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Brain Tumor Classification Based on Fuzzy Method and Optimized Transfer Learning

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Abstract: Correct diagnosis of the type of brain tumor plays an important role in diagnosis and treatment decisions. Machine learning techniques are very useful for classifying tumors with deep features without manual intervention. Development in deep learning and learning transfer using deep convolution neural networks (CNN) has made great strides. In this study, deep transfer learning method has been used to extract deep features without hand intervention and to detect different types of tumors using fuzzy method method.Transfer learning is a way of transferring information during training and testing. In this study, extract of deep features from image using CNN were used to diagnose tumors. Here, fuzzy meThod classifier is used for diagnosis and the accuracy of tumor diagnosis is 99.9%. The results show that the proposed method has a high accuracy for diagnosing different types of tumors.Based on the obtained results, it can be concluded that the proposed method is an effective and reliable approach for detecting brain tumors.

Keywords: Brain tumor detection, deep learning, transfer learning, convolution neural networks, Fuzzy Method.

1. INTRODUCTION

The brain is the most important and sensitive organ in the human body that controls the functioning of the human body, and according to the National Brain Tumor Association, about 700,000 people in the United States live with brain tumors, and that number is growing every year [1].

Brain tumors are the tenth leading cause of death worldwide. Brain tumors have a long and bad psychological impact on a patient's life. A brain tumor is caused by a tissue abnormality that develops inside the brain and interferes with the proper functioning of the brain. Brain tumors have been identified as benign and malignant. Benign brain tumors do not contain cancer cells and grow gradually. They do not spread and usually remain in one area of the brain, while malignant brain tumors contain cancer cells that grow rapidly and spread to other areas of the brain.

Brain tumors are diagnosed using various methods such as CT scan, and magnetic resonance imaging (MRI) [2].

MRI is the most effective and widely used diagnostic method. MRI uses powerful and effective magnetic fields and radio waves to produce images of organs. MRI provides more accurate information about the organs and is therefore more effective than CT scans [3].

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In recent years, due to artificial intelligence and deep learning, significant advances have been made in medical science, such as medical image processing, which helps physicians to diagnose the disease quickly and accurately [4].

Therefore, computer-assisted technology is much needed to overcome these limitations, as the medical field needs efficient and reliable techniques to diagnose life-threatening diseases such as cancer, which is the leading cause of global patient mortality.

2. RELATED WORKS

Artificial intelligence and deep learning are mainly used in image processing techniques to segment, identify and classify medical images [5]. Much work has been done on the detection of brain MRI images.

[6] A new method for the classification of brain tumors is proposed in which MRI imaging of the tumor is detected with 89% accuracy. In [7], the classification of multistage tumors using the amplified method in MRI images and then their adjustment using a pre-trained CNN VGG-19 model is proposed.

In another paper, for MRI classification of tumors using polynomial logistic regression and KNN algorithms, it was suggested that this approach was 83% accurate [8].

Elsewhere, Alex-Net used CNN to classify healthy and unhealthy brain MRI images, which achieved 91% accuracy [9].

In [10] a convolutional neural network was used to classify three types of brain tumors.

He also used a CNN model with image processing techniques to identify different types of brain tumors and achieved an average accuracy of 93.33% to 94.39% [11].

[12] CNN, previously trained, used a data-driven learning method to classify normal and abnormal brain MRI images.

[13] He also used three different CNN-trained models (VGG16, AlexNet, and GoogleNet) to classify brain tumors into pituitary, glioma, and meningioma. During this transfer learning approach, VGG16 achieves a maximum accuracy of 98.67%.

[14] The ResNet model showed 97.2% accuracy in detecting tumors and non-tumors.

The unavailability of labeled data is one of the most important barriers to the penetration of deep learning in medical health care. Because the recent development of deep learning applications in other fields has shown that the larger the data, the better the accuracy of the result. Data segmentation and data amplification are performed using in-depth learning in the literature, and various models taught by CNN using the transfer learning method have been used to classify brain tumors. Most of the literature expresses classification efficiency using the transfer learning approach.

