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Brain Tumor Classification With Inception Network Based Deep Learning Model Using Transfer Learning

***Abstract*—Brain tumor classification is one of the most important aspects in the fields of medical image analysis. As tumors are regarded as precursor to cancers, efficient brain tumor classification can prove life saving. For this reason, Convolutional Neural Network(CNN) based approaches are widely being used for classifying brain tumors. But there lies a dilemma, CNNs are accustomed to large amount of training data for giving better result.It is where transfer learning comes useful. In this paper, we propose 3-class deep learning model for classifying Glioma, Meningioma and Pituitary tumors which are regarded as three prominent types of brain tumor. Our proposed model by adopting the concept of transfer learning uses a pre-trained InceptionV3 model which by extracting features from the brain MRI images employees softmax classifier method for classifying them. The proposed system achieves a mean classification accuracy of 99%,outperforming all previous methods being evaluated with a patient-level five-fold cross-validation process on CE-MRI dataset from figshare. Other performance measures such as precision, recall, F-score are also used in this study.The corresponding code is avaiable in github repository at this link**

I. Introduction

Brain tumor is regarded as one of the deadliest and also considered as one of the common form of cancers both in young and adults according to statistics[1].Brain tumor classification into sub type is a challenging problem because brain tumors vary heavily in shapes and sizes[2]. Moreover, different types of brain tumors may possess similar appearances thus making classification task more complex[3]. Among the sub types of brain tumors, three such as Meningioma,Pituitary and Glioma are most prominent which can roughly be compared with three stages of cancer[4].So an early and efficient detection and classification of brain tumors is very important and can save lives to a great extent.That's why Medical image analysis is heavily focused on developing better classification techniques for classifying brain tumors.Cheng et al.[2] proposed an approach which relied upon manually delineated tumor borders to extract feature from the region of interests of T-1 MRI images where the best performance was achieved by an SVM model on bag of words(BOW) features and this is also regarded as one of the first works on figshare brain MRI image dataset[5]. Ismail and Abdel-Qadar[6] proposed to use Gabor filter and discrete wavelet transform for feature extraction and then multi-layer perceptron for classification. The limitation of these approaches is that both of them use somewhat manual techniques for feature extraction.It is where CNNs hold clear advantage as they do not require manually segmented regions and can extract necessary features alone.That's why researchers are employing Convolutional Neural Network(CNN) based deep learning models for getting highly efficient brain tumor classification system. But problem with CNN is that it requires comparatively large amount of data for training. Due to the complexity of brain tumors, for classifying them from the MRI images,comparatively deep convolutional neural network is required but usually brain MRI image datasets are not that large. These two opposing conditions create a dilemma. For solving this dilemma, transfer learning [7] comes as a great option. Through transfer learning, one can use a deep pre-trained CNN model which was developed actually for another related application[5]. Adopting the concept of transfer learning, Khan Swati et al.[8] used pre-trained VGG-19 model for classifying brain tumors from figshare brain MRI image dataset.S.Deepak et al.[5] applied modified GoogLeNet model on the same figshare dataset using the same concept of transfer learning.

In this paper, our study focuses on classifying three types of brain tumors(Meningioma, Glioma, Pituitary tumors) from the very same figshare brain MRI image dataset using pre-trained InceptionV3[9] model.InceptionV3 model has previously been used by Justin Ker et al.[10] for brain histology classification where histology slides were classified from brain and breast tissues. Rachna Jain et al.[11] used InceptionV4 model for classifying Alzheimer disease from MRI images of brain. S.Deepak and P.M Ameer[5] used GoogLeNet which is also regarded as InceptionV1,precursor to the development of InceptionV3,for classifying brain tumors achieving 92% accuracy. But InceptionV3 model hasn't been used widely for brain tumor classification.Our implementation uses a transfer learned InceptionV3 model to extract the features from the brain MRI images and classifying them into three categories(Meningioma,Glioma and Pituitary) using proven softmax classifier.The proposed system recorded the best classification accuracy while being evaluated on the open CE-MRI dataset from figshare.

II. Methodology

A. Dataset

The proposed model was trained and validated on CE-MRI brain image dataset from figshare[12].The figshare brain MRI image dataset is an imbalance dataset which consists of 3064 T1-weighted contrast brain MRI images from 233 patients of three respective types-Meningioma(708 slices),Glioma(1426 slices) and Pituitary tumor(930 slices).The brain MRI images varies across axial,coronal ans sagittal views.The images of the figshare dataset are divided into 5 sub-directories.The MRI images are in matrix form and of size 512×512 pixels.

