Classification Of Alzheimer’s Disease Using Deep Learning

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Abstract— Alzheimer’s disease is the most common form of dementia. It is a neurodegenerative brain order that has currently no cure for it. Alzheimer’s disease is more common in people over the age of 65, but some people have early onset Alzheimer’s disease and show symptoms as early as their 40s or 50s. The accurate diagnosis of Alzheimer’s disease plays a significant role in patient care, especially at the early stage. Progression of Alzheimer’s disease can be slow down by diagnosing at early stage. In this project brain MRI images are used for diagnosing Alzheimer’s disease. Now a days deep learning is getting more attention in solving real world problems, especially problems related to health. Convolutional neural network (CNN) is a deep learning model mostly used for image classification. In this project ResNet152V2, a pre-trained CNN model used for classifying brain MRI images into Nondemented, Very Mild Demented, Mild Demented, Moderate Demented. This categorization tells severeness of Alzheimer’s disease.

Keywords— CNN, ResNet152V2, Brain MRI images.

I. INTRODUCTION

Alzheimer's disease (AD) is a neurological condition that typically develops gradually and gets worse over time. It is the root of 60–70% of dementia cases. The most prevalent initial sign is trouble recalling recent events. Language difficulties, disorientation (including a tendency to get lost easily), mood swings, a lack of desire, self-neglect, and behavioural problems can all be indicators of advanced Alzheimer's disease. As a person's health deteriorates, they frequently isolate themselves from friends and family. Body functions gradually deteriorate, which eventually results in death. The usual life expectancy upon diagnosis is three to nine years, however the rate of development might vary.

It is unclear what causes Alzheimer's disease. There are several genetic and environmental risk factors connected to its development. The most potent genetic risk factor originates from an APOE allele. A history of head trauma, severe depression, and high blood pressure are additional risk factors. Amyloid plaques, neurofibrillary tangles, and a loss of neuronal connections in the brain are all major contributors to the disease process. Based on the patient's medical history, cognitive testing, imaging studies, and blood tests to rule out other potential reasons, a likely diagnosis is made. Initial symptoms are frequently confused with ageing processes. For a certain diagnosis, brain tissue examination is required, but this can only be done after someone has passed away. healthy eating, exercise, and social interaction are In 2019, clinical trials were being conducted to investigate these potential benefits, which are known to be generally advantageous in ageing and may aid in lowering the risk of cognitive decline and Alzheimer's. There are no drugs or nutritional supplements that have been proven to lower risk. Although some therapies could momentarily lessen symptoms, none can stop or reverse the disease's course. A load is frequently placed on the carer as affected persons depend more and more on others for help. Social, psychological, physical, and economic factors can all play a role in the stress. Exercise regimens may be advantageous in terms of everyday activities and may even boost results. Antipsychotics are frequently used to treat behavioural issues or psychosis brought on by dementia, however this is seldom advised due to the limited benefits and increased risk of premature mortality. Existing systems using CNN architectures like VGG-16, LeNet-5 to diagnose the Alzheimer’s disease. These trained models are less complex and having few layers to classify the brain MRI image to diagnose the disease. These models are trained on brain MRI images Which are collected from ADNI. These models are trained to classify brain MRI image, whether this image belong to healthy person or person with Alzheimer’s disease. These models also tells whether disease in starting state or severe, if brain MRI image belong to or person with Alzheimer’s disease. In our proposed method we are using the Convolutional Neural Network (CNN) based transfer learning algorithm of the deep learning which is ResNet152V2. This model been used to train the brain MRI images which considered in the four classes as the Non demented which is not affected with any disease and the other classes which were affected with Mild Demented, Very Mild Demented, Moderate Demented.

