Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 9, August 2021: 1560 – 1569

Research Article

Transfer Learning Based Classification of Brain Tumors using MRI Images

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Abstract

In this paper, a novel representation for Magnetic Resonance Image classification is proposed using transfer learning which exploits the classification of Brain Tumor into No Tumor, Glioma, Meningioma and Pituitary. In this work MRI images were taken. MRI scans are manually analysed by radiologists to detect abnormal conditions in the brain. It takes a long time and it is difficult to manually interpret a large number of photos. However, the complexity associated with the MRI system makes this task non-trivial. Especially, distinguishing between different types of tumors namely Glioma, Meningioma, and Pituitary is not easy and is highly subjective. To address this issue, computer-based detection helps in accurate, fast and exact diagnosis of the disease. In the proposed work,Resnet50 and VGG19 models were used. InitiallyResnet50 and VGG19 network model all the layers were trained, the dense layer is added with the softmax classifier which classifies the brain Tumor into four types namely no tumor, Glioma, Meningioma and Pituitary, the weights are frozen before layer46 for Resnet50 and Layer15 for VGGnet19. By comparing all the results Resnet50(all the layers were trained) the accuracy is 85.64 and VGG19 (all the layers were trained) the accuracy is 88.94.In Resnet50 (Freezing of layers) the accuracy is 76.10 and the VGG19Resnet50 (Freezing of layers) the accuracy is 85.64.

Keywords: Magnetic Resonance Imaging (MRI), Pituitary, Glioma, Meningioma, Residual Network (Resnet) VGG..

1 INTRODUCTION

Brain tumors are known as the masses formed by the abnormal proliferation of the brain cells [1]. Brain is an enormous complex organ that controls the whole nervous system. It contains around 100-billion nerve cells [2]. The kind of abnormality that exists in brain may put human health to danger.

A brain tumor is one of the most common causes of cancer-related death in both children and adults around the world. Early accurate classification of a brain tumor is critical for effective prognosis and treatment planning[3].Generally brain Tumor can be divided into two types: Benign and Malignant. A benign tumor grows and affects the healthy tissues. Outside the brain, malignant tumors grow, and this is referred to as brain cancer [4].

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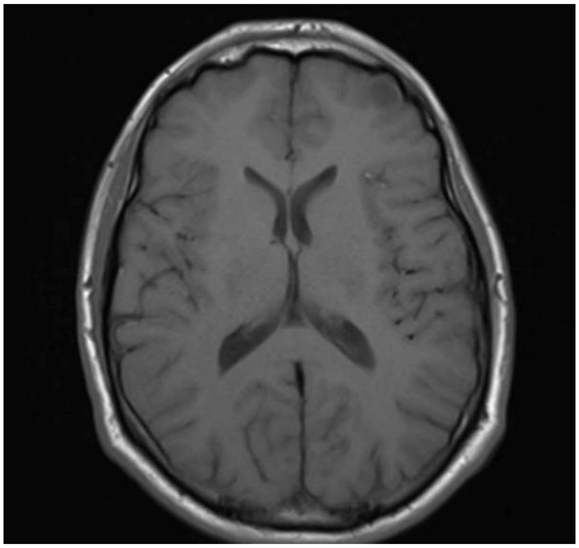

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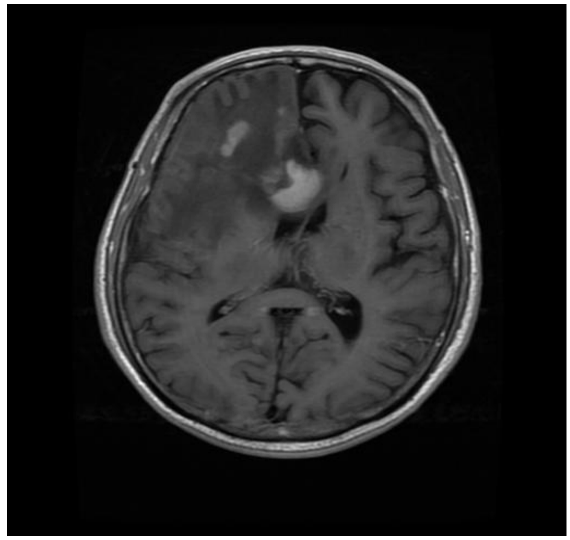

