DEEP LEARNING FOR ALZHEIMER'S DISEASE EARLY STAGE DETECTION

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Abstract

A neurologic ailment that causes the brain to shrink and brain cells to die, Alzheimer's disease (AD) is progressive. Although there is no known cure for AD, medicines may momentarily lessen or delay the progression of symptoms. As a result, stopping the progression of AD depends heavily on early stage identification. The major goal is to provide a complete framework for early AD diagnosis and medical image categorization for different stages of AD. We used transfer learning to pre-trained models like VGG 16 and ResNet 50 as well as bespoke CNN when using the deep learning technique. There are four categorization metrics in use: Moderate AD might be considered demented, very mildly demented, moderately demented, or not demented. We have developed a web application for remotely assessing and testing AD in order to make it more comfortable for patients and physicians. Based on the AD spectrum, it also establishes the patient's AD stage. In order to classify AD and its prodromal phases, this project incorporates the MRI data obtained from Kaggle. This experiment demonstrates that ResNet 50 and VGG16 have been calibrated to an accuracy level of 95% and 84%, respectively. Also, we created a unique scratch model that classified the 2D multi-class AD stage with an accuracy of 93%.

Keywords: Convolutional neural network (CNN), deep learning, transfer learning, brain MRI, medical picture categorization

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1. Introduction

According to the Alzheimer's Association, AD is the sixth most common cause of mortality in the country. A third of elderly people pass away from AD or another type of dementia. Dementia strikes someone somewhere in the globe every three seconds. The most prevalent type of dementia in seniors is AD. A brain illness called dementia severely impairs a person's capacity for memory, mental control, and language use. The condition still has no known treatment as of yet. The proportion of persons afflicted by AD according to their ages is shown in the figure below, and it can be seen that those who are older are more impacted.

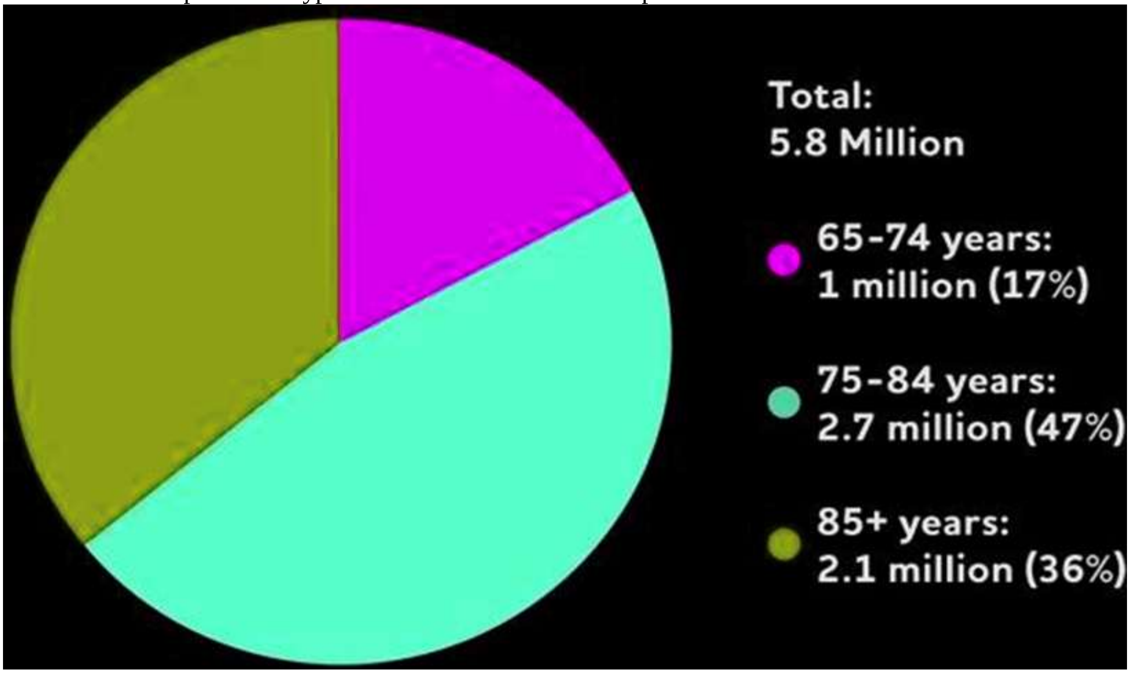


Figure 1: A percentage of those with AD, broken down by age, in 2020

Therefore, a great deal of work has gone into creating methods for AD early detection in order to slow the disease's progression. The main issue facing Alzheimer’s experts is that no proven therapy exist for AD thus far. Despite this, the available treatments for AD can reduce symptoms or halt their development. Hence, the early diagnosis of AD in its prodromal stage is crucial. In this study, we propose a model for diagnosing AD that focuses on deep learning techniques and convolutional neural networks for the classification of Alzheimer's in its early stages using magnetic resonance imaging (MRI). The aim is to correctly classify patients that contain AD and who do not have the disease with high precision. This medical picture categorization is applied utilising three approaches. The first technique uses a customised CNN model with 12 layers of Convo 2D and 12 layers of Max Pooling. Convolutional neural networks (CNN) and a few pre-trained models were used in the second method. CNN is a sort of feed forward artificial neural network. It is a CNN that is 16 layers deep; you may load a pre-trained version of the network trained on more than a million photos from the ImageNet database. ResNet 50 is another model that was employed. It is a ResNet model variant with 48 Convolution layers, 1 MaxPool layer, and 1 Average Pool layer. In addition, a web application for checking Alzheimer's is suggested using the final qualified architectures. It enables doctors and patients to remotely monitor AD, identify the AD stage, and provide patient advice in line with the AD stage.

2. Literature Review:

- In this paper(Islam & Zhang, 2017), CNN is applied on Desert spring 3 dataset in Information gave in X-ray by Desert garden 3. Proposed design contains 5 Conv2D layers and 5 MaxPooling layers alongside 2 thick layers. The preparation informational index was 75% and the approval informational index was 25%. Accuracy is exceptionally useful on the grounds that they need to be certain of gauge, since it lets us know the number of the qualities expected as sure are really sure. They got a normal of 97% of accuracy and review.
- Convolution brain network-based Alzheimer's sickness grouping utilizing half breed improved free part examination based portioned dark matter of T2 weighted attractive reverberation imaging with clinical valuation.(Taheri Gorji & Kaabouch, 2019)
- This study describes a method for separating the grey matter from an MRI of the human brain and utilising CNN to classify the data. A Gaussian filter is utilised to improve the

voxels, and the skull stripping technique is employed to eliminate unimportant tissues. Gray matter that had been segmented was the CNN's input. Using the suggested method, clinical valuation was carried out. They achieved 90.47% accuracy, 86.66% recall, and 92.59% precision in comparison of their system with physician decision.(Mehmood et al., 2020)