Algorithm

Deep learning models known as convolutional neural networks (CNNs) are frequently employed for computer vision tasks including object recognition and picture categorization. A succession of convolutional layers, which apply filters to the input picture to find patterns and characteristics, is how CNNs learn and extract features from images automatically. A pooling layer is used to minimise the size of the feature map and make the network more resistant to changes in the input by receiving the output from each convolutional layer. Large datasets of labelled pictures are used in CNN training to teach the network how to link particular characteristics to various object classes. The weights of the network are changed during training to reduce the discrepancy between the actual label and the expected output. Overall, CNNs have demonstrated outstanding performance in a wide range of image identification tasks and have established themselves as key tools in the deep learning space.

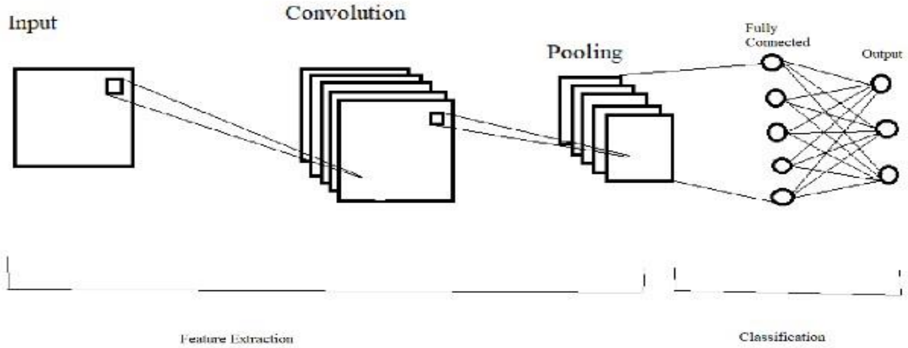

Figure 1. CNN Architecture

ResNet 152V2 Model

ResNet152V2 is a convolutional neural network (CNN) architecture that belongs to the ResNet family. It is a variant of the original ResNet architecture introduced by Microsoft Research. ResNet152V2 has 152 layers, which makes it a deep neural network, and it has achieved state-of-the-art performance in various image classification tasks. ResNet152V2 uses residual connections, which allow it to learn very deep representations without suffering from the vanishing gradient problem. It also uses batch normalization and a variety of activation functions such as ReLU, sigmoid, and softmax. The architecture of ResNet152V2 is similar to other ResNet152V2 models, with the addition of some new blocks and layers that improve its performance. It has a large number of parameters, which makes it computationally expensive to train, but it can achieve high accuracy on image classification tasks. ResNet152V2 deep model. In the second model, ResNet152V2 is used as a feature extraction model, instead of the VGG19-CNN model. The model has initial weights because it is a pre-trained model, which can help to gain acceptable accuracy faster than a traditional CNN.

ResNet152V2 Model Architecture

The ResNet152V2 architecture is a deep convolutional neural network consisting of 152 layers. The general architecture of ResNet152V2 is similar to other ResNet152V2 models, but with some modifications to improve its performance. The following is a brief overview of the ResNet152V2 architecture: 1. Input layer: The first layer of ResNet152V2 is the input layer, which takes the input image and passes it through a convolutional layer. 2. Convolutional layers: The convolutional layers in ResNet152V2 use filters to extract features from the input image. The output of each convolutional layer is passed through a batch normalization layer and an activation function, typically ReLU. 3. Residual blocks: The ResNet152V2 architecture includes residual blocks, which are a key feature of the ResNet family of models. Each residual block consists of several convolutional layers, batch normalization layers, and a skip connection that bypasses one or more layers.

