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Deep Learning- Based Classification for diagnosis of Alzheimer's Disease from medical images.

Preetinanda Parida , Yogesh Kumar Rathore

PG(M.tech) Scholar Department of Computer Science Engineering Shri Shankaracharya Institute of Professional Management and Technology ,Raipur
pritiparida109@gmail.com

Assistant Professor Department of Computer Science Engineering Shri Shankaracharya Institute of Professional Management and Technology ,Raipur
y.rathore@ssipmt.com

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Abstract

Alzheimer's disease (AD) is a neurological disorder that leads to gradual memory loss, psy- chosis, and delusive thoughts. In America, 5.1 million people are affected by AD. There is no proper healthcare facility to AD. AD can regulate requirements in the medical field. In the past year, Alzheimer's has consistently disrupted the lives of countless individuals. Therefore, developing targeted medications is crucial to slow down the progression of the disease and minimize the extensive damage that can occur in the brain. To detect the initial AD is time taking and data gathering process is expensive. Networks are naturally exact more estima- tion person also assisted the medical opinion of the network is used since artificial factors are not enslaved to them. Based on earlier investigations on AD such as MRI scans, bio-marker, and digital information are developed for removing the Magnetic resource imaging scan to this disease. Humans are unbalanced in deciding can be alerted or not ((Janghel *and* Rathore (2021)), (Helaly et al. (2021)), (Odusami et al. (2021))). Additionally, time was analyzed quickly for improved human communication than for automatically decreased AD analysis. The overall cost was reduced by proving a better exact outcome. i.e., whether the patient is forecasted insane by evaluating Magnetic resource imaging scans, the method implemented for forecasting. we can reach the best precision.

KEYWORDS- CNN

1.Introduction

Most people with dementia have Alzheimer's disease. Statistics on the maturing of the global populace predict that the proportion of the population over 65 will continue to rise. The el- derly population is growing, and with it the prevalence of Alzheimer's disease

(AD), a form of dementia. Both the direct clinical costs and the indirect social costs of caring for people with AD are on the rise. Dementia sufferers and their loved ones have it tough because of the general public's lack of knowledge about Alzheimer's disease.

According to this strategy, lowering or eliminating bias against people with Alzheimer's dis- ease begins with raising awareness of the condition. The name ”Alzheimer's Disease,” origi-nally used in 1910, was coined to honour the German psychiatrist Alois Alzheimer, who first brought the disease to the attention of the medical community. Science and medicine have come a long way in a short amount of time, and as a result, there are now better ways to di- agnose and treat AD ((Nawaz et al. (2021)), (Eroglu et al. (2022)), and (Tuan et al. (2022)). Future path-tracking research on illness-altering systems at the onset of illness is anticipated, despite the fact that the ebb and flow of high-impact treatment is constrained. A person is said to have dementia if they are experiencing a decline in cognitive ability to the point where it causes problems with performing routine tasks of daily living. Memory loss is often cited as one of the earliest indicators of Alzheimer's disease (AD). The patient's condition deteriorates and linguistic and perceptual problems become more noticeable as the disease progresses.The decline is caused by the death of nerve cells in the brain, which causes a slow but steady loss of mental capacity. Furthermore, AD symptoms arise similarly to other forms of dementia. This is why there are different names for Alzheimer's disease. A million households and national healthcare systems have been impacted by AD's socioeconomic difficulties. The weight of this disease's permanent effects and lack of therapy has fallen heavily on the families of those who suffer from it [14].

2.Literature Review

In the early analysis of AD, a DL-based deep CNN System was developed by (Janghel and Rathore (2021)). Before employing VGG-16 using feature extraction, three images are resized using 3D to 2D conversion. Eventually, for categorizing Linear Discriminate, SVM, K means clustering, Decision tree neural networks, and K means clustering, can be utilized. While comparing with evaluation matrices like accuracy, specificity, and sensitivity, the suggested yield greater performance. To detect the initial stage of AD, Deep Learning based CNN was developed by (Helaly et al. (2021)). DL approaches and CNN can be used to prove a throughout AD detection at the initial stage and classify the (E2AD2C) structure. The E2AD2C structure for medical image also classifying also the AD diagnosis is suggested. According to DL, CNN design is an advanced structure. There are two methods that may be used to classify medical images. First, a simple convolutional neural network architecture from the Alzheimer's Disease Neuroimaging Initiative database is used. This architecture is made for both two- and three-dimensional skull images. The second method uses transfer learning to make use of pre-trained models. With this method, the process of classifying medical images may make use of existing model structures and their learned characteristics.