- In this paper, the execution is finished utilizing picture division. How much extension will group the patient as Sound patient, first stage Promotion, second Stage Promotion, Gentle Mental hindrance cases. Precision: 0.9166. Primary drawback the investigation was performed on just 12 X-ray test of Alzheimer's infection Patient Analysis utilized the neuroimaging information.
- A clever profound learning based multiclass characterization technique for Alzheimer's sickness location utilizing cerebrum X-ray information. In this paper(Helaly et al., 2022), characterization is finished on the Desert spring data set. In this methodology, a profound CNN network is carried out considering the Origin V4 organization. The model order X-ray pictures into four classes that are non-deranged, exceptionally gentle, gentle and direct Alzheimer's. The precision acquired in this approach is 73.75%. This approach is computational exorbitant as the exactness got is exceptionally low. Carried out the proposed profound CNN model for Alzheimer's illness discovery and grouping utilizing Tensorflow (Al-Khuzaie et al., 2021) and Python and utilized 70% as preparing information, 10% as approval information and 20% as test information. The ongoing exactness of the technique is 73.75%.(Odusami et al., 2021)
- A profound learning approach for determination of gentle mental disability in view of X-ray pictures In the paper, the CNN with changed design was utilized to get the excellent highlights from the cerebrum X-ray to characterize individuals into solid, early gentle mental weakness (EMCI), or late gentle mental hindrance (LMCI) gatherings. The outcomes showed the order between control typical (CN) and LMCI bunches in the sagittal view with 94.54 precision. The proposed technique yielded a 94.54% grouping precision (94.84% F-score and 99.40% AUC) for CN versus LMCI, 93.96% order exactness for the sets of CN/EMCI (94.25% F-score and 98.80% AUC), and 93.00% characterization precision for the order of the sets of EMCI/LMCI (93.46% F-score and 98.10% AUC) which every one of the previously mentioned results accomplished from the sagittal view.(Odusami et al., 2021; Patro & Nisha, 2019)

2. Methodology

Early recognition of Alzheimer's Illness assumes a vital part in forestalling and controlling its encouraging. We want to propose a start to finish model for early identification and grouping of stages in Alzheimer's sickness. There will be far reaching clarification of proposed model work process, preprocessing calculations and profound learning approaches in the following subsections. The proposed system includes five stages, which are as per the following:

Stage 1: Information Procurement:

The dataset containing all train and test information is gathered from Kaggle Alzheimer's dataset in 2D , X-ray methodology.(Jiang et al., 2020) This comprises of 6400 pictures each isolated into the seriousness of Alzheimer's. All pictures were determined with a size of 107 x 238 pixels in 2D organization. Both train and test dataset comprised of four indexes:

1. Mild Sick - 896 pictures
2. Very Gentle Sick - 2240 pictures
3. Non Sick - 3200 pictures
4. Moderate Sick - 64 pictures

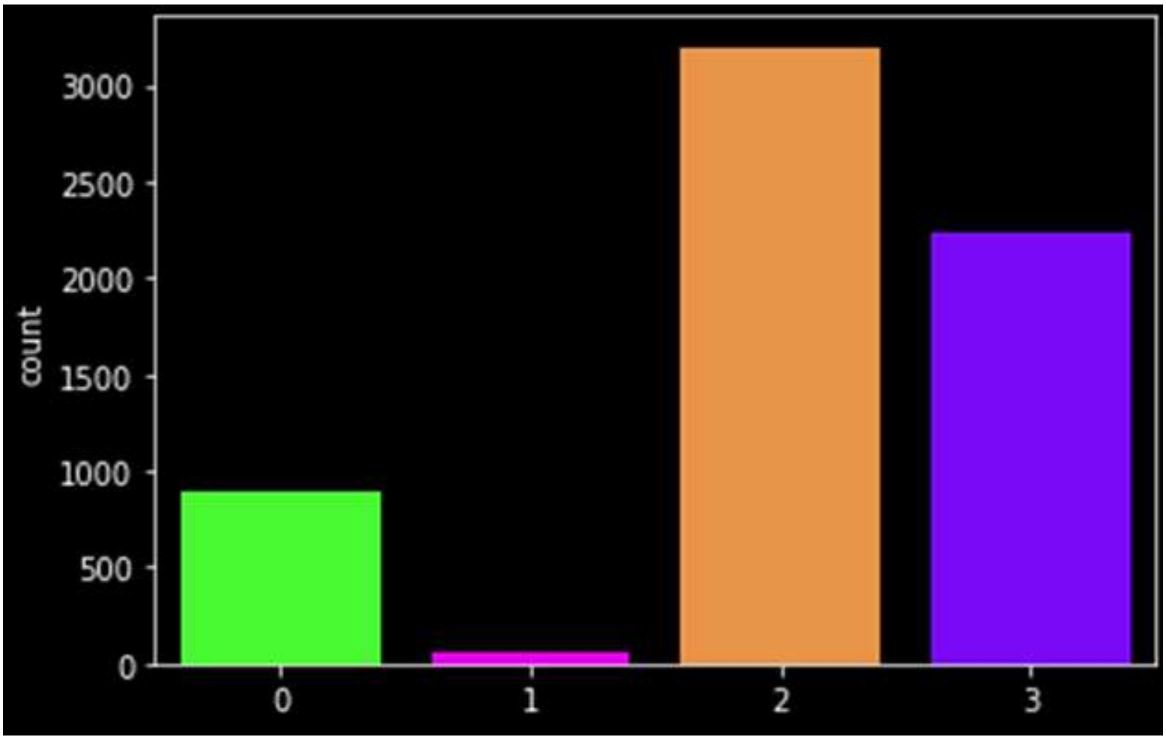


Figure 2: Information imported

Stage 2: Information PRE-Handling: The gathered information comprised of lopsidedness information of various classes. In the dataset of X-rays the train information comprised of cross-area pictures and test information were longitudinal pictures, which gave extremely less precision . To beat this issue, we rearranged the train and test information physically. Then, at that point, split it into train and test at a proportion of 70:30 separately .This gave us 4480 train pictures dataset and 1920 test pictures dataset. The dataset is then handled, standardized, normalized, resized to 224 x 224 pixels and switched over completely to a reasonable organization.(Ali et al., 2020)

Stage 3: Attractive Reverberation IMAGING (X-ray) Grouping : In this step, four phases of Promotion range (I) Gentle Hysterical , (II) Exceptionally gentle sick , (III) Nondemented ,and (IV)Moderate Psychotic Promotion are multi-ordered. This Grouping model is finished utilizing three techniques. First strategy relies upon CNN model which is our custom model. This CNN design is worked without any preparation. Next strategy is utilizing Move learning approach by pre-prepared models - VGG16 and RESNET50.(Cao et al., 2020)

Stage 4: Assessment Step: The three strategies and the CNN structures are assessed by execution measurements utilizing accuracy and review. We likewise have a correlation table in the outcomes segment.(Chen et al., 2021)

Stage 5: Application Step: Considering the proposed qualified models, an Alzheimer's checking web application is proposed. It helps specialists and patients to check Promotion from a distance, decides the Alzheimer's phase of the patient in view of the Advertisement range, and prompts the patient as per its Advertisement stage. In this web application we can transfer any X-ray picture ,it recognizes and shows the phase of Promotion.

4. Proposed classifications techniques

Convolutional Neural Networks:

Convolutional Neural Networks are very effective in reducing the number of parameters without losing on the quality of models. Feature extraction, feature reduction, and classification are three essential stages where traditional machine learning methods are composed. By using CNN, there is no need to make the feature extraction process manually. Its initial layers' weights serve as feature extractors, and their values are improved by iterative learning. CNN gives higher performance than other classifiers.