B. Data Pre-processing

Each brain MRI image in the dataset are of the size 512×512.But as Inception-V3 is designed for receiving colored image having an input layer of size $224 \times 224 \times 3$,pre-processing is mandatory.At first,the intensity values of the images were normalized with Z-score normalization such that they have a mean value of 0 and standard deviation of 1.The standardization was performed for each image according to the equation 1,

$$z = \frac{x - \mu}{s} \tag{1}$$

where x is a training sample,μ is the mean and s is the standard deviation of the training sample.Then the images were resized to 224×224. After resizing the images were still in gray-scale

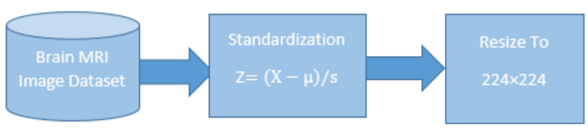

Fig. 1: Data pre-processing stages

form.For converting them into colored form,three channels were created by replicating the grayscale values three times for each image[5].

C. Transfer Learning

Transfer learning is regarded as a technique by which knowledge gained from an already trained model is used to learn another set of data[5].InceptionV3 model has 159 layers and about 24 million trainable parameters(weights)[13].Training and optimization of this type of deep model requires large dataset which is why InceptionV3 was trained on ImageNet dataset consisting of about 1.2 million images of 1000 different categories.So for smaller datasets like figshare brain MRI dataset,there is a high probability that the model will suffer from overfitting.It is where Transfer learning comes into play.Instead of training the model from scratch,for smaller datasets like figshare dataset we initialize the model with pre-trained weights and then fine tune the model for making it capable of performing the desired task which in our case is classifying brain tumors.

For classifying brain tumors some structural modification is required for InceptionV3 model as it was originally developed for a somewhat different task.Here,the last three layers of the InceptionV3 model was modified for adapting it to the desired task.The average pooling layer of the original model was replaced with a flatten layer and the fully connected layer of InceptionV3 which was designed for classifying 1000 different classes was also removed and replaced with a new FC layer of output size three.The softmax activation layer following the FC layer was also changed and replaced with a new one.

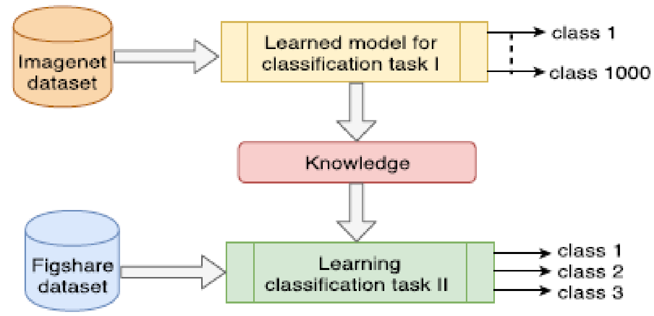

Fig. 2: Transfer Learning settings[5]

D. Evaluation Procedure

For evaluating the designed model for brain tumor classification on figshare dataset,patient level 5-fold cross validation technique was used where the entire dataset of 233 patients was divided into 5 disjoint subsets of equal size and one at a time worked as test set while the rest formed training set.This cross validation procedure ensured that every subset performs as test set once.

III. Experiments and Result Analysis

We implemented the proposed classification model in Python-3 using Tensorflow framework on Google Colaboratory Environment having specifications of 12GB RAM and 12GB NVIDIA Tesla K80 GPU.The hyperparameter settings of our experiment is listed in Table I. In this experiment,we

TABLE I
Experimental Parameters

Parameters	Values
Learning Rate	0.0001
Batch Size	32
Optimization algorithm	RMSprop
Loss function	Sparse Categorical Crossentropy
Number of epochs per fold	10

used confusion matrix,precision,recall,specificity as other performance measuring indices along with classification accuracy and compared each of them with performances of previous works.

A. Classification Accuracy

Accuracy in classification is defined as the ratio of correctly predicted samples and total number of samples.Table II shows the validation accuracy of the model at each test of 5-fold cross validation process.

Comparison between accuracy of proposed classifier and previous works on same figshare dataset is shown in Table III. The comaprision shows that the proposed model with average validation accuracy of more than 99% outperforms all other previous models.

TABLE II
Validation Accuracy for 5-fold cross validation

Validation Set	Validation Accuracy
Validation set-1	97.55302%
Validation set-2	99.83687%
Validation set-3	100.00%
Validation set-4	100.00%
Validation set-5	99.8366%
Average	**99.4453%**

TABLE III
Comparison of accuracy with related works

Work	Method	Accuracy
Cheng[2]	BOW-SVM	91.28%
Ismail[6]	DWT-Gabor-NN	91.90%
Swati[8]	VGG-19(Transfer Learning)-Softmax	94.82%
Deepak[5]	GoogLeNet(Transfer Learning)-SVM	98%
Proposed	**InceptionV3(Transfer Learning)-Softmax**	**99.4453%**

B. Performance Metrices

A confusion matrix summarizes the correct and incorrect predictions of a classifier in matrix or tabular form[5].The confusion matrix for our proposed model being applied on figshare dataset is shown in Table IV.From,the confusion matrix we can see that,proposed model just failed to classify **single** Glioma tumor correctly which is far better than model proposed by Deepak[5] which miss classified **65** MRI images of the same dataset.