For the work being done to create a ground-breaking Alzheimer's disease treatment, this chapter has laid a solid foundation. The classification and segmentation of Alzheimer's disease has been the subject of numerous author proposals. Neural network models and a range of deep learning techniques were studied. In addition, this chapter highlights the need for additional Alzheimer's disease research.

3.Methodology

In this process, MRI scans reach the different causes of preprocessing stages. Consequently, the proportions of images modify in the preprocessing stages. The method of Alzheimer's disease recognition also the group are classified into four classifications. In this study, we sug- gested DL based method was developed for classifying and detecting engaged for utilized in MRI images. The stages are separated into binary classes such as request and preprocessing. A new format was obtained by utilizing the collection of data and magnetic resonance imaging pictures. New information consisted refined with the preprocessing stage that can change the

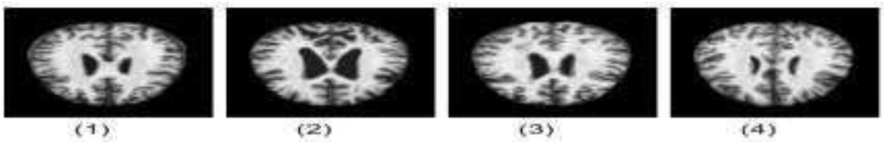

Fig. 3.1 1) Mild Demented (2) Moderate Demented (3) Non-Demented (4) Very Mild Demented.Pre- process of images using magnetic resonance imaging.

dimension picture of 224 × 224 × 3.This method modified the classification of pre-trained methods like InceptionResNetV2, ResNet50V2, DenseNet121, Xception, VGG16, and Mo- bileNetV2, and VGG16 is in the second layer of transfer learning that the stage was deter- mined.

This suggested method developed DL based model for detecting and classifying AD over a

two-step artificial neural network process using a pre-trained method. The suggested method wasdescribed in detail are shown in (fig.3.1).

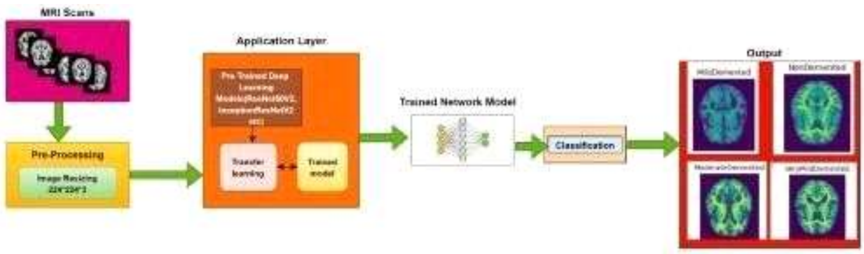

Fig. 3.2 Basic Architecture of Proposed Methodology

Classification using Two-Phase Transfer Learning

Alzheimer' Disease is classified into four layers the proposed model adopted the binary arti- ficial neural networks method. The implementation framework for the binary artificial neural networks method is represented (in Fig. 3.2) In this process, the artificial neural network model.

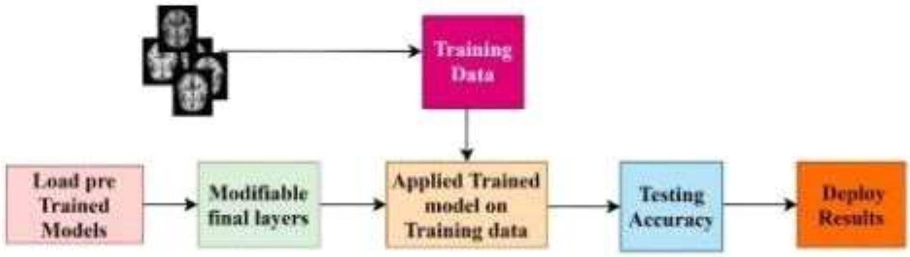

Fig. 3.3 Basic Architecture of Proposed Methodology

Algorithm:

Input P(Y),$Y = \{y1, y2, . . . yn\}$no. of samples in the dataset

Pre-Training

for the length of samples do

Pre-Trained Network from Source Domain (*Ds*) The training set in Target Domain (*Dt*)
The validation set in Target Domain (*Dt*)

Training/Validate Samples

end for

Fine-Tuning

For (y) length of features **do**

Fine-tuning Specific layers of pre-trained model {*Y*, (*y*)}
Fine-tuning the pre-trained model on the training Dataset (*Dt*) Deploy the fine-tuned model on Test Dataset (*Dt*)
end for
Output

Categorized Images from Test Dataset.