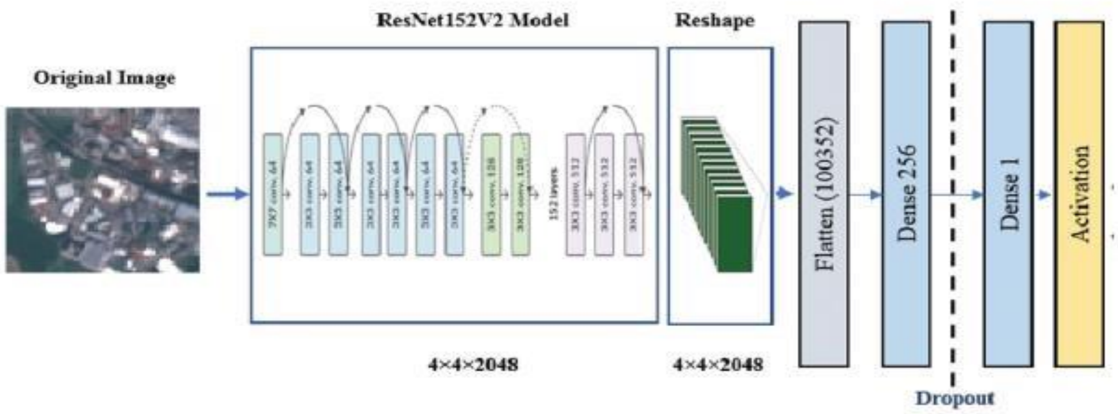

Figure 2. ResNet152V2 Model Architecture

skip connection helps to prevent the vanishing gradient problem and allows for the efficient training of very deep neural networks. 4. Global average pooling: The output is sent through a layer of global average pooling after the convolutional layers and residual blocks. In order to create a single feature vector for each channel, this layer averages the feature maps over all of their spatial dimensions. 5. Fully connected layer: ResNet152V2's last layer, which converts feature vectors into class probabilities, is a fully connected layer. Summary In conclusion, the ResNet152V2 architecture is an extremely deep convolutional neural network that effectively trains deep neural networks by using residual connections. Convolutional layers, residual blocks, global average pooling, and a fully linked layer are all components of the design.

System Architecture

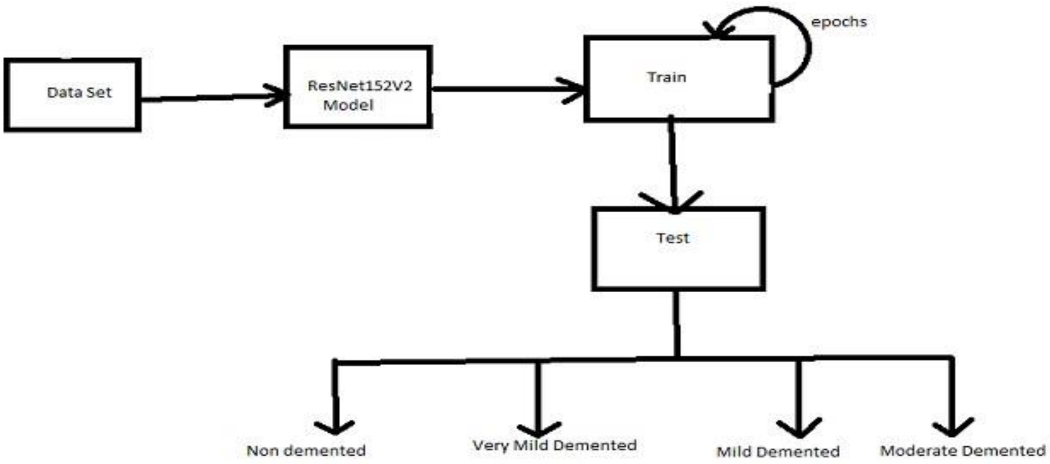

Figure 3. System Architecture

II. METHODOLOGY

The following actions are part of the suggested system: employing a deep learning-based strategy to (1) takes the MRI (2) Processing The MRI images or uploaded dataset with trained dataset ResNet152V2, and (3) it classifies that uploaded dataset With a unique dataset we gathered, we optimize the ResNet152V2 architecture for classification of Alzheimer's disease as four stages like non demented and very mild demented and mild demented moderate demented. The Trained model gave us accuracy of 91+

III. RESULT

In this project we trained, pretrained ResNet152V2 model with brain MRI images to diagnose the Alzheimer's disease. The trained model is predicting the unseen brain MRI image accurately as expected. It is classifying the brain MRI image into non demented or very mild demented or mild demented or moderate demented accurately. It has accuracy rate of 91.14%. Our model is predicting with high accuracy rate.