To solve the problems of machine learning methods, deep learning has been introduced to extract relevant information from raw images and use it efficiently for the classification process [15].

In deep learning, features are not extracted manually. In recent years, in-depth learning based on convolutional neural network (CNN) in the field of biomedical image analysis for microscopic images [16], tumor diagnosis [17], skin disease [18], diagnosis and classification [19] and sleep [20] has been used.

To overcome the need for large amounts of data, transfer learning with data with different domains has received much attention.

3. METHOD

In this study, a new method for extracting deep CNN-based features without manual intervention is used, and common architectures including AlexNet, ResNet, VggNet, MobileNet, DarkNet and GoogleNet are examined. Then ANFIS method was used to diagnose and classify the tumor. 3.1. Dataset

In this study, we have used a CE-MRI dataset available at (https://figshare.com/articles/brain_tumor_dataset/1512427). Here, 4 data sets are used for average accuracy and transitional learning.(Archive 1 to 4)and 500 data items were used from each group.Fig.1.

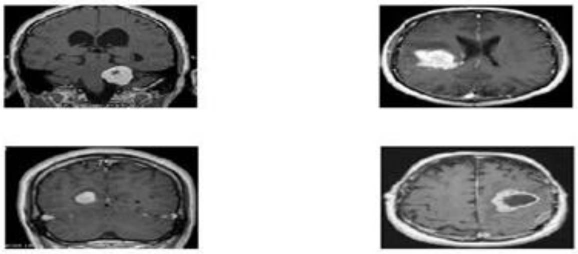

Figure 1. show the brain tumor from dataset in matlab software

The data was recorded during 2005-2010 from Nanfang Hospital, Guangzhou, China. The dataset contains three types of tumors (glioma, meningioma, and pituitary) shown in Fig. 1 from 233 patients with 3064 images.

3.1. Data pre-Processing and Processing

In this study, all deep features are extracted without hand intervention. AlexNet, ResNet, VggNet, MobileNet, DarkNet and GoogleNet are defined as deep network architectures with a number of learnable layers [21].

In the proposed method, the transfer learning method is used to diagnose and classify the tumor. The size of the input images has been changed to the standard size.

We classify brain tumors into three types

3.2. Deep features of the image

Feature extraction from images is a very useful and sensitive task to identify and classify that the better this feature extraction is done, the better the detection and separation.

Here, deep features of images are extracted using convolutional neural network.

Here, convolutional neural network with 5 architectures AlexNet, ResNet, VggNet, MobileNet, DarkNet and GoogleNet is used to extract deep features.

Then, using ANFIS system, three types of tumors were identified based on transfer learning.

3.3. AlexNet Architecture

Deep Convolution Neural Networks is a pre-trained image classifier that won the ImageNet 2012 Large Scale Visual Recognition Challenge (ILSVRC-2012). Although there are more network metrics that have since appeared with many more layers, according to [22] the network performs better.

This network has 8 layers, the first five layers are convolutional and the last three layers are completely connected. In between, there are layers called integration and activation. Figure 2 shows the overall structure of the network. In this research, the Alexnet neural network with three fully connected layers is used, which you can see in Figure 2.

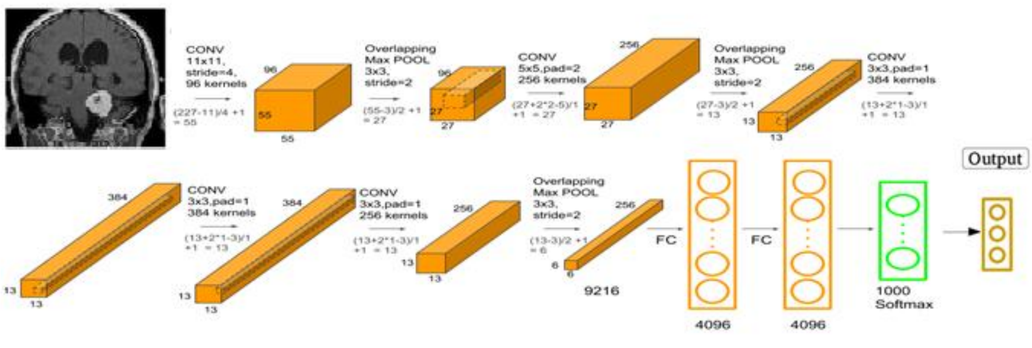

Figure 2. AlexNet convolution neural network image

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3.4. ResNet architecture

In fact, ResNet was not a network that used shortcuts, it introduced a gateway shortcut network. These parameterized gates control how much information is allowed to flow in the shortcut. Therefore, ResNet can be considered as a special case of deep networking [23]. You can see the ResNet network in Figure 3.