- Pre-Trained Models with Two-Phase Transfer Learning

- VGG16

In this process, Visual Geometry Group methods contain 1 SoftMax layer, 2 fully connected layers, and 13 convolutional layers which are utilized for complexities and also can be classified the information in fully connected layers. Karen and Andrew developed the 16-layer network. The primary example mere 3 × 3 convolutional layers. In the convolutional layer of first and second there having 64 kernel features of filters size of size 3× 3 handled. The depth of the Rigid Gas Permeable image is 3 was shipped over the convolutional layer of first and second in the conversion of the proportions. The outcome after transferring the highest layer of pooling with a tread of 2. The convolutional layer of the third and fourth was used in 124-feature kernel edited with a pervade size of 3× 3. Binary phases are followed by pooling layers that are added within thread 2, the final dimension of the outcome is 56× 56× 128. Con- volutional layers of the fifth, sixth, and seventh are made up in the size of 3× 3 essence. The base among any one of them was a group of 256 working models. The layers after coming to the high layer of pooling within the thread of 2. A binary set of 3× 3 convolutional layers was situated in places 8 over 13. A Set of all convolutional layers are utilized by 512-part kernel filters. Whenever a high pooling layer was finished within the threat 1 has been increased. The level was finished in the fourteenth and fifteenth and was connected to the invisible layer of 4096- section one arrived for the outcome of the SoftMax layer. Classification of AD using artificial neural networks utilized in layers of thelast five methods.

Densenet121

The DesneNet121 model is made up of five convolutional blocks. The Convolved image was sent to Conv2 size 56× 56 from the max pooling block, the initial convolution block (Block-1) processes the image to fit Conv1 size 112× 112. Following the transfer of the obtained features to
the dense layer, the output (Block 2), Conv 3 for 28× 28, Conv 4 for 14× 14, and Conv 5 for 7× 7 were obtained. Convolutional CNNs frequently calculated the output layers (lth) by applying a non-linear transformation H l (.) to the output of the preceding layer $X(l-1)$

$$Xl = Hl\ (Xl{-}1)$$

The layer output functionality maps and the inputs are concatenated by DenseNets instead of being truly added together. DenseNet can easily improve information flow across layers by using a simple Convolutional model. The features of all earlier layers provide input to the layer below: Following that, the equation is:

$$Xl = Hl([X0, X1, X2,\ \ Xl{-}1])$$

where $[X0,\ X1,\ X2,\ .\ .\ .\ ,\ Xl1,\ ]$ is created by joining the output maps of earlier layers into a single tensor. Out of the functions, Hl(.) represents a non-linear transformation function. There are three main operations in this function: Batch normalization (BN), activation function (ReLU), and convolution (CONV). In this architecture, the growth rate k aided in the following generalization of the lth layer

$$K^{(l)} = (K[0] + K(l-1))$$

MobilenetV2

In MobileNetV2, two distinct block types can be seen. The first is a residual block with a stride of one. Another way to reduce this is with a two-stride block. Three levels separate the two kinds of blocks. This time around, the convolution that took place in the first layer was a simple 1x1 one that used ReLU6, whereas the convolution that took place in the second layer was more involved. Another 1×1 convolution without nonlinearity made up the third layer.

When used again, ReLU was said to limit the power of deep networks to a linear classifier, at least for non-zero volume output domain regions. There were 155 layers total in MobileNetv2, including a categorization layer. This model comprises 154 pre-trained network layers (convolutional basis) and 2 additional layers. The pre-train transferring lose its learned information if all 156 layers are trained since the classifier's random weights will cause very large gradient updates. By freezing the convolutional basis during training, weight updates are stopped. The pre-trained model's layers are all frozen by setting the trainable flag of the entire model to false.

