Hybrid Architecture for Brain Abnormality Detection on brain MR Scans via FastAI

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Abstract

With lot happening in the field of Deep Learning, classification of brain tumor is still a matter of concern. Brain tumor segmentation and classification using MRI scans has achieved lot of interest in the area of medical imaging. The emphasis still lies on developing automatic computer-aided system for early predictions and diagnosis. MRI of brain Tumors not only varies in shape but sometimes gives less contrasted details also. In this paper, we present a FastAI based Transfer Learning tumor classification in which pre-trained model with segmented features classifies tumor based on its learning. The proposed model with the technique of Deep learning applies ResNet152 as base model to extract features from the MRI brain images. With certain changes in the last 3 layers of ResNet152, 97% accuracy in Dataset-253, 96% accuracy in Dataset-205 is achieved. Models such as Resnet50, VGG16, ResNet34 and Basic CNN is also evaluated. The model improved from ResNet152 has provided improved results. The observations suggest that usage of Transfer Learning is effective when the Dataset is limited. The prepared model is effective and can be collaborated in computer-aided brain MR images Tumor classification.

1. Introduction

Modern Artificial Intelligence techniques of computer vision has brought rapid improvement in Medical Diagnosis. For a better treatment of cancer exact and accurate diagnosis is need of the hour. Brain Cancer is an unwanted growth of a tissue which could be deadly [1]. Early and correct treatment plays a significant role. The treatment required is directly dependent on the tumor grade and stage. Brain MR Images was the medium of database taken for tumor classification. Pre-trained network model of Deep Learning can give better results in large brain MRI databases. MR images of brain these days are the most effective way for detection. It is a non-invasive technique for finding various abnormalities of brain [2].

Brain tumor abnormality classification using MR scans is a challenging field. It needs accurate and précised outcomes as the matter is concerned to subject's health [19]. MR scans of brain reveals most of the details in relation to physical, genetical and chemical abnormalities existing in a brain [20]. In order to detect, tumor existence ample classification methodologies have been proposed. The conventional methods carry out classification on brain MR scans via pre-processing, exact tumor portion segmentation, extracting the relevant features and then feeding into classifier for training and validation testing. These broad steps lead to separation of benign images and malignant images.

Few conventional machine learning methods for tumor classification are employed in [21]. Certain hybrid approaches involve the combination of genetic algorithm for reducing the features, further classified benign and malignant tumor by Support Vector Machine Kernel [1]. Techniques like fuzzy clustering Bayesian segmentation of region of tumor [7] with hybrid autoencoder is also implemented for tumor classification. Method of symmetry segmentation with active contour in [8] are followed for classification of tumor portion. Classifiers like CNN architecture [14], are used. Square centroid gray level distribution

method with refined gravitational search technique is employed in [15]. Such early techniques help in providing direction to computer-aided way of brain MR scans tumor classification.

The recent research involves solutions improved through optimization algorithms. Techniques like Particle Swarm Optimization [18], Firefly optimization [16] and Ant-Bee colony optimization [17] when combined with neural networks give better classification accuracy rate.

2. Methodology And Material

In the proposed work, the concept of transfer learning is employed by using a pre-trained CNN with Resnet152. In addition, the Resnet152 is improvised further for classifying tumor. The proposed methodology is validated to classify tumorous and non-tumorous data on Dataset-253. Similarly, classification of High Grade Glioma (HGG) and Low Grade Glioma (LGG) is also validated in Dataset-205.

2.1 Transfer Learning

The concept of transfer learning focuses on fetching knowledge from a previously trained model on learning related problem. In other words, a previously trained model on the same type of image classification data is preferred instead of developing model from the scratch. Transfer learning is beneficial in instances when there is lesser number of data present for model training. Formally, transfer learning is useful for improving the target domain (T_D) learning. The improvement is directly proportional to the pre-gained knowledge in root domain (R_D) and learning task (L_D). On the basis of task type and nature of dataset available in root and target domain, different setting changes are implied for transfer learning [4]. When $R_D \neq T_D$ and not even root task is equal to target task, the concept is known as basic transfer learning. In such cases, the dataset with small brain sample data gets knowledge from pre-trained large brain data model [5].