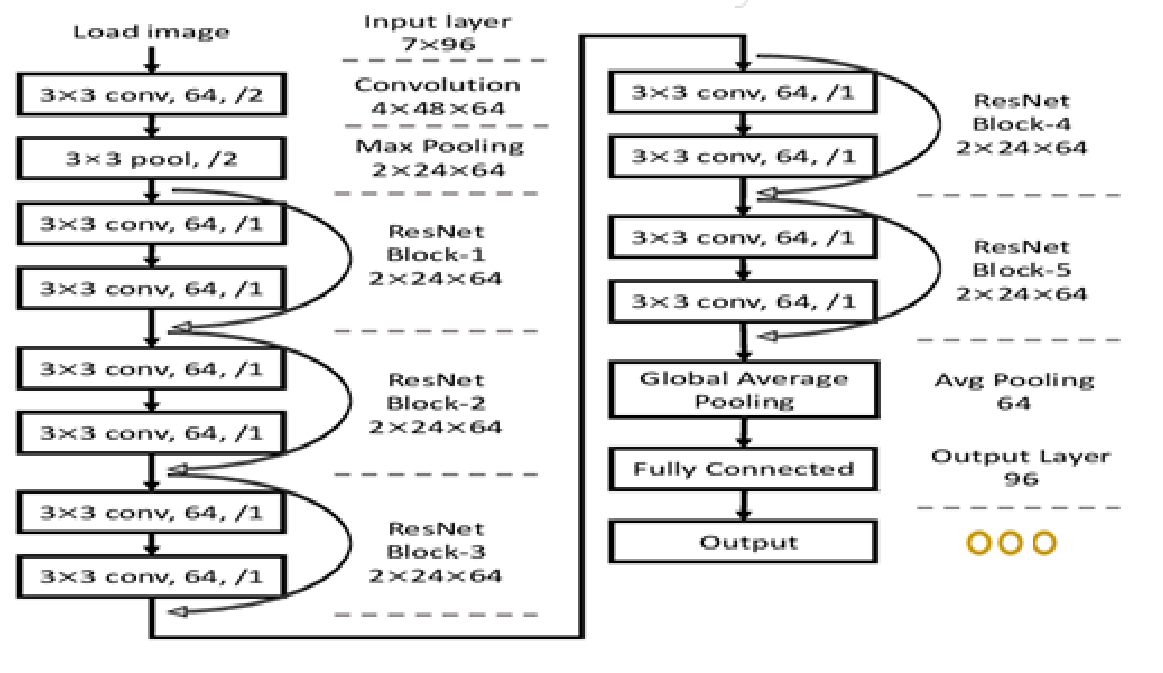

Figure 3. ResNet convolution neural network image

3.5. VggNet architecture

VGGNet is a convolutional neural network architecture proposed by Karen Simonian and Andrew Zisserman of Oxford University in 2014. VNG-based convNet input is a 224 x 224 RGB image. It takes the RGB image preprocessor layer with pixel values in the range 0 to 255 and subtracts the average image values calculated throughout the ImageNet tutorial [24]. Input images are passed through these weight layers after pre-processing. Instructional images are passed through a stack of convolutional layers. In VGG16 architecture, there are a total of 13 convolutional layers and 3 fully connected layers. VGG has smaller (3 * 3) filters with more depth instead of large filters. Finally, it has the same effective input field as if you only had one 7 × 7 convolutional layer. You can see the VggNet network architecture in Figure 4.