Convolutional Neural Networks (CNN):

CNN are exceptionally viable in diminishing the quantity of boundaries without losing on the nature of models. Highlight extraction, include decrease, and grouping are three fundamental stages where conventional AI strategies are created. By utilizing CNN, there is compelling reason need to make the component extraction process physically. Its underlying layers' loads act as element extractors, and their qualities are worked on by iterative learning. CNN gives better execution than different classifiers.

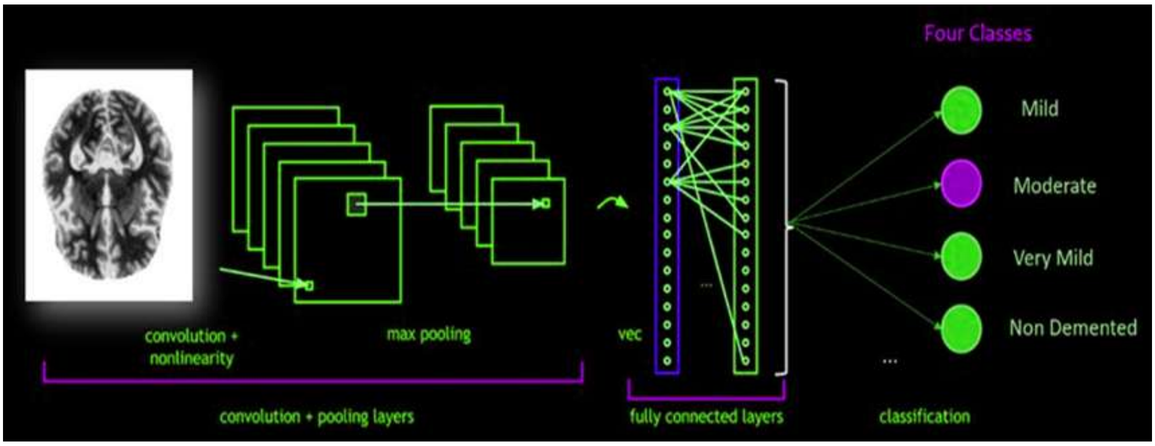


Figure 3: CNN Model

This model comprises of four layers of 1. 2D convolutional + Relu layer, 2.Max pooling layer, 3.Flatten layer 4.Dense layer . Convolutional brain networks apply a channel to an information picture to make an element map that sums up the presence of recognized highlights in the info. When an element map is made, we can pass each worth in the component map through a nonlinearity, for example, a ReLU The last result of our convolutional layer is a vector. Convolutional layer plays a straightforward direct change over input information, this doesn't have such a lot of force for muddled errand, for example, picture net order To defeat what is happening ReLU is the powerful enactment capability to forestall that. As Relu is the least difficult nonlinear capability it is proficient for calculation. The numerical meaning of the ReLU capability:

$$f(x) = \max(0, x)$$

or on the other hand communicated as a piece-savvy characterized capability.

$$f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

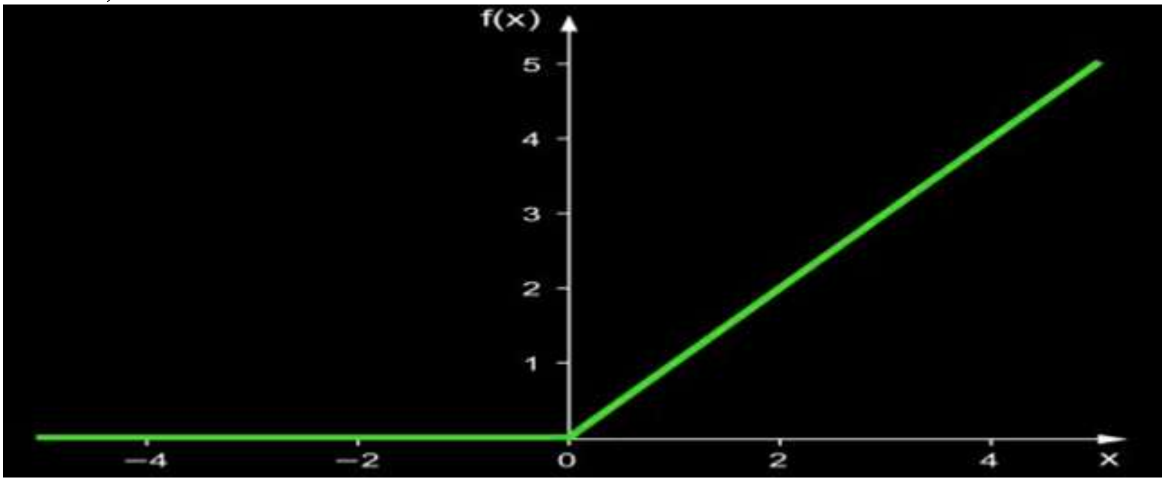


Figure 4: Relu

Next Max-Pooling Layer is added to a model. Max-pooling diminishes the dimensionality of pictures by lessening the quantity of pixels in the result from the past convolutional layer. Max pooling extricates the main highlights like edges though, normal pooling removes includes so without a hitch. Max pooling is better for extricating the outrageous highlights. It helps in Aspect Decrease and Rotational/Position Invariance Element Extraction. Presently next we added a Straighten layer to change over the result of the convolutional part of the CNN into a 1D component vector . This activity is called smoothing. It gets the result of the convolutional layers, then it straightens all its design to make a solitary long element vector to be involved by the thick layer for the last order. Next finally phase of model we add thick and dropout layer. A Thick Layer is utilized to group picture in view of result from convolutional layers. A thick layer addresses a lattice vector increase. So we get a m - layered vector as result. A thick layer hence is utilized to change the elements of our vector.

VGG16: VGG is an abbreviation of Visual Calculation Gathering, which is a profound convolutional brain network model that got second spot in the ILSVRC-2014 contest with 92.7%

grouping precision .This model researches the profundity of layers with a tiny convolutional channel size (3 × 3) to manage huge scope pictures. The design of VGG16 is depicted as follows:

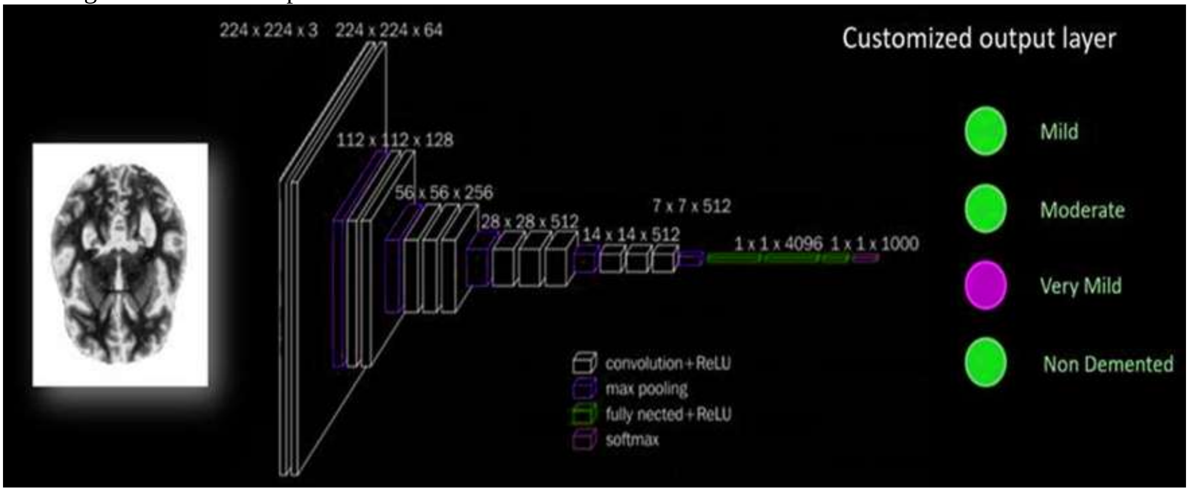


Figure 5: Approach of utilizing VGG

VGG16 in our model is made from 13 convolutional layers, 5 max-pooling layers, and 3 completely associated layers. Consequently, the quantity of layers having tunable boundaries is 16 (13 convolutional layers and 3 completely associated layers). For this reason, the model name is VGG16. The quantity of channels in the main block is 64, then, at that point, this number is multiplied in the later blocks until it comes to 512. This model is done by two completely associated secret layers and one result layer. The result layer comprises of 1000 neurons relating to the quantity of classifications of the Imagenet dataset.

ResNet50: For research reason we needed to notice the exhibition of ResNet50 and contrast it and VGG16 and CNN. ResNet50 is utilized to fabricate networks contrasted with other plain organizations and all the while track down an improved number of layers to discredit the disappearing inclination issue. The engineering of ResNet50 has 5 phases as displayed in the graph beneath. Consider the info size as 224 x 224 x 3 so every ResNet design plays out the underlying convolution and max pooling utilizing 7×7 and 3×3 bit measures separately. Subsequently, Stage 1 of the organization starts and it has 3 Remaining blocks containing 3 layers each. The size of parts used to play out the convolution activity in every one of the 3 layers of the block of stage 1 are 64, 64 and 128 separately. We get the size of info diminished to half. As we progress starting with one phase then onto the next, the channel width is multiplied, and the size of the info is diminished to half. At last, the organization has a Normal Pooling layer followed by a completely associated layer having 1000 neurons.

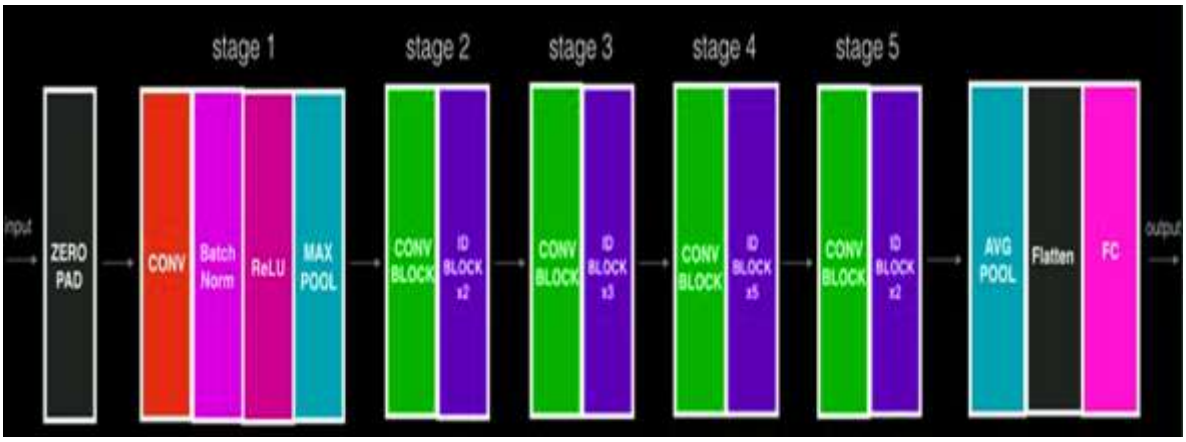
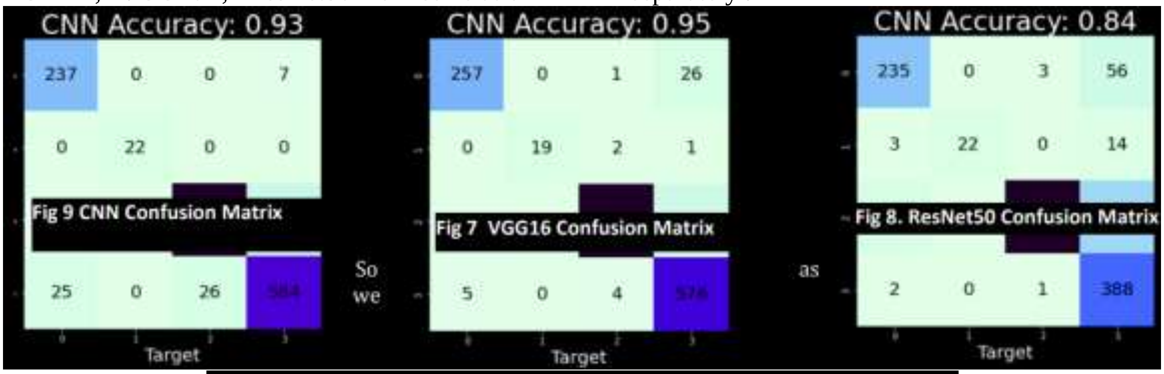


Figure 6: ResNet50 engineering

4. Test Results and Model Assessment:

The proposed models think about various circumstances. The trial results are examined concerning six execution measurements: precision, misfortune, disarray lattice, F1 Score, review, precession. We have broken down them consecutively, Following are disarray frameworks of CNN , VGG16 , ResNet50 for correlation separately .