Some of the results we got for classification of alzheimer's disease a are depicted below

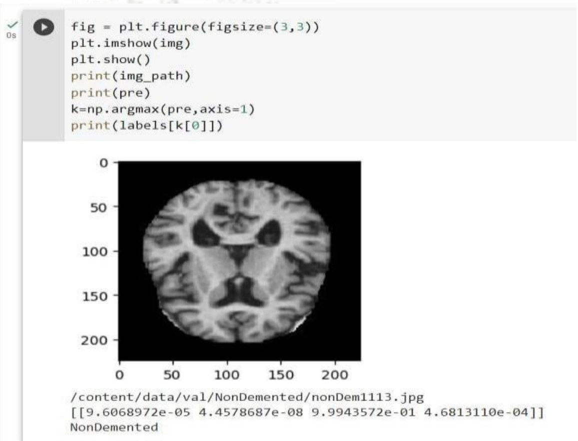

Fig 4. Non Demented

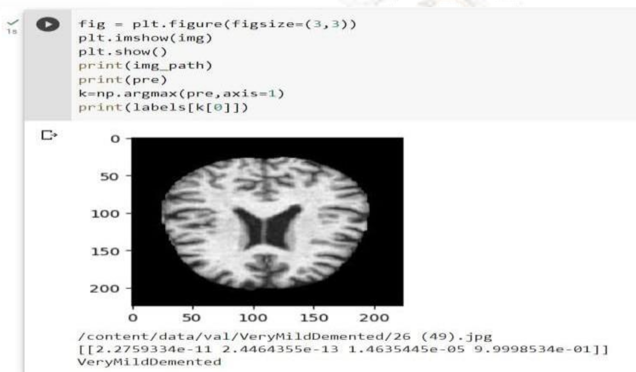

Fig 5. Very Mild Demented

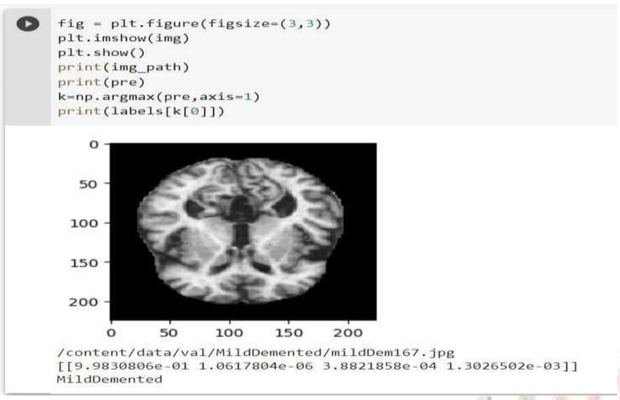

Fig 6. Mild Demented

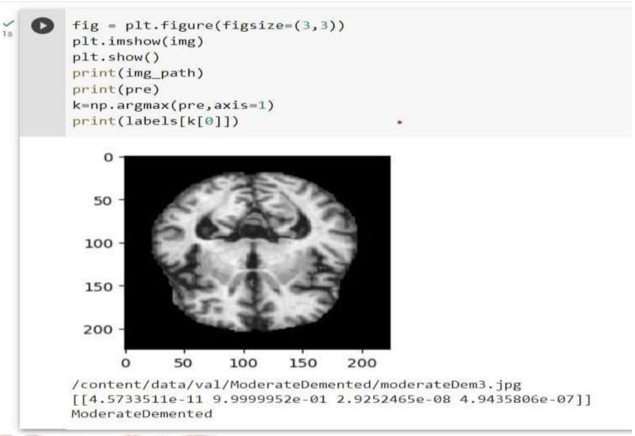

Fig 7. Moderate Demented

IV. CONCLUSION

In this project we trained, pretrained ResNet152V2 model with brain MRI images to diagnose the Alzheimer's disease. The trained model is predicting the unseen brain MRI image accurately as expected. It is classifying the brain MRI image into non demented or very mild demented or mild demented or moderate demented accurately. It has accuracy rate of 91.14%. Our model is predicting with high accuracy rate.

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