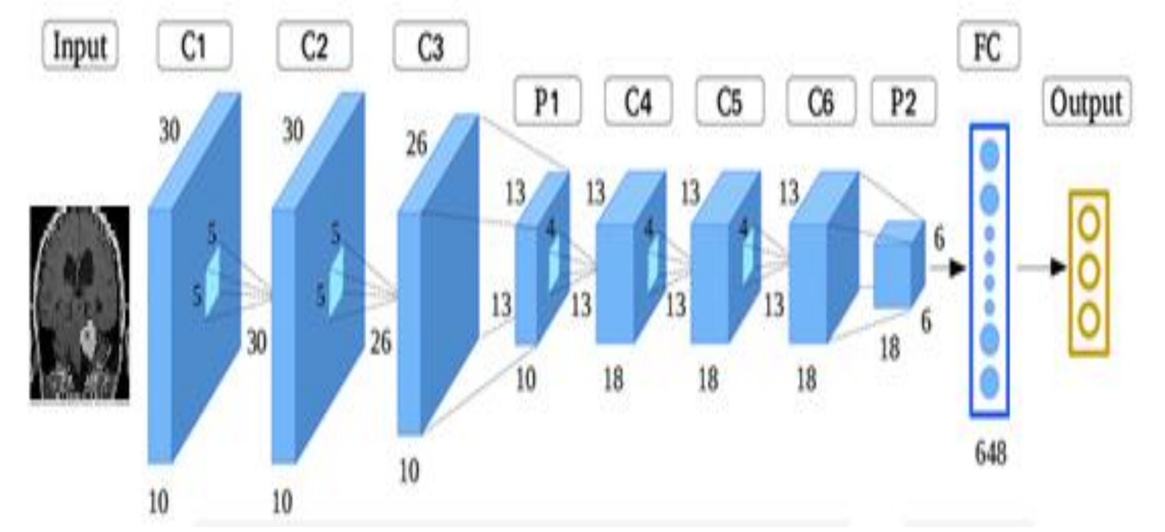

Figure 4. VggNet convolution neural network image

3.6. MobileNet architecture

MobileNet is a convolutional neural network with 53 layers of depth. A pre-trained network of over one million images. A pre-trained grid can classify images into 1000 object categories. As a result, the display network has learned rich features for a wide range of images. This network has an image input size of 224 by 224 [25].

You can see the MobileNet network in Figure 5.

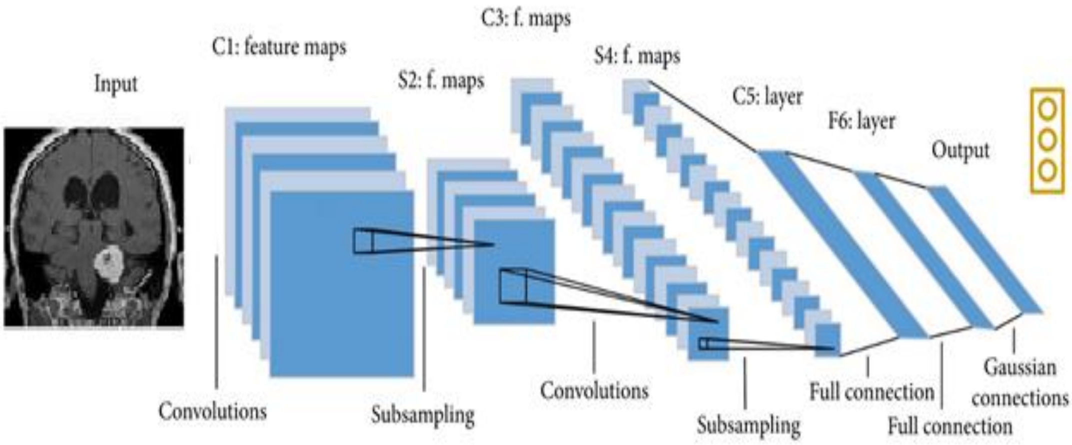

Figure 5. MobileNet convolution neural network image

3.7. DarkNet architecture

Darknet is an open source neural network framework and a convolutional neural network with 19 deep layers. A pre-trained network of over one million images. This network has the ability to categorize 1000 groups. As a result, the display network has learned rich features for a wide range of images [26].