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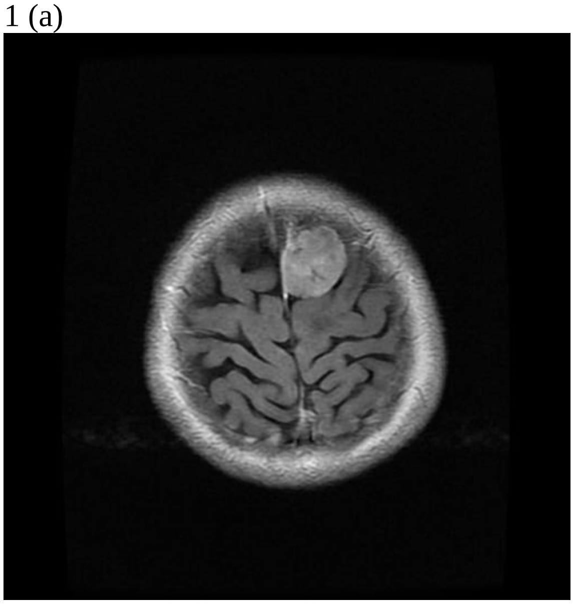

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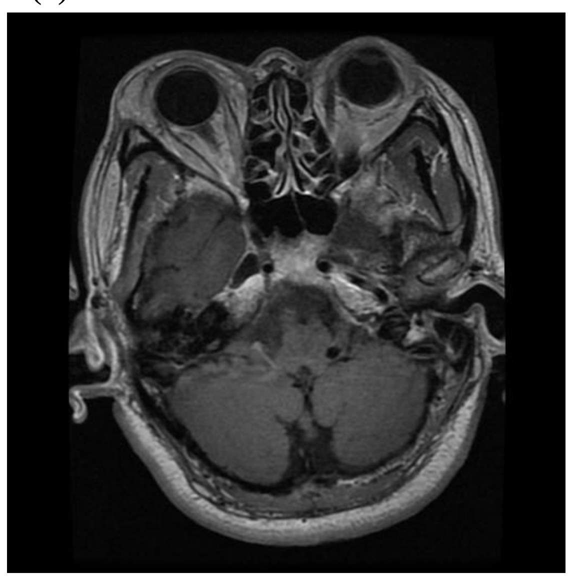

1 (d)

Fig. 1(a)Normal MRI image of brain, 1(b) Glioma affected image, 1(c) Meningioma affected image and 1(d) Pituitary affected image.

The uncontrolled and the unnatural growth of the brain of the cells in brain is called as brain Tumors. Generally it is classified into Primary Tumor and Secondary Tumor. The primary Tumor is present in the brain whereas secondary tumor extend to the other parts of the human body to the brain tissue through the blood stream [5].The primary tumors are Glioma and Meningioma is the two major categories of brain tumors which may lead to death if not diagnosed at the early stage. The most common type is the Glioma [6].Fig.1 shows the normal, Glioma, Meningioma, Pituitary MRI image of Brain.

The World Health Organization (WHO) brain tumors are classified into four grades. Meningioma is graded as grade 1 and grade 2 since it is considered as the lower – level tumors. Glioma is graded the Grade 3 and Grade 4 since it is considered as severe ones. The incidence rate of Meningioma, Pituitary and Glioma tumors are approximately 15 %, 15% and 45 % respectively [7]. Fig. 2 shows the block diagram of the proposed work.