The concept of deep neural network [6] with pre-trained weights is applied. The method gives fruitful outcomes when dealt with large MR Image datasets. Other pre-trained models such as ResNet50 [26], VGG16[25], ResNet34[27] and ResNet152[23] were also experimented for tumor classification on the 2 brain MRI datasets. The classification as tumorous and non-tumorous is performed on Dataset-253 and Dataset-205. In continuation, further classification with improved model is done. The Fig. 1 below gives the basic layout of the transfer learning concept applied in our proposed work.

The mechanism of proposed methodology follows three basic steps: FastAI ResNet152 model creation, optimal learning rate detection, and Fine-Tune and model unfreezing. The details are described in below sub-sections.

FastAI ResNet152 model creation

FastAI being a deep learning library focusses on two basic goals i.e., being approachable and to have a rapid productivity[29]. The application of FastAI are vision, text, tabular and collab. The vision module

includes functions which for a computer vision task can easily define the data and do model training. For this, four submodules are vision.image, vision.transform, vision.data and vision.learner. This top hierarchy helps user to avoid learning usage of lowest level API.

The deep learning ResNet152 model architecture is a pre-trained model from the repository of ImageNet data, where 1 million computer vision images exist from class 1 to class 1000. The model is a commonly practised framework for deep learning outcomes. Residual Network models are state-of-the-art Convolutional Neural Networks that are reconstructed newly for the research area of Computer Vision. The ResNet152 model connects fast in comparison to models like inception and VGG due to one parameter adjustment [30]. When compared with inception and VGG, ResNet is simple to use in different kind of datasets. Even if the network is deeper with increase in layers, gradient is easily maintained in ResNet by passing input data further avoiding information loss whereas it cannot be easily updated in inception and VGG. The Fig. 2 below shows the basic ResNet152 architecture and the concept of skip connections adapted.

Optimal learning rate detection

In order to get increment in model working an effective optimal learning rate is detected. The optimal learning rate plays significance in controlling quick adaption of model to the problem. Learning rate being a hyper-parameter controls adjustment of weights in network with reference to the loss gradient. Setting of small learning rate results in slow progress in model training with minute updates in network weights. Even setting high learning rate can lead to undesirable divergence in loss function. Thus, learning rate significantly controls the model performance.

Adam Optimizer

The Adam optimizer is chosen due to its better learning rate and is parameter specific in adapting the nature of learning. Adam optimizer helps in minimizing the loss function while model training.

Fine-Tune and model unfreezing

Fine-Tune of a Convolutional Neural Network model is done not only to make updations in its architecture but also to provide it re-training for the learning of new image object classes. Fine-Tune gradually makes adjustments in the weights of pre-trained neural network model. A new dense layer and its re-training with CNN base of ResNet152 is done including the fine-tuning of base models parameters. Unfreezing of model contributes in training only a specific layer at a time.

The Fig. 3 below represents the block diagram of the proposed method for brain tumor image classification of brain MRScans.

2.2 Dataset

The Dataset-253[28] collected from Kaggle, consists of 98 non-tumorous images and 155 tumorous data. Dataset-205 collected from[11] contains 172 High Grade Glioma(HGG) images and 56 Low Grade

Glioma(LGG). For making data larger in size Data Augmentation applied. 15^{o} Rotation angle for every horizontal and vertical flip. The Fig. 4 and Fig. 5 shows augmented images for both Dataset-253 and Dataset-205.