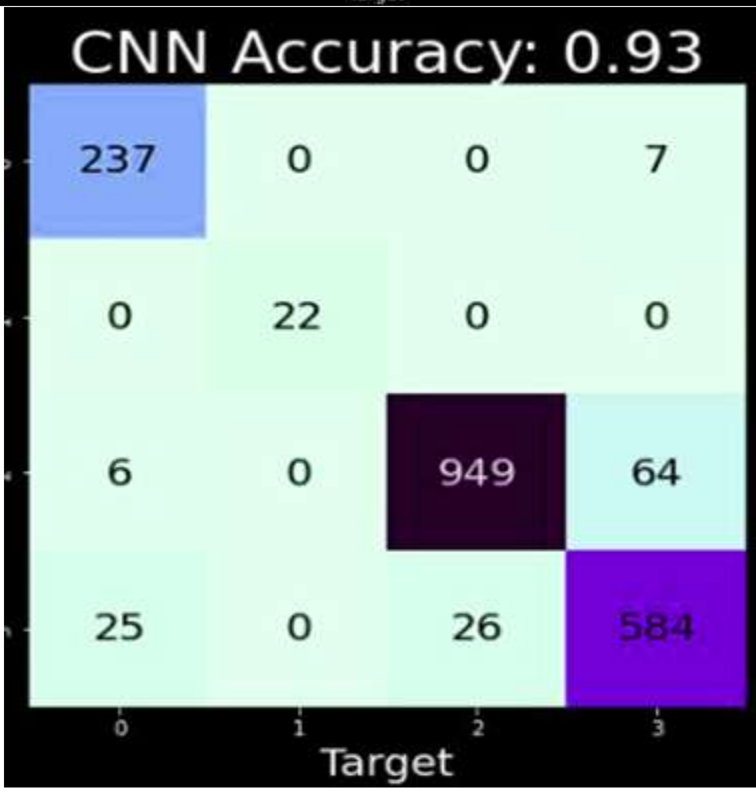


Figure 7: Confusion matrix of CNN model

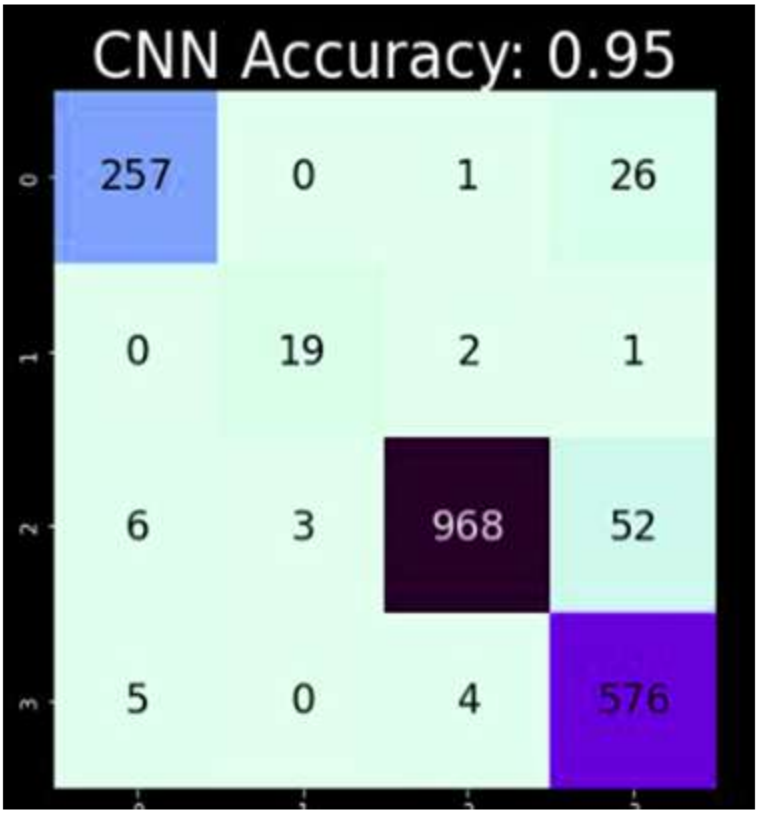


Figure 8: Confusion matrix of VGG16 model

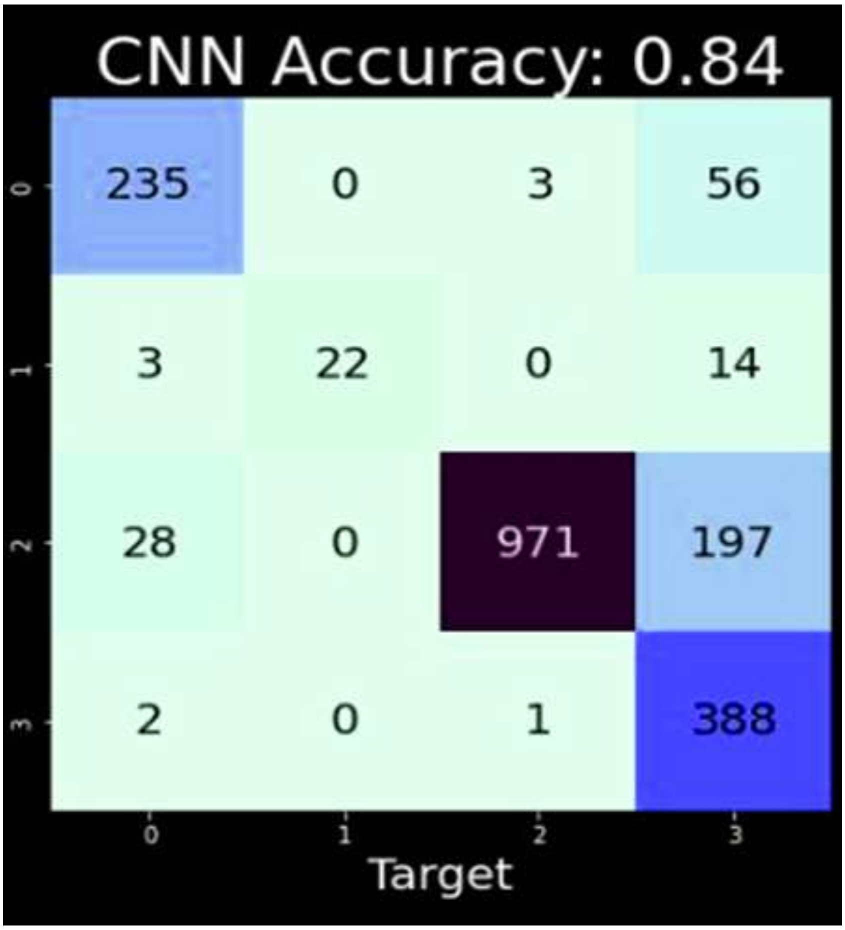


Figure 9: Disarray network of ResNet 50 model

So as we see that proposed move learning model VGG16 accomplishes most noteworthy precision of 95%. The custom CNN model accomplished second most noteworthy precision of 93%. The proposed ResNet50 model accomplishes 84% exactness. For multi-class and paired clinical picture arrangement techniques applied, we propose straightforward CNN design models called Custom CNN, VGG16, ResNet 50. As per the precision metric, these models will be assessed by contrasting their presentation with other cutting edge models, as displayed in Table underneath