Xception

The Xception model, which is composed of depth-wise separable convolution layers, was broken down into three fundamental sections: the input flow, the middle flow, and the exit flow. The Xception model first recognized three flows in the visual data: the input flow, the middle flow, which occurred eight times total, and the exit flow. The batch normalization method was applied to each convolutional layer, each layer that cloud, be subdivided into a smaller number of layers. The network's feature extraction was based on the model's 36 convolutional layers. The top-1 accuracy of the Xception model for four classes was 79% then trained on 299 × 299 ImageNet images. The design of a regression model with only one class as the output requires using a pre-trained Xception ImageNet model. Before introducing a max pooling layer, the Xception model's last completely linked layer was removed. In addition to this, the output layer was enlarged to incorporate a dense layer composed of a single neuron with a linear activation function. The model was trained over 50 iterations using an Adam optimization approach with a learning rate of 0.001. The image dataset was divided into 16 micro batches to facilitate training. The four groups were classified using MRI images using a distinct pre-trained Xception model.

InceptionResNetV2

The residual Inception Block is the fundamental unit of Inception-ResNet-V2. Following each block is a 1×1 convolution filter expansion layer, which scales the dimensionality before addition to match the input depth. Only the traditional levels of this architecture utilize batch normalization. The image input size for Inception-ResNet-V2 is 299×299, and there are 164 layers in total. The Residual Inception Block employs convolutional filters of various sizes and residual connections. This design takes advantage of residual connections to address the problem of deep normalization dation and accelerate training. Max Pooling was implemented instead of Flatten after this core design to minimize overfitting in the convolutional structure naturally because there were no parameters to be tuned and by strengthening the connection between the feature importance and label category. Due to this, max Pooling is also more parameter-efficient than the Flatten technique. According to Szegedy, Ioffe, Vanhoucke, and Alemi Addition of a Dropout layer with a fixed value of 0.8 is made.

$$\sigma(x)_i = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{y_i}}$$

The dense layer was activated using the SoftMax activation function, as shown in equation 5.9, where x and y represent input and output, K represents the number of classes, and e represents the common exponential function, which in this instance is e = 2.718.

$$w' = w - \alpha \times \nabla\ (w; x^{(i)}; y^{(i)})$$

The iterative Stochastic Gradient Descent (SGD) technique was used for optimization during backpropagation. Its equation is given in equation 5.10, where w stands for weight, α for learning rate, and ∇ (w; $x^{(i)}$; $y^{(i)}$) for the gradient to weight, input, and output/label, respectively.

Proposed ResNet50V2 with 2PTL

ResNet50v2 is one of the well-known models that excel in solving various computer vision issues. Some of the models are VGG16, DenseNet121, Xception, MobileNetV2, and Incep- tionResNetV2. These models are developed using a huge quantity of data from many different image categories. Transfer learning algorithms can use these trained model weights to solve a variety of computer vision problems with a constrained number of datasets and computing resources. This study used a sizable dataset of medical image data, and we carried out a trans- fer learning with ten distinct pre-trained weights derived from the ResNet50v2 model. The ResNet50v2 Two Phase Transfer Learning model's architecture and its 10 various pre-trained weights are covered in the following sections. A CNN model called the ResNet50v2 model has 50 layers.Figure-**2.3**depicts the architecture of the Proposed ResNet50v2 model's archi- tecture

and its fine-tuning setup for ResNet50v2 Transfer Learning.