This grid has an image input size of 256 by 256. See Figure 6.

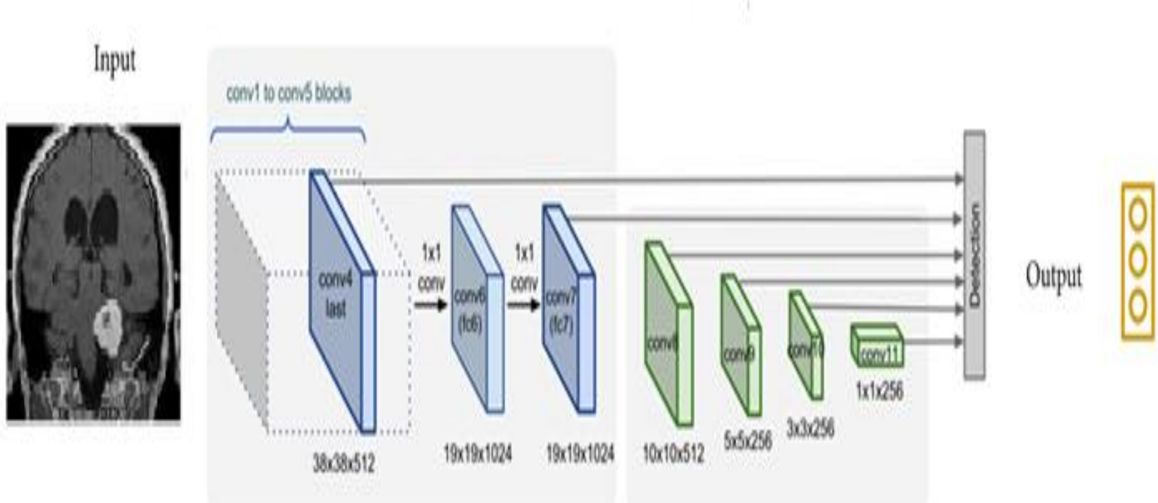

Figure 6. MobileNet convolution neural network image

3.8. GoogleNet architecture

Google Net was suggested by Google Research (in collaboration with various universities) in a 2014 research paper entitled "Going Deeper with Convolutions." This architecture won the ILSVRC 2014 Image Classification Challenge. There was a significant reduction in error rates compared to previous winners AlexNet (ILSVRC 2012 winner) and ZF-Net (ILSVRC 2013 winner) and a significantly lower error rate than VGG (2014 runner-up).

This architecture uses techniques such as 1.1 convolution in the middle of the architecture and integration of the global average. The GoogLeNet architecture is very different from previous architectures. It uses a variety of methods such as 1.1 convolution and global average integration, which allows it to create a deeper architecture [27].

The overall architecture is 22 layers deep. The architecture is designed to have computational performance in mind. The idea behind this is that architecture can be implemented on individual devices even with limited computing resources. The architecture also includes two auxiliary classification layers that are connected to the output of the Inception (4a) and Inception (4d) layers. You can see the Google Net architecture in Figure 7.