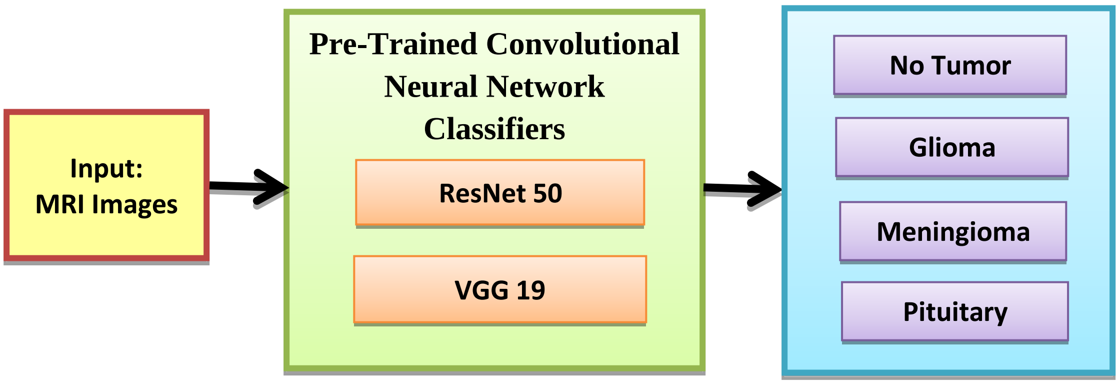

Fig. 2 Block diagram of the proposed work

2 LITERATURE OF THE WORK

An automated system were proposed on machine learning to diagnose the lump (mass of Tissue) in the brain which could be malignant (marginal adhesion) or benign (clump thickness) by classification [8]. For pre-processing adaptive median filter is used, Grey Level Co-occurrence Matrix were used to extract the features and classified using Neural Networks which was compared with Adaboost (Adaptive Boosting) in which neural networks gives the highest accuracy of 96.6 %.

For brain tumor prediction and localization, a new two-phase multi-model automatic diagnosis model was implemented. The system was developed in the first phase by pre-processing, feature extraction using a Convolutional Neural Network (CNN), and feature classification using the Error-Correcting Output Codes Support Vector Machine (ECOC-SVM) methodology [9]. The initial system phase's goal is to detect brain tumor by categorising the MRI imagesinto normal and abnormal. The second phase's goal is to use a fully constructed five-layer region-based convolutional neural network (R-CNN)to locate the tumor inside the irregular MRIs. AlexNet, Visual Geometry Group (VGG)-16, and VGG-19 were used to evaluate the first phase's performance, with AlexNet achieving a maximum detection accuracy of 99.55 percent utilising 349 pictures collected from the standard Reference Image Database to Evaluate Response (RIDER) Neuro MRI database. The DICE score for the brain tumor localization phase was 0.87, based on 804 3dimension MRI images from the Brain Tumor Segmentation (BraTS) in 2013 database. When related to other non-deep-learning systems in the literature, the suggested deep learning-based system performed exceptionally well in tumor identification[10]. The obtained results also show that the suggested approach is superior in terms of tumor detection and localization.

Anew multi-grade brain tumor classification method based on convolutional neural networks (CNNs) was proposed. In the beginning, deep learning technique is used to segment the tumor regions from an MRI image[11]. Then, considerable data augmentation is used effectively to train the proposed system, eliminating the lack of data problem that can occur when using MRI for multi-grade brain tumor classification. Finally, enhanced data is used to fine-tune a pre-trained CNN model for brain tumor grade classification. The proposed system is assessed experimentally on both augment and original data, and the results reveal that it outperforms existing approaches.

To extract characteristics from brain MRI scans, the proposed classification method employs deep transfer learning and a pre-trained GoogLeNet. To classify the retrieved features, the proven classifier techniques are used. On MRI dataset from figshare, the experiment uses a patient-level 5-fold cross-validation approach. The suggested system outperforms all current approaches with mean classification accuracy is 98 %. The area under the curve (AUC), precision, recall, F-score, and specificity are some of the other performance indicators employed in the study. In addition, by testing the system with less training examples, the paper addresses a practical element[12]. Transfer learning seems to be a helpful strategy when the availability of medical images is limited, according to the findings of the study. Misclassifications are also discussed analytically in this paper.

3 PRE-TRAINED CONVOLUTIONAL NEURAL NETWORKS

3.1 Transfer Learning

Resnet50

Resnet50 is otherwise called the Residual network used to identify mapping by shortcuts. It is the commonly used model in CNN [12].Residual Networks comprises of various subsequent residual modules, which are the basic foundations block of Resnet. As the network goes deeper and deeper, the training is more difficult. Generally, the input feature map will be followed by the convolutional filter, non-linear activation function and a pooling operation and finally the output is the next layer. Here, back propagation algorithm is implemented. As the network goes deeper and deeper, it is hard to converge.

The architecture of ResNet50 is depicted in Fig. 2.The construction of ResNet50 has 4 stages as shown in Fig 5.4. The input size of the image is 224 x 224 x 3. Every ResNet structure makes the first convolution and max pooling using 7 x 7 and 3 x 3 kernel sizes distinctively. Next, first stage of the network commences and it comprises of 3 Residual blocks containing with 3 layers each.