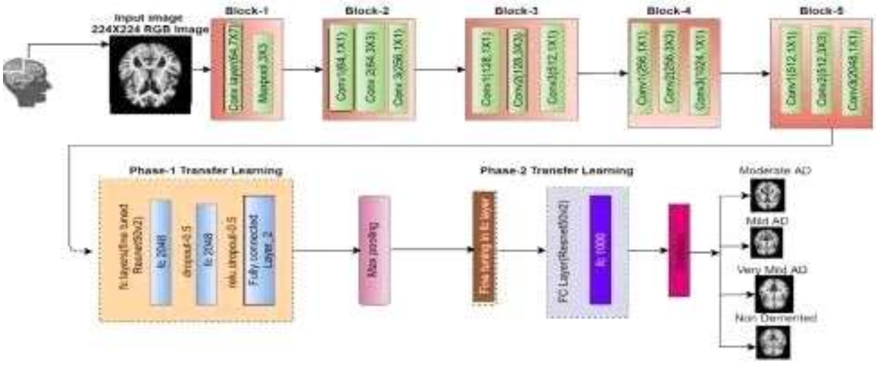

Fig. 3.4 The architecture of the Proposed model Modified ResNet50V2 with 2PTL

Also, the architecture for the proposed fine-tuned ResNet50v2 Two-Phase Transfer Learning is presented in Table-3.2. Some convolutional layers make up the ResNet50v2 design. The first convolutional layer has 64 distinct kernels, a stride size of 2, and a filter size of 7 × 7. Then up to 3 × 3 pooling with a step size of 2 is used. Three layers of convolution (1 × 1,64 kernel), (3 × 3,64 kernel), and (1 × 1,256 kernel) exist in the next convolution,

Table 3.5 Description of Resnet50v2 Two-Phase Transfer Learning

Layers	Outside Size	Layer
Conv1	112 × 112	7×7,64,Stride 2
Conv2*x*	56 × 56	3 × 3 Maxpooling , Stride= 2 [1 × 1, 64 3 × 3, 64 1 × 1, 2 56] × 3
Conv3*x*	28 × 28	1 × 1, 128 3 × 3, 128 1 × 1, 512] × 4
Conv4*x*	14 × 14	1 × 1, 256 3×3,256 1 × 1, 1024] ×6
Conv5*x*	7 × 7	[1 × 1, 512 3 × 3, 512 1 × 1, 2048] ×

			3
Fully Layer1	connected	1 × 1	max pooling Features-in=2048,Features-out=2048
Fully Layerc2	connected	1 × 1	dropout= 0.5
Fully Layerc3	connected	1 × 1	Features-in =2048,Features-out=2048 Relu, dropout= 0.5 Features-in =2048, Features-out =2

repeated three times. The same procedure was followed for each of the three convolutional layers

(1 × 1,128 kernels), (3 × 3,128 kernels) and (1 × 1,512 kernels), three convolutional layers

(1 × 1,256 kernels), (3 × 3,256 kernels) Repeated 4 times and (1 × 1,1024 kernel) for 6 iterations

each, and 3 layers of convolution (1 × 1,512 kernels), (3 × 3,512 kernel) and (1 × 1,2048 kernel) for 3 iterations each. It is followed by Max pooling (max pool). A convolution layer, batch normalization, and ReLU are frequently combined with hidden layers.

The original ResNet50v2 model ends with a fully connected (FC) layer that has 1000 out-features (for 1000 classes). To enhance the ResNet50v2 model, a group of fully connected layers replaces this one. When a dropout occurs, the first similar feature layer is chosen (with 2048 out features) and the chance of using that layer is set to 0.5. The second fc layer is then followed by a ReLU and dropout layer with a probability of 0.5. For four-class classification, the final FC layer only has 4 out-features and 2048 in-features. i.e., mild demented, moderate demented, very mild demented, non-demented. In this study, we evaluated transfer learning using 10 different ResNet50v2 model pre-trained weights. Several datasets were used to construct these pre-trained weights. These datasets had several variations, as we were dealing with medical image datasets.

4.Result and Discussion

The model for classifying data was developed using TensorFlow, which supported transfer learning. Stochastic gradient descent with momentum (SGDM) was utilized as the optimizer to determine the weight and bias variables, minimize the loss function, and decrease the loss function during the training of 20,926 images. These 50 were epochs utilized, a small batch size of 512, a learning rate of 0.0001, and an early stopping parameter of 4 for the validation Testing. The number of iterations needed to finish 1 epoch in our case was 107. Overfitting can be minimized by evaluating the model’s reliability after a validation test or by adding an extra epoch to the data set. Since accuracy is the critical evaluation parameter, the impact of changing the learning rate from 1e-2 to 1e-5 on the training and testing accuracy of the model was examined. Even though the model’s best output was obtained at a learning rate of 1e-4,that rate was still substantially faster than the average. We used a learning rate of 1e-4 to test every model. The performance of a classification model can be evaluated using the confusion matrix, which was used to measure precision. In this study, we examined 6 different models with the same data. An Alzheimer's disease detection model was used to assess the quality of an MRI scan. The total number of images in the dataset was 20,926, four categories, and each class had 5,231 images. This ensured that all classes were represented equally in the dataset. Using 50 epochs of data, the network was trained from the basics. Data from each experiment comprised 30% of test data and 70% of training data. Different evaluation criteria might be used to assess the outcomes.