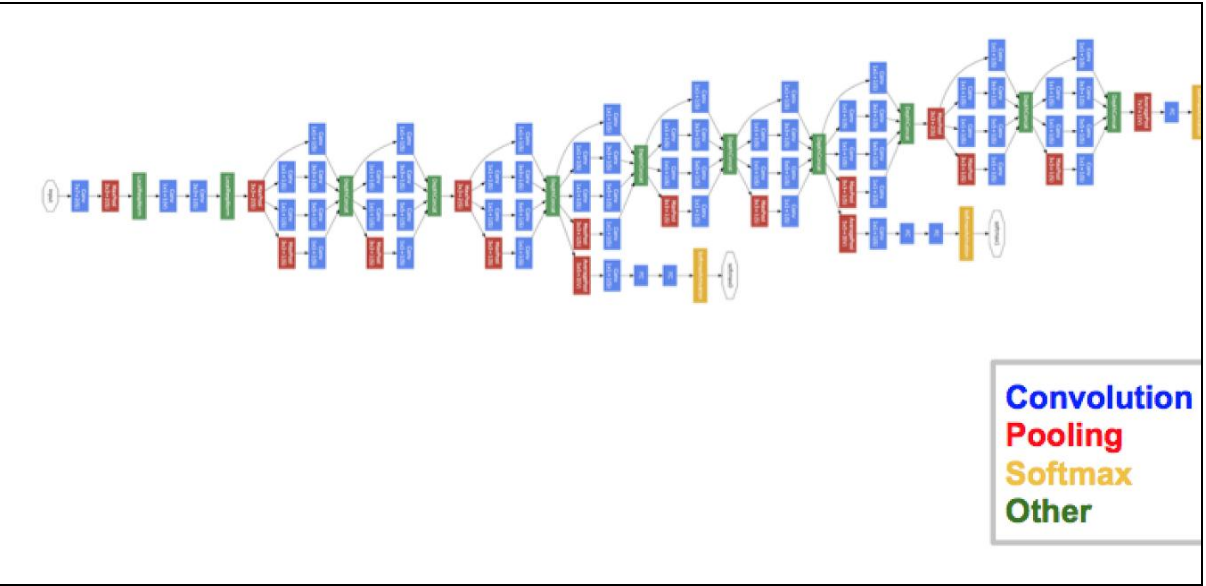

Figure 7. GoogleNet convolution neural network image

4. RESULTS

Three datasets have been collected and entered into MATLAB 2021 b software.

Reduce potential initial noise and change the standard image size of the convolutional grid for processing and insertion into the grid. The results of all steps are reported.

TABLE 1: Results of AlexNet

Transfer learning		Network	Accuracy %	Sensitivity %
Train Data	Test Data			
Data archive 1	Data archive 2	AlexNet	96.64	95.48
Data archive 1	Data archive 3	AlexNet	95.47	95.23
Data archive 1	Data archive 4	AlexNet	96.27	96.1
Data archive 2	Data archive 1	AlexNet	95.98	94.76
Data archive 2	Data archive 3	AlexNet	97.32	97.16
Data archive 2	Data archive 4	AlexNet	96.48	96.28
Data archive 3	Data archive 1	AlexNet	96.32	95.84
Data archive 3	Data archive 2	AlexNet	98.74	97.54
Data archive 3	Data archive 4	AlexNet	95.64	94.54

Table 1 shows the transfer learning results of 9 modes of training and testing with different data with the AlexNet network.

TABLE 2: Results of GoogleNet

TRANSFER LEARNING		NETWORK	ACCURACY %	SENSITIVITY %
TRAIN DATA	Test Data			
DATA ARCHIVE 1	Data archive 2	GoogleNet	94.34	93.29
DATA ARCHIVE 1	Data archive 3	GoogleNet	92.45	91.53
DATA ARCHIVE 1	Data archive 4	GoogleNet	90.34	90.1
DATA ARCHIVE 2	Data archive 1	GoogleNet	92.56	93.74
DATA ARCHIVE 2	Data archive 3	GoogleNet	96.34	95.92
DATA ARCHIVE 2	Data archive 4	GoogleNet	95.65	94.34
DATA ARCHIVE 3	Data archive 1	GoogleNet	94.54	93.93
DATA ARCHIVE 3	Data archive 2	GoogleNet	96.24	93.1
DATA ARCHIVE 3	Data archive 4	GoogleNet	93.43	92.74

Table 2 shows the transfer learning results of 9 modes of training and testing with different data with the GoogleNet network.

TABLE 3: Results of VGGNet

Transfer learning		*Network*	*Accuracy %*	*Sensitivity %*
Train Data	Test Data			
Data archive 1	Data archive 2	VGGNet	93.45	92.65
Data archive 1	Data archive 3	VGGNet	93.57	91.84
Data archive 1	Data archive 4	VGGNet	96.63	95.82
Data archive 2	Data archive 1	VGGNet	94.63	93.73
Data archive 2	Data archive 3	VGGNet	95.56	95.26
Data archive 2	Data archive 4	VGGNet	93.72	92.7
Data archive 3	Data archive 1	VGGNet	93.5	93.2
Data archive 3	Data archive 2	VGGNet	97.21	95.13
Data archive 3	Data archive 4	VGGNet	92.71	91.03

Table 3 shows the transfer learning results of 9 modes of training and testing with different data with the VGGNet network.

