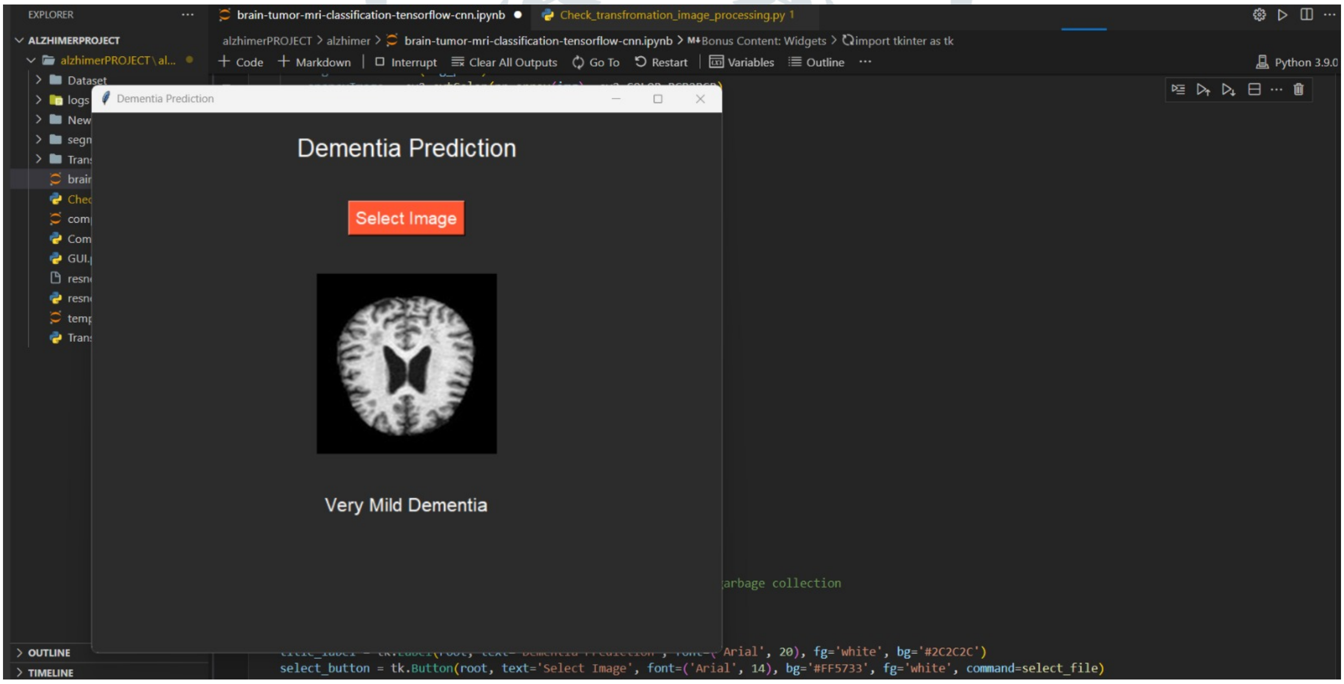
STEP I



STEP II



STEP III



STEP IV

VI CONCLUSION

The purpose of early detection of Alzheimer's disease is achieved. Image pre-processing techniques and transfer learning techniques are being used. Deep learning approach to predict the Alzheimer's disease using Deep learning algorithms is successfully implemented and gives greater prediction accuracy results.. The amount of enlargement will classify the patient as Healthy patient, Mild demented, Non demented. The majority of the existing research works focus on binary classification, this model provides significant improvement for multi-clas classification. Accuracy of this model 87.17 %. This network can be very beneficial for Carly- stage AD diagnosis.

VII ACKNOWLEDGEMENT

We are very thankful to all the teachers who have provided us valuable guidance towards the completion of this project work on USING COMBINATION OF DEEP LEARNING NETWORKS CLASSIFICATION OF ALZHEIMER DISEASE. We express our sincere gratitude towards cooperative department who has provided us with valuable assistance and requirements for the project work. We are very grateful and want to express our thanks to Ms. S. S. Bhosle for guiding us in right manner. Correcting our doubts by giving her time whenever we required, and providing her knowledge and experience in making this project work. We are also thankful to the HOD of our Electronics and Telecommunication department Dr. S. K. Jagtap for his moral support and motivation which has encouraged us in making this project work. We are also thankful to our principal Prof. Dr. A. V. Deshpande, who provided his constant support and motivation that made significant contribution to the success of his project.

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