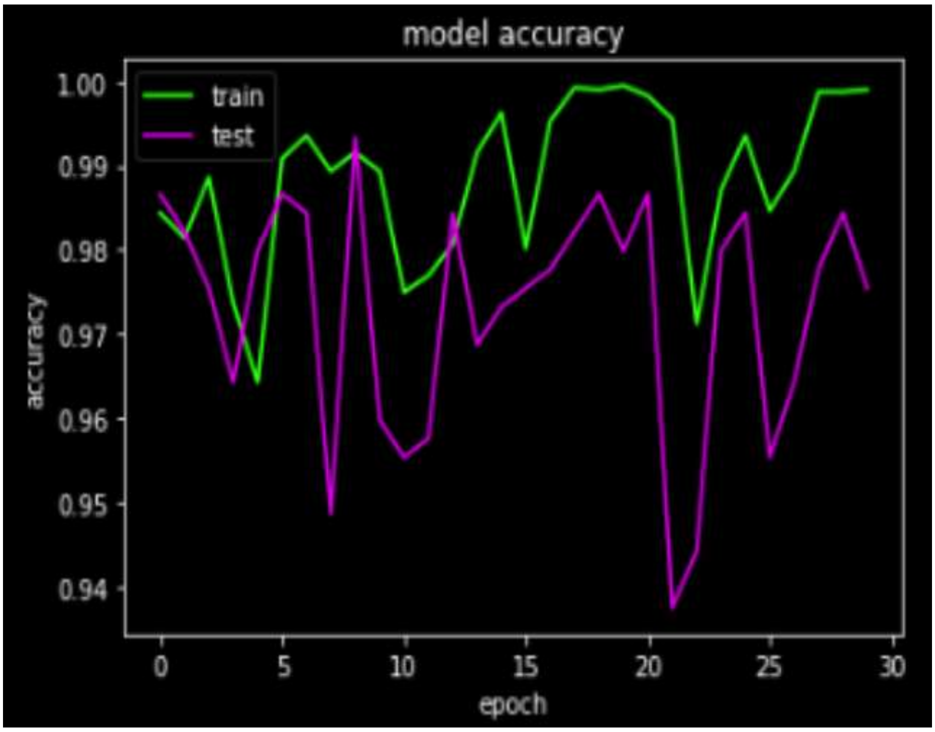


Figure 10 Preparation and approval exactness of CNN Model

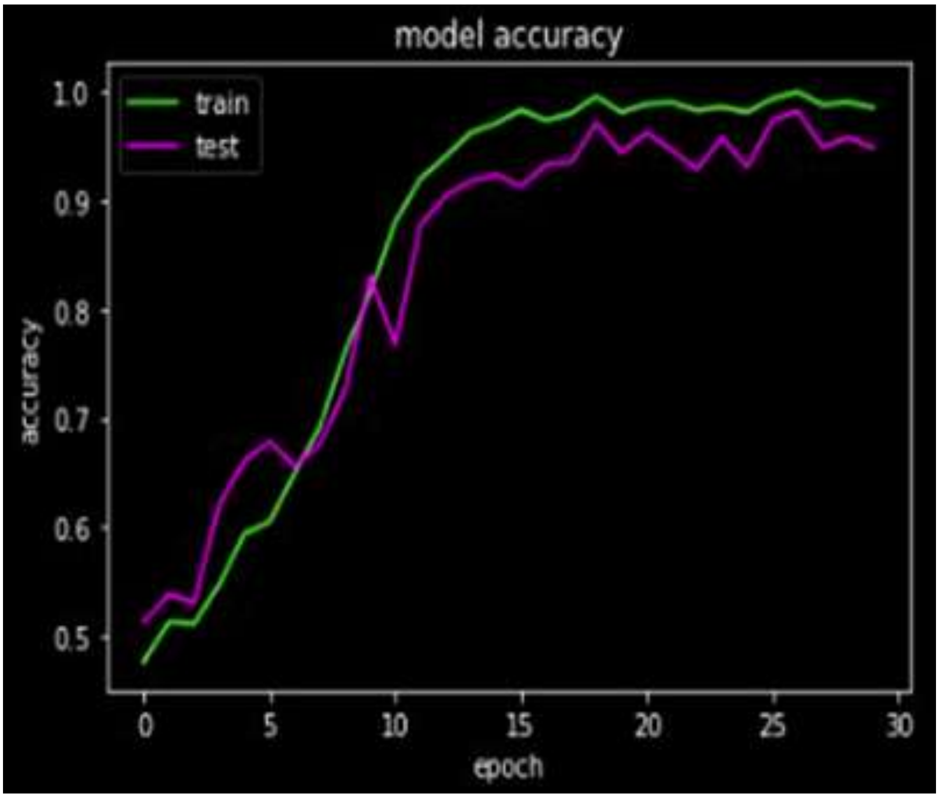


Figure 11 Preparation and approval precision of VGG16 Model

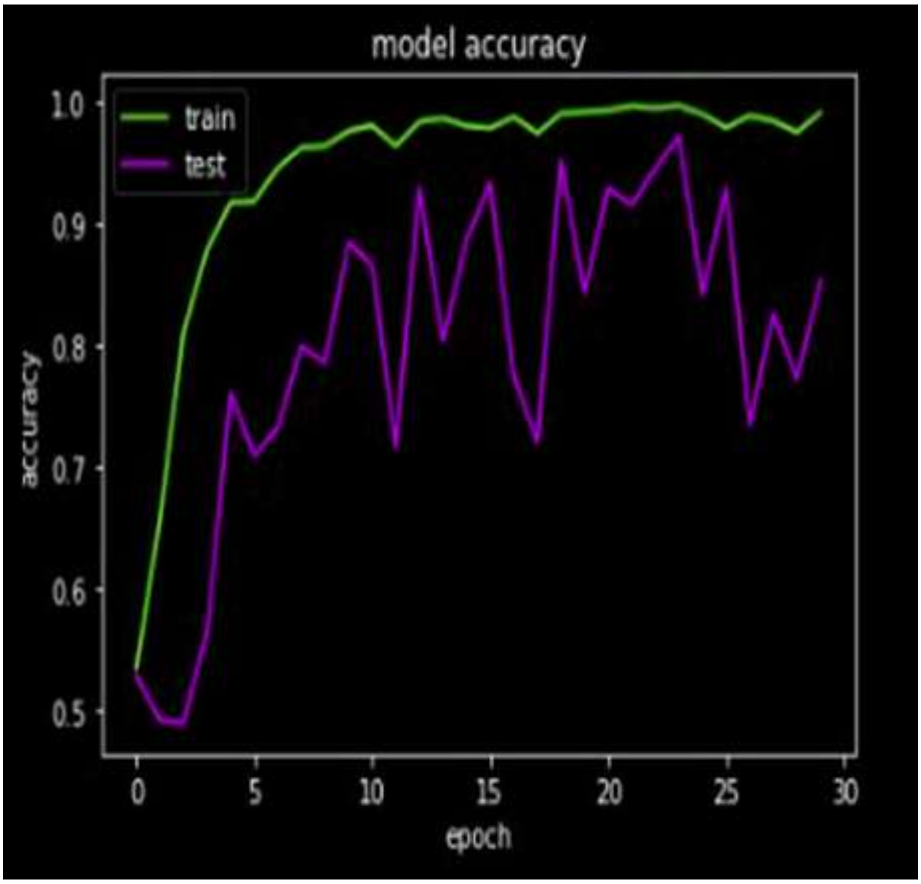


Figure 12 Preparation and approval exactness of ResNet 50 Model

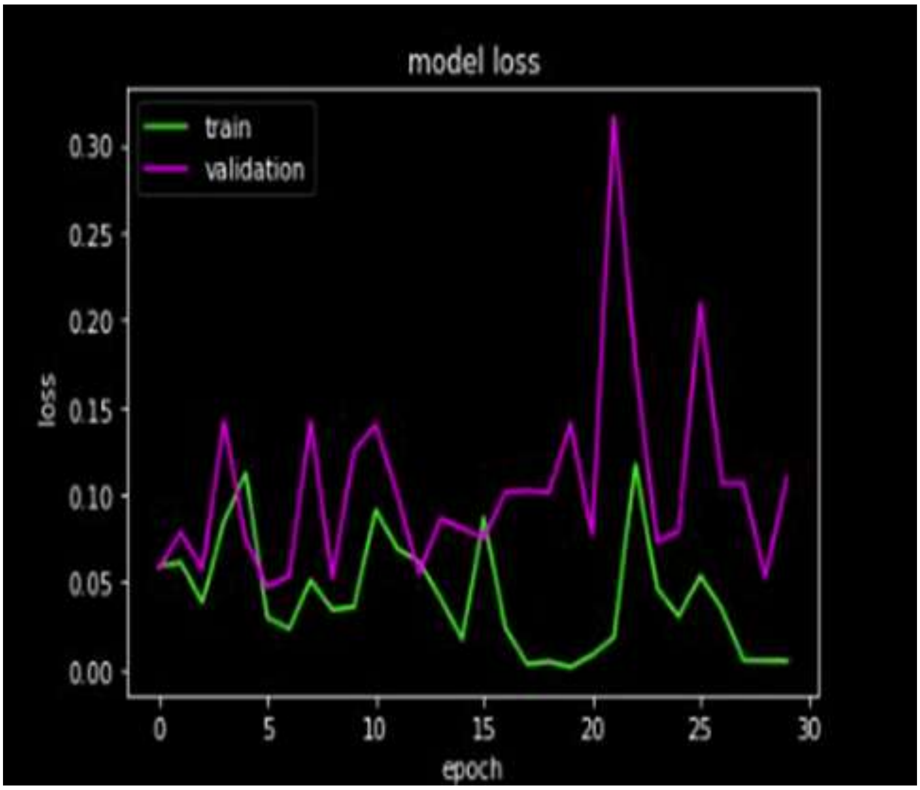


Figure 13.Training and approval loss of CNN Model

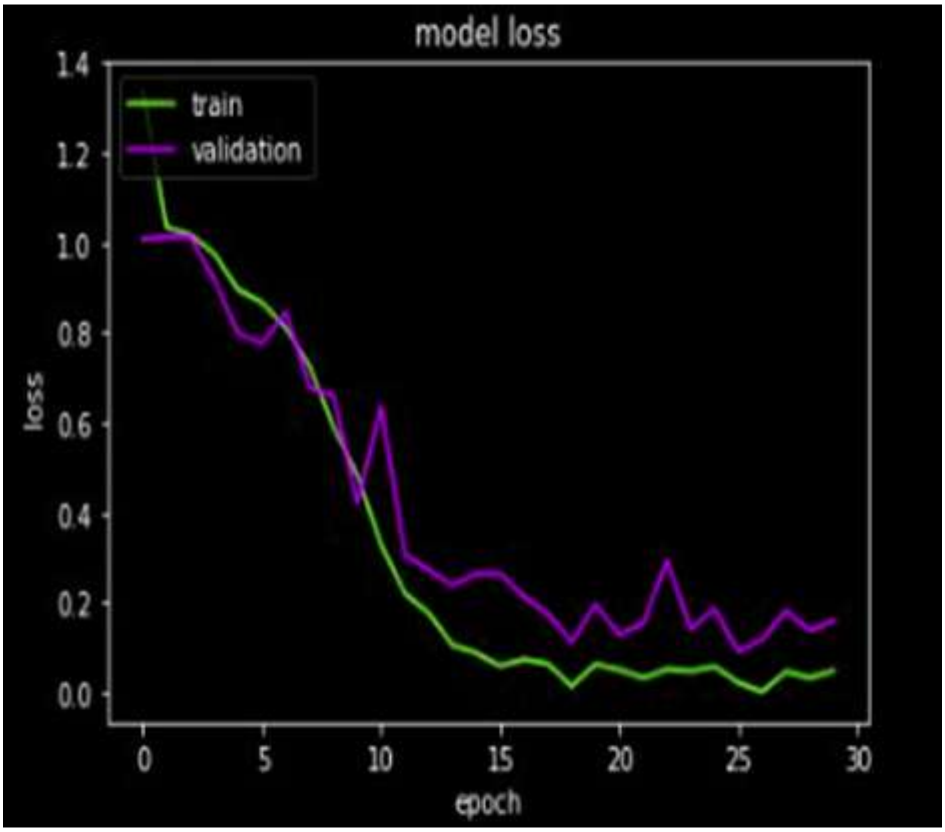


Figure 14 Preparation and approval deficiency of VGG16 Model

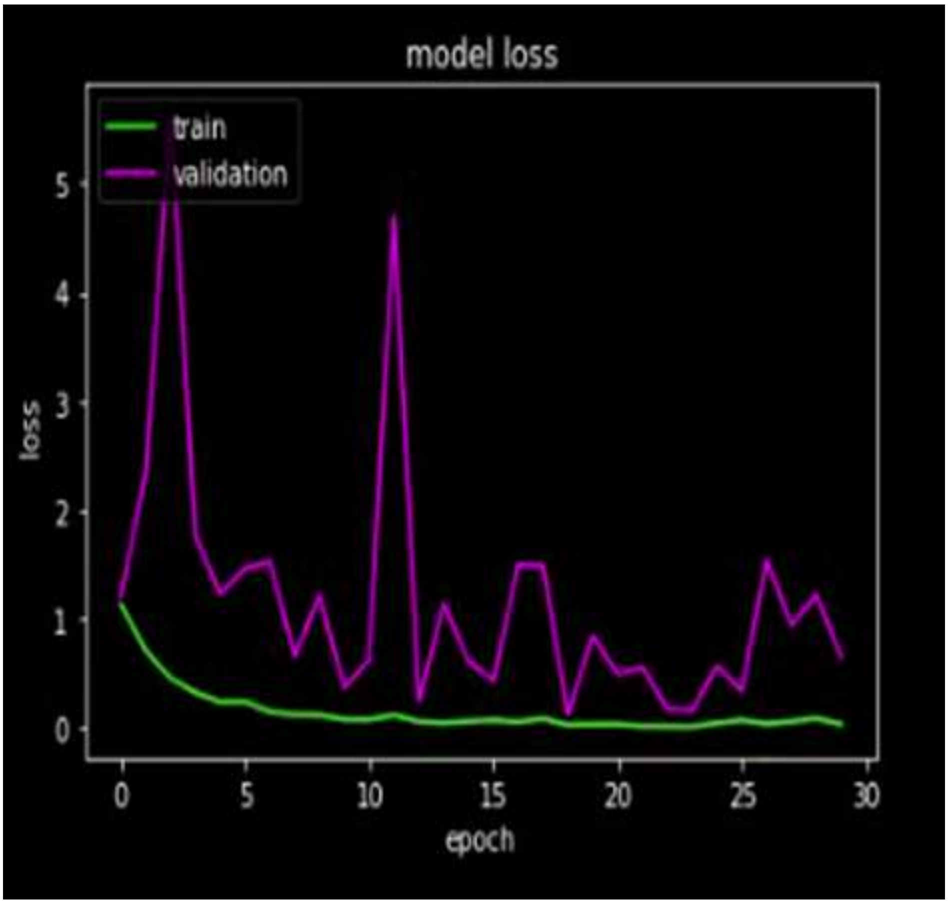


Figure 15 Preparation and approval loss of ResNet 50 Model

In this manner, from the exact outcomes, it is demonstrated that the proposed models are appropriate straightforward designs that decrease computational intricacy, memory prerequisites, over fitting, and give reasonable time. They likewise accomplish exceptionally encouraging precision for double and multi-class arrangement. In Figure 10, Figure 11, Figure 12 we have contrasted Preparing and approval exactness and regard to prepare and test information for CNN,VGG16 and ResNet 50 models. In Figure 13, Figure 14, Figure 15 we have contrasted Preparing and approval misfortune and regard to prepare and test information for CNN, VGG16 and ResNet 50 models.