TABLE 4: Results of ResNet

Transfer learning		*Network*	*Accuracy %*	*Sensitivity %*
Train Data	Test Data			
Data archive 1	Data archive 2	ResNet	98.34	97.23
Data archive 1	Data archive 3	ResNet	97.35	96.34
Data archive 1	Data archive 4	ResNet	98.98	98.2

Data archive 2	Data archive 1	ResNet	99.2	98.9
Data archive 2	Data archive 3	ResNet	99.9	99.6
Data archive 2	Data archive 4	ResNet	98.45	97.43
Data archive 3	Data archive 1	ResNet	98.94	97.76
Data archive 3	Data archive 2	ResNet	98.8	97.89
Data archive 3	Data archive 4	ResNet	98.98	97.87

Table 4 shows the transfer learning results of 9 modes of training and testing with different data with the ResNet network.

TABLE 5: Results of DarkNet

Transfer learning		*Network*	*Accuracy %*	*Sensitivity %*
Train Data	Test Data			
Data archive 1	Data archive 2	DarkNet	96.56	95.9
Data archive 1	Data archive 3	DarkNet	96.23	96.12
Data archive 1	Data archive 4	DarkNet	98.35	97.45
Data archive 2	Data archive 1	DarkNet	97.45	95.34
Data archive 2	Data archive 3	DarkNet	98.8	97.87
Data archive 2	Data archive 4	DarkNet	97.84	96.72
Data archive 3	Data archive 1	DarkNet	95.63	94.87
Data archive 3	Data archive 2	DarkNet	95.65	94.54
Data archive 3	Data archive 4	DarkNet	97.5	95.78

Table 5 shows the transfer learning results of 9 modes of training and testing with different data with the DarkNet network.

TABLE 6: Results of MobileNet

Transfer learning		*Network*	*Accuracy %*	*Sensitivity %*
Train Data	Test Data			
Data archive 1	Data archive 2	MobileNet	97.34	96.85
Data archive 1	Data archive 3	MobileNet	97.3	96.25
Data archive 1	Data archive 4	MobileNet	98.34	97.81
Data archive 2	Data archive 1	MobileNet	97.34	96.45
Data archive 2	Data archive 3	MobileNet	98.56	98.1
Data archive 2	Data archive 4	MobileNet	97.78	96.98
Data archive 3	Data archive 1	MobileNet	96.45	95.34
Data archive 3	Data archive 2	MobileNet	95.45	95.12
Data archive 3	Data archive 4	MobileNet	97.34	96.81

Table 6 shows the transfer learning results of 9 modes of training and testing with different data with the MobileNet network.

TABLE 7: Results of all networks

Transfer learning				
		Network	*Accuracy %*	*Sensitivity %*
Train Data	Test Data			
Data archive 3	Data archive 2	AlexNet	98.74	97.54
Data archive 2	Data archive 3	GoogleNet	96.34	95.92
Data archive 1	Data archive 4	VGGNet	96.63	95.82
Data archive 2	Data archive 3	ResNet	99.9	99.6
Data archive 2	Data archive 3	DarkNet	98.8	97.87
Data archive 2	Data archive 3	MobileNet	98.56	98.1

The classification results according to different architectures are given in Tables 1 to 6. To achieve the results, deep features have been extracted by different architectures and three types of tumors have been separated by ANFIS classifier.

5. CONCLUSIONS

Here we review 9 different modes for each of the 6 network architectures and announce the results. The best result from the 54 modes performed, as you can see in Tables 7, is related to the RESNET architecture.

The best ranking result is related to CNN ResNet network and 99.9% accuracy.

As you can see, the proposed method is more accurate than other methods and has acceptable results.

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