The size of the kernels utilized to perform the convolution operation with all 3 layers of the block of the first stage is 64, 64 and 128 distinctively. The curved arrows refer to the identity connection.

The dashed connected arrow represents that the convolution operation in the Residual block is executed with stride 2, therefore, the size of input will be decreased to half in relation to height and width but the channel width will be doubled.Fig. 3 shows the architecture of ResNet50.

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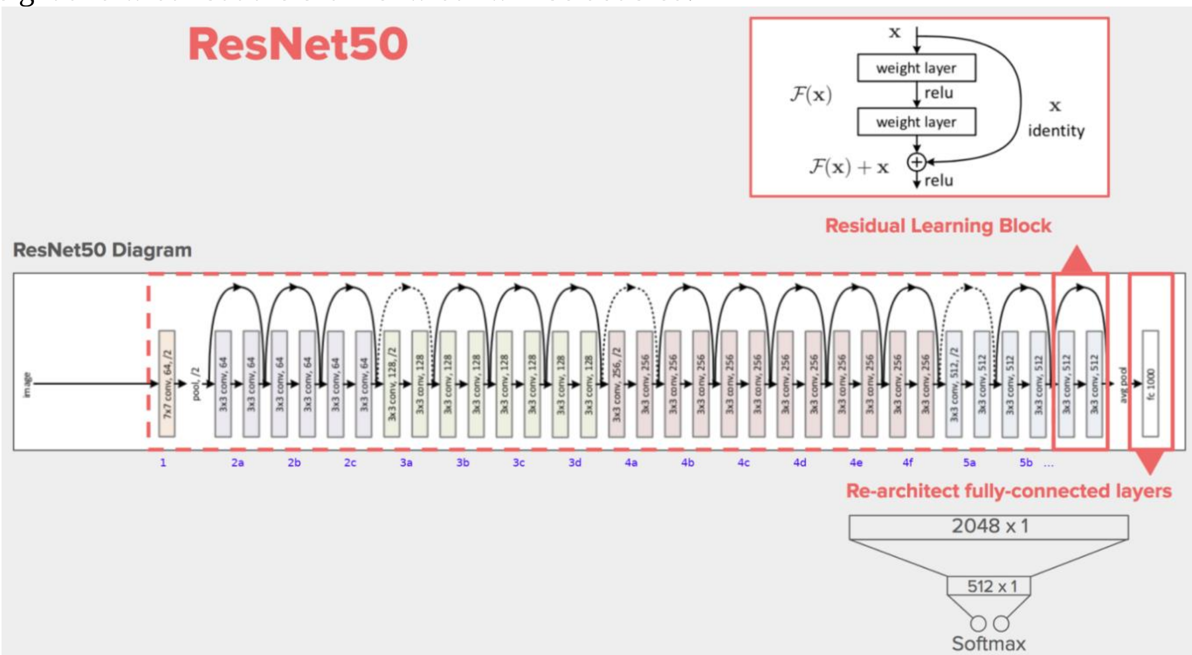

Fig. 3 Architecture of ResNet50

As we move from one stage to the next, the channel width is increased twice as much and the size of the input is decreased to half. For deeper networks like Resnet50, Resnet152, etc, bottleneck design is used. For each residual function F, 3 layers are stacked one over the other. The three layers are 1x1, 3x3, 1x1 convolutions. The 1x1 convolution layers are responsible for decreasing and then replacing the dimensions. The 3x3 layer remains as a bottleneck with less input/output dimensions. Finally, the network has an average pooling layer by a connected layer with 1000 neurons. Sine this model is pre-trained for different ImageNet database classified for 1000 classes, in the proposed work the final network layer is removed and replaced with the softmax classifier which classifies into four types namely no tumor, Glioma, Meningioma and Pituitary Tumor.The performance of the proposed model of Resnet50 is given in Table 1 and Fig. 4 shows the accuracy of the proposed model.