TABLE IV
Confusion Matrix of Proposed Model

		Predicted		
		Meningioma	**Glioma**	**Pituitary**
Actual	**Meningioma**	708	0	0
	Glioma	1	1425	0
	Pituitary	0	0	930

From confusion matrix,different performance metrices such as precision,recall,specificity,sensitivity,F_1 score can be generated which are calculated by following equations shown in equation 2,3,4 and 5.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

Here TP,FP,TN and FN are the number of images which are classified as True Positive,False Positive,True Negative and False Negative respectively.The average category specific values of precision,recall,specificity for proposed model is shown in Table V.
Comparision of precision and recall score between the proposed model and related works is shown in Figure 3 and 4 respectively.

TABLE V
Average Category Specific Values of Performance Metrices

Category	Precision	Recall	Specificity	F_1 Score
Meningioma	98.83	98.98	99.66	98.90
Glioma	99.56	99.85	99.65	99.71
Pituitary	99.69	99.23	99.85	99.46

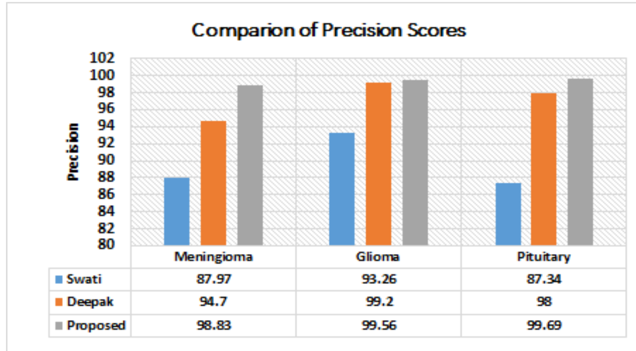

Fig. 3: Comparison of Precision with related works

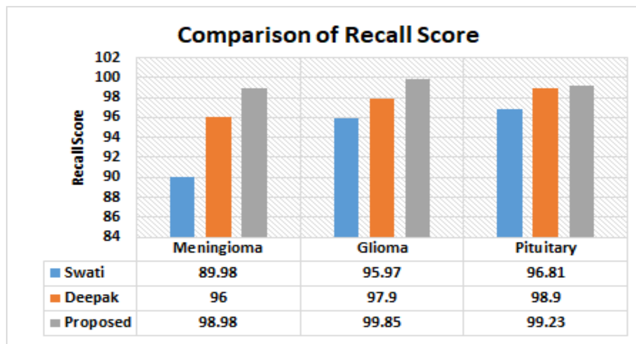

Fig. 4: Comparison of Recall with related works

From Figure 3 and figure 4,we can see that for each and every class,proposed model's precision and recall scores are significantly better specially in the case of Meningioma type tumors where proposed model outperforms closest previous model with a considerably wide margin.
Comparision of Average F_1 score and specificity of proposed model and relative works is shown in Figure 5 and 6 respectively.

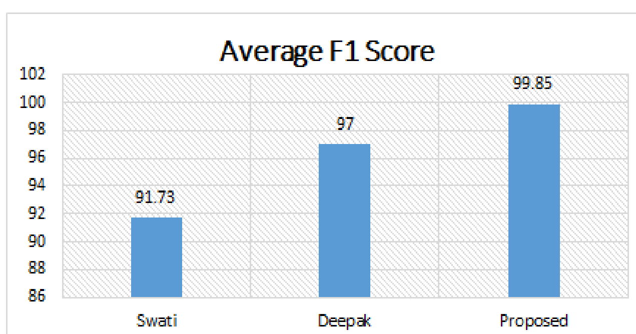

Fig. 5: Comparison of F_1 Score with related works

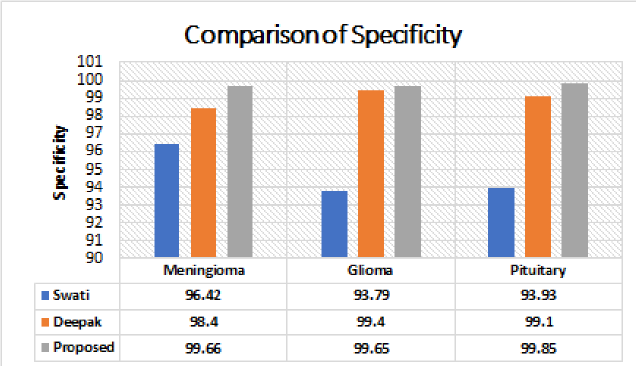

Fig. 6: Comparison of Specificity with related works

Proposed model shows high specificity for each and every class compared to it's counterparts as can be seen from Figure 6.Comparatively Higher average F_1 score(99.35%) as observed in Figure 5 represents overall better performance of proposed model than it's counterparts.

IV. Conclusion

In this paper,we presented a transfer learning based classification model for brain tumor classification from MRI images.With minimum data preprocessing,our proposed model showed best classification accuracy compared to related works.Being evaluated on other performance metrics,our proposed model also significantly performed better than all state of the art approaches on the same dataset.Despite the achievements which are mentioned in this paper,several improvements remain possible like this model fails to handle brain MRI images with no tumor.In future,we will add normal brain MRI image to the dataset for improving classification task further.

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