Table 4.1 Confusion matrix generated by testing DenseNet121

Class label	ND	VMD	MD	MOD	TotalData	Accuracy
ND	1399	45	109	76	1629	85.88
VMD	126	1289	75	110	1600	80.05
MD	20	35	1482	32	1569	91.43
MOD	32	42	40	1366	1480	92.29

Table 4.2 Confusion matrix generated by testing MobileNetV2

Class label	ND	VMD	MD	MOD	TotalData	Accuracy
ND	1465	45	59	60	1629	89.93
VMD	127	1365	48	60	1600	85.31
MD	20	15	1511	23	1569	96.30
MOD	15	22	18	1425	1480	96.29

Table 4.3 Confusion matrix generated by testing VGG16

Class label	ND	VMD	MD	MOD	TotalData	Accuracy
ND	1465	45	59	60	1629	89.93
VMD	77	1465	23	35	1600	91.05
MD	12	10	1536	11	1569	97.80
MOD	15	22	18	1425	1480	96.29

Table 4.4 Confusion matrix generated by testing Xception

Class label	ND	VMD	MD	MOD	TotalData	Accuracy
ND	1479	45	39	66	1629	90.79
VMD	26	1489	55	30	1600	93.06
MD	20	25	1502	22	1569	95.72
MOD	22	32	30	1396	1480	94.32

Table 4.5 Confusion Matrix generated by testing Inception Resnetv2

Class label	ND	VMD	MD	MOD	TotalData	Accuracy
ND	1608	6	10	5	1629	98.71
VMD	18	1540	30	12	1600	96.25
MD	6	10	1543	10	1569	98.34
MOD	0	8	6	1466	1480	99.04

Table 4.6 Confusion Matrix generated by testing Resnet50v2

Class label	ND	VMD	MD	MOD	TotalData	Accuracy
ND	1592	18	10	9	1629	97.72
VMD	8	1580	2	10	1600	98.75
MD	2	6	1559	2	1569	99.36
MOD	0	4	6	1470	1480	99.32

In Table: 4.6, can be observed that Resnet50v2 was successful in classification and appropriately classified. Thus, Resnet50v2's overall testing accuracy was 99.25%. Moreover, other models like VGG16, DenseNet121, Xception, MobileNetV2, and InceptionResNetV2 had good testing accuracy as well, as shown in Tables 4, 5, and 6 accordingly. With training and testing accuracy of 99.34% and 99.25%, ResNet50v2 outperforms other models. On the other hand, Resnet50v2 outperformed its competitors with the highest test accuracy and was subse- quently selected as thebest model for classifying AD.

Table 4.7 Comparative results of Alzheimer's disease MRI images with different models

Models	Training Accuracy	Testing Accuracy
DenseNet121	89.5	88.5
MobileNetV2	91.4	92.3
VGG16	93.5	94.5
Xception	96.5	93.8
InceptionResNetV2	98.9	98.7
Proposed Model	**99.3**	**99.2**

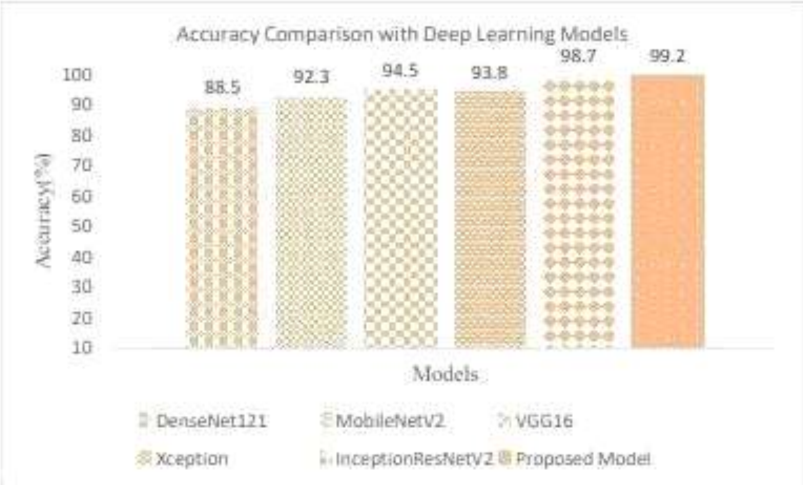

Fig. 4.8 Graphical representation for comparative results of Alzheimer's disease classification