Table 1 Performance of Resnet50

	Precision (in %)	Recall (in %)	F-Score (in %)
No Tumor	90.00	83.12	81.10
Glioma	82.15	80.11	79.21
Meningioma	89.23	78.12	76.45

Pituitary	81.20	78.12	76.21

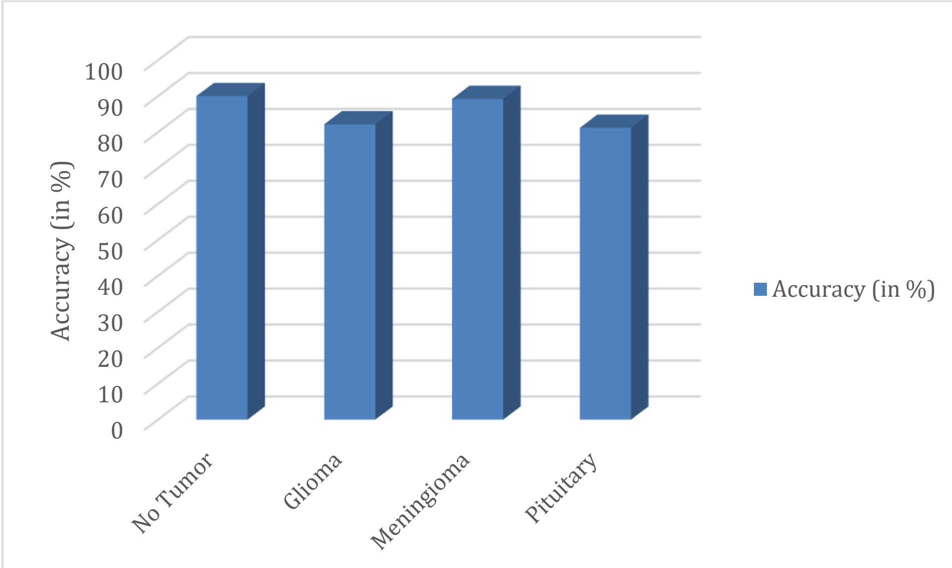

Fig. 4 Accuracy of Resnet50

In the proposed work for fine-tuning Renet50 the following steps are applied.

- Load ResNet50 model without the top Layer (which consists of the fully connected (FC) layers).
- Each layer has a parameter and it is called as trainable in Keras. In this proposed work the weights of 46 layers are freeze and the parameter is set to False, indicating that these layers should not be trained, the remaining four layers are set to true and it is trained.
- Set the trainable parameters to the base network by adding the classifier on top of the convolutional base.
- Add the FC layer followed by a softmax layer with 4 outputs
- The data is separated into training and validation.
- Now the model is created and we set up the data for training.

From the above analysis, by freezing of the layers in in Resnet50 the accuracy that is attained is 85.64 %.

VGG19

VGG19 is a deep Convolutional Neural Network (DCNN) that is used to classify images.The input size of VGG19 is 224 x 224 RGB image which is given as the input to the network. It means the matrix of the shape (224,224,3). For pre-processing the mean RGB value from each pixel is computed over the training set.The kernel size is 3 * 3 with the stride size of 1 pixel is covered throughout the image. The spatial padding is used to preserve the spatial resolution of the image. The max pooling is performed over a 2 * 2 pixel windows with stride 2 followed by Rectified Linear Unit(ReLu) is introduced for non-linearity to make the model class classify better and to improve computational time Fig.5shows the overall block diagram of VGG19.