Looking at Accuracy, Review and F1 Score for the proposed models - CNN, VGG16 and ResNet50 model

Models	**Precision**	**Recall**	**F1 Score**
Custom CNN Model	93%	93%	93%
VGG16	95 %	95%	95%
ResNet 50	87%	84%	83%

Figure 16 Correlation of the presentation measurements of the three proposed models (CNN model, VGG16 model, ResNet 50 model)

Alzheimer Checking Web Administration:

Considering the Coronavirus pandemic, it is challenging for individuals to go to emergency clinics occasionally to keep away from social events and diseases. Consequently, a web administration in view of the proposed CNN models is laid out. It plans to help patients and specialists in diagnosing and checking Alzheimer's sickness from a distance by sharing their X-rays. It likewise decides in which Alzheimer's stage the patient experiences considering the Promotion range. First, we need to open the web application and pick the X-ray archive from our nearby PC. After the patient transfers the X-ray picture, the program arranges the X-ray as having a place with one of the periods of Alzheimer's sickness ((I) Gentle Maniacal, (II) Extremely gentle hysterical, (III) Noncrazy, and (IV)Moderate Deranged). Subsequent to clicking Foresee the screen shows the Alzheimer's Stage . In addition, the application directs the patient with counsel depended on the ordered stage.

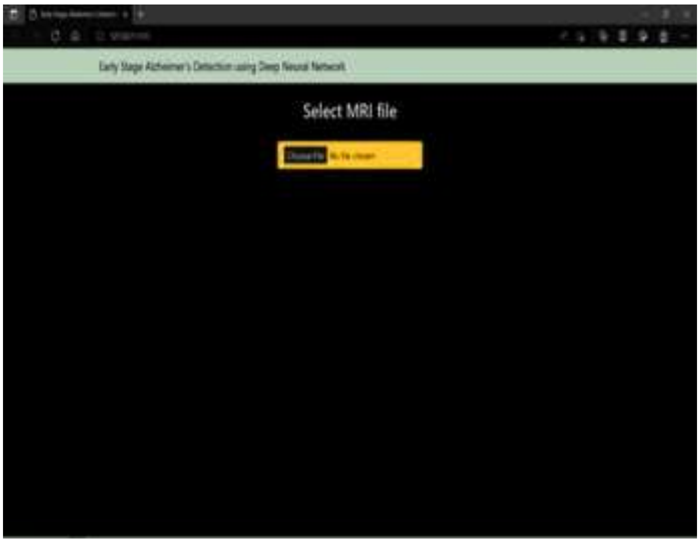


Figure 17: Transfer the report in site page

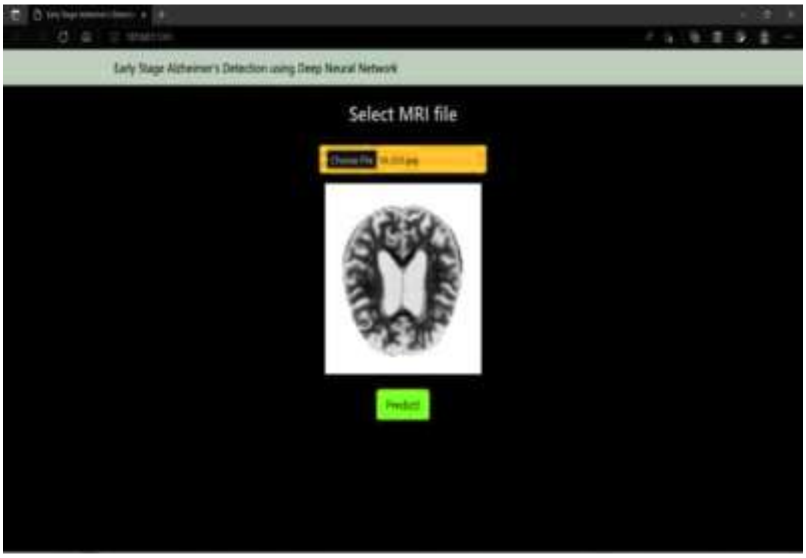


Figure 18: Snap on the foresee

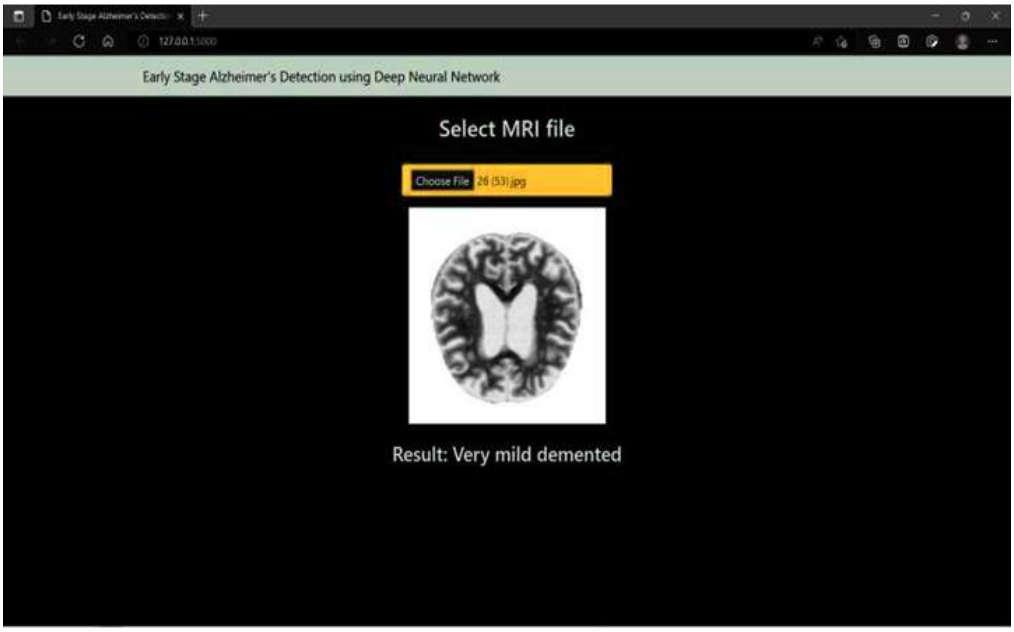


Figure 19: Shows the outcomes

5. Future Directions:

1. We can have the web administration and make it simple available.
2. Make a Chatbot with the web application for direct meeting.
3. Add different elements like booking meeting with specialist, checking close by clinics, side effects checker, and simple access with your clinical records.
4. Add leftover portion and warnings.
5. Doctor and patient discussion utilizing video conferencing.

6. Conclusion

In this report we concentrated on different profound brain organizations and we will utilize them to analyze Alzheimer's sickness in its beginning phase . We checked on the two convolutional brain networks pre-prepared on the ImageNet dataset completely and a custom CNN model worked without any preparation. As we noticed the exploratory outcomes ,VGG16 accomplishes the most noteworthy precision of 95% . We will involve VGG16 as our base model since it has best execution. Thus, the VGG19 model is adjusted and utilized for multi-class clinical picture groupings. Scratch model and Resnet50 likewise accomplish the promising exactness of 93% and 84% separately. The exploratory outcomes demonstrate that the proposed models are appropriate basic designs that diminish computational intricacy, memory prerequisites, over fitting, and give sensible. Also, Alzheimer's checking web application is proposed utilizing the last qualified proposed designs. It helps specialists and patients to check Promotion from a distance, decides the Alzheimer's phase of the patient in view of the Promotion range, and prompts the patient as per its Promotion stage.

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