5.Summary

As a result of the investigation in this study, it is clear that deep learning is an effective tool for classifying Alzheimer's disease from MRI images. When it comes to making precise decisions based on large, complicated datasets, deep neural networks are undoubtedly very effective.

Therefore, learning has a fundamental method for solving a problem and producing dynamic findings for the research topic. Deep learning can play a significant role in this process as it can automate the tasks for neurologists and is not subject to errors caused by humans. In this study, we employed transfer learning to properly categorize MR images into four classes using a variety of deep learning models, including VGG16, DenseNet121, Xception, MobileNetV2, InceptionResNetV2, and Resnet50v2 as the basic model. These models could classify the data and had been successfully trained using our datasets. The proposed model had the best training and testing accuracy of the model, with 99.34% and 99.25%, respectively. Resnet50v2 with

Two-phase transfer learning is thus undeniably a successful method for classifying MR images.

6.Conclusion

Alzheimer's disease is a degenerative condition that can result in symptoms ranging from minimal memory loss to a lack of social connection and engagement. Alzheimer's patients have damage to their brain's cognitive, memory, and language processing centers. The most common form of dementia is Alzheimer's disease, according to the Centers for Disease Control and Prevention (CDC). Age is the main known risk factor for dementia, even though these diseases are not a normal part of aging (like Alzheimer's). Although it certainly increases risk, Alzheimer's disease is not directly brought on by old age. The disease mostly affects those over 65. Every five years after age 65, the probability of developing Alzheimer's increases. Due to the complexity of the human brain, Alzheimer's disease is one of the most challenging brain diseases to cure.

Clinical studies based on theories about beta-amyloid and tau protein have so far been ineffective. The most up-to-date data about Alzheimer's disease diagnostic procedures, treatment options, and physical examination In order to accommodate research and development, the World Health Organization (WHO) has pushed back the target date for discovering an effective therapy for Alzheimer's disease from 2025 to 2030. At the 2013 G8

Dementia Summit, a quick deadline was established. 60– 70% of all instances of dementia can be attributed to Alzheimer's disease. Studies conducted by the World Health Organization show that the incidence of Alzheimer's disease among the elderly is projected to rise from 4% to 5% between the years 2000 and 2050. The growth rate for the elderly (defined as those 85 and up) is greater than 5% in 11 of the nations analysed. The number of people with Alzheimer's disease is predicted to rise fivefold or more as the older population grows in many nations. However, researchers are still trying to pin down the illness's precise oriin.

7.Future Scope

Researchers involved in the Meridian Agreement cite factors including depression, sedentary lifestyle, diabetes, and smoking as major contributors to this illness. The incidence of obesity, high cholesterol, and high blood pressure in middle 66 age are other factors. According to research from the American Heart Association, maintaining a healthy, regular diet, quitting smoking, and exercising often have all been demonstrated to reduce the risk of acquiring Alzheimer's disease in old age.Early diagnosis can be aided by a newly discovered blood test that measures p-tau181 levels. Researchers showed that the test might identify differences well before memory impairment sets in, which raises the possibility that the findings would have far-reaching implications. As of right now, the test is a reliable method of identifying early-stage Alzheimer's disease. As a result, doctors and scientists had an easier time diagnosing and following up on the problem. Aducanumab is the first completely new therapeutic option for almost twenty years, all because of modern science and technology. There has never been a medicine before that has been given the green light in India. Treatment has been shown to slow cognitive deterioration in Alzheimer's patients by focusing on the protein beta-amyloid. Drugs that promise to delay the advancement of Alzheimer's disease, the most prevalent type of dementia, have the potential to shed light on the condition. It's worrisome that the participants' ailments were in their infancy at the time of the research. This demonstrates two things, the first of which is that development hasslowed considerably. The amyloid hypothesis, another explanation for Alzheimer's disease, has also been proven to be accurate.

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