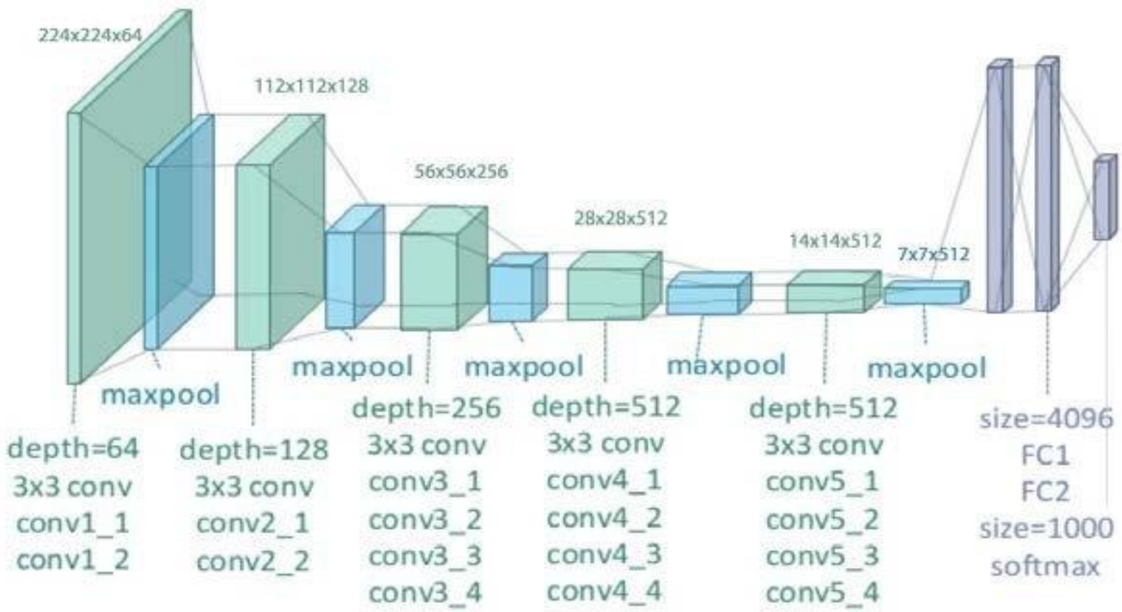

Fig. 5 Block diagram of VGG19

The three FC layers from which first two were of size 4096 and after that a layer with 1000 channels for 1000-wayILSVRCclassification and the final layer is a softmax function. Since this model is pre-trained for different ImageNet database classified for 1000 classes, in the proposed work the final network layer is removed and replaced with the softmax classifier which classifies into four types namely no tumor, Glioma, Meningioma and Pituitary Tumor. Table 2 shows the performance of the proposed model of VGG19 is given below and Fig. 5 shows the accuracy of the proposed work.

Table 2 Performance of VGG19

	Precision (in %)	**Recall (in %)**	**F-Score (in %)**
No Tumor	84.11	82.56	80.24
Glioma	86.13	85.13	83.21
Meningioma	95.24	92.51	90.23
Pituitary	90.26	90.12	89.21

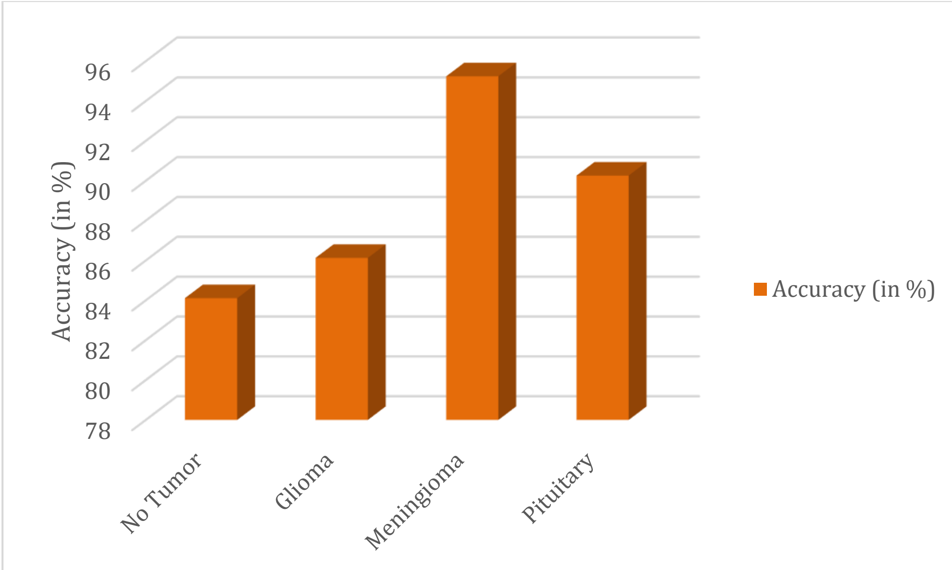

Fig. 5 Accuracy of VGG19

In the proposed work for fine-tuning Renet50 the following steps are applied.

- Load VGG19 model without the top Layer (which consists of the FC layers).
- Each layer has a parameter and it is called as trainable in Keras. In this proposed work the weights of 15 layers are freeze and the parameter is set to False, indicating that these layers should not be trained, the remaining four layers are set to true and it is trained.
- Set the trainable parameters to the base network by adding the classifier on top of the convolutional base.
- Add the FC layer followed by a softmax layer with 4 outputs
- The data is separated into training and validation.
- Now the model is created and we set up the data for training.

In the proposed work fine-tuning is applied. The steps involved are

- Load VGG19 model without the top Layer (which consists of the FC layers).
- Each layer has a parameter and it is called as trainable in Keras. In this proposed work the weights of 15 layers are freeze and the parameter is set to False, indicating that these layers should not be trained, the remaining four layers are set to true and it is trained.
- Set the trainable parameters to the base network by adding the classifier on top of the convolutional base.
- Add the FC layer followed by a softmax layer with 4 outputs
- The data is separated into training and validation.
- Now the model is created and we set up the data for training.

From the above analysis, by freezing of the layers in in Resnet50 the accuracy that is attained is 76.10 %.

4 EXPERIMENTAL RESULTS

4.1 Datasets

The datasets have been collected from Kaggle datasets. A total of 3264 images were collected from Kaggle dataset of T2-weighted MRI images. 2870 imageswere used for training and 394 were used for testing. In training 395 for no tumor, 826 for Glioma, 822 for Meningioma, 827 for Pituitary were used for training. For validation, a total of 394 were used, in which 105 for no tumor images, 100 for Glioma, 115 for Meningioma, 74 for pituitary were used.

5 PERFORMANCE MEASURES

From the above experiments, by comparing Resnet50 with freezing and without freezing, similarly VGG19 with freezing and without freezing it is observed that in Resnet50 without freezing of layers the accuracy that we attained is 85.64 %. Likewise, by freezing of 46 layers and learning the classifier on the top of it and training the last 4 layers we attained the of 76.10 %. In VGG19, without freezing of layers the accuracy is 88.94 %. Likewise, by freezing of 46 layers and learning the classifier on the top of it and training the last 4 layers the accuracy is 78.23 %. Finally VGG19 without freezing of layers gives the highest accuracy of 88.94 %.

Table 3 Overall Accuracy of the Proposed Work

	ResNet50 (in %)	**VGG19 (in %)**
Freezing	85.64	88.94
Non Freezing	76.10	78.23

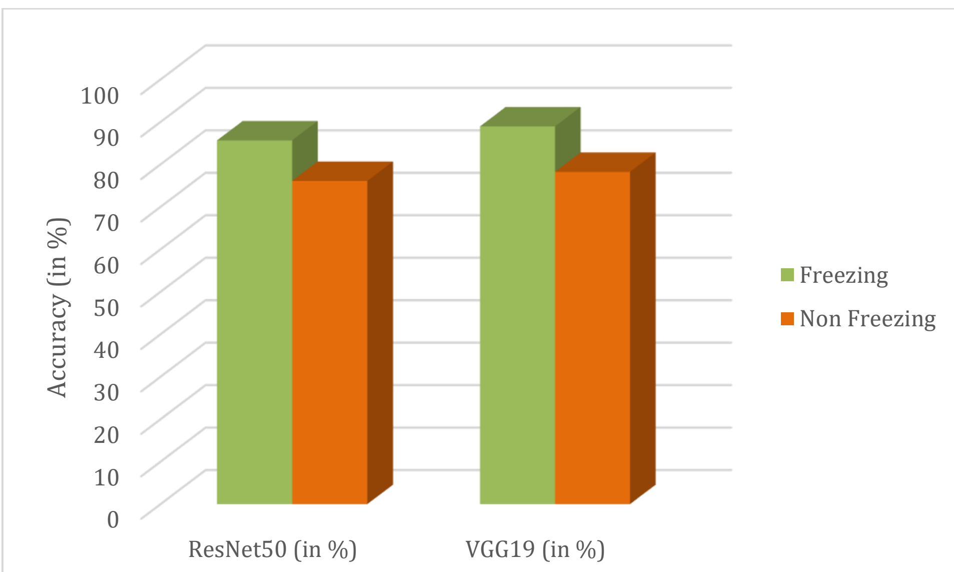

Fig. 6 Accuracy of ResNet50 and VGG19

CONCLUSION

In this work a transfer learning based classification model for brain tumour using MRI images were proposed. Here Pre-Trained CNN is used as a classifier namely Resnet50 and VGG19 model. The freezing and without freezing is done for both classifiers. Inthis proposed work the pre-trained CNN classifier VGG19 without freezing gives high accuracy of 88.94% when compared to the other classifiers.

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