3. Experiment And Discussions

The experiments were performed on Python with i7 processor, GPU card and RAM capacity 8 GB. FastAI[28] framework vision library was imported for building a tumor classifier. The results of FastAI based transfer learning are obtained by creation of FastAI pre-trained model, locating optimal learning rate and deep learning architecture fine-tuning for model fitting. The model performance is evaluated on each strategy. The step by analysis of training the model is carried in three steps: 1) FastAI model creation; 2) Detecting optimal learning rate; 3) Fine-Tune and unfreezing for model enhancement

3.1. Step 1: FastAI model creation

ResNet152 [13, 24] architecture is employed as the base model for tumor and non-tumor brain images classification. ResNet152 architecture is a pre-trained model on ImageNet and is included using FastAI package. A callback_fns functions is applied in order to check improvement in model via graphs. In function Metrics, accuracy is used as a metric for outcome. The model is trained and validated using binary-cross entropy. This is done for two class binary classification. The Fig. 6 below gives a layout model summary of ResNet152 after model training of base Convolutional architecture. The model depicts total trained parameters with the help of Adam Optimizer.

Table 1
Model summary ResNet152 after training base Convolutional architecture

Layer(type)	Output Shape	Param #	Trainable
conv2d	[63,113,113]	11,408	T
BatchNorm2d	63,113,113	128	T
ReLu	[63,113,113]	0	F
MaxPool2d	[62,58,58]	0	F
Conv2d	[62,58,58]	4096	T
BatchNorm2d	[2048,9,9]	4096	T
ReLU	[2048,9,9]	0	F
AdaptiveAvgPool2d	[2048,1,1]	0	F
AdaptiveMaxPool2d	[2048,1,1]	0	F
Flatten	[4096]	0	F
BatchNorm1d	[4096]	8190	T
Dropout	[4096]	0	F
Linear	[512]	2096,664	T
ReLU	[512]	0	F
BatchNorm1d	[512]	1024	T
Dropout	[512]	0	F
Linear	[2]	1026	T

3.2. Step 2: Detecting optimal learning rate

With the basic training of the model, the optimal learning rate is found with in-built learner object functionality. It helps to find ranges in learning rates. This is done for model training. The optimal learning rate is achieved by fitting the model for a few epochs. The learning rate when the loss starts degrading is saved. The function learner.lr_find() is used for finding the learning rates and learner.recorder.plot() function constructs the learning rate curve. The learning rate with steepest slope and decreasing loss curve is chosen. The Fig. 7 below shows learning rate curves for brain MRI Dataset-253 and Dataset-205 respectively. The initial value of learning rate is chosen in our case as e-02. There is a gradual increase in learning rate and decrease in validation loss. For one cycle, model training done for few epochs. In our case we did for 10 epochs. After training, again learning rate is updated for the next learning cycle. This is basically model fitting and is also known as Annealing of learning rate[19].

Further, we fit our improved ResNet152 model with a learning rate e-02 for both Dataset-253 and Dataset-205. A maximum of 10 epochs considered for one cycle. The Fig. 8 below depicts training and validation loss for each epoch before unfreezing. The function learner.fit_one_cycle() is used each time. Figure 5 clearly demonstrates that the model needs re-training for another cycle by finding optimal learning rate.

Table 2
Training and Validation Loss for each epoch before unfreeze for the Brain Datasets.

epoch	train loss	Valid loss	Accuracy	Time
0	0.572963	0.518684	0.730196	00:15
1	0.675802	054281	0.706348	00:15
2	0.541887	0.830186	0.658721	00:16
3	0.52735	0.518714	0.768942	00:16
4	0.540524	0.469857	0.809521	00:17
5	0.454532	0.433384	0.912689	00:18
6	0.457034	0.228426	0.968524	00:18
7	0.405162	0.163970	0.960371	00:18
8	0.335286	0.193147	0.961025	00:19
9	0.300564	0.153146	0.961025	00:20

Table 3
Training and Validation Loss for each epoch before unfreeze for the Brain Datasets-2.

epoch	train loss	Valid loss	Accuracy	Time
0	0.682155	0.384258	0.834333	00:17
1	0.569142	0.670802	0.680478	00:17
2	0.609180	1.375989	0574127	00:18
3	0.591071	0.313821	0.888784	00:18
4	0.534628	0.269821	0.912589	00:19
5	0.413801	0.269522	0.870314	00:19
6	0.435617	0.234831	0.888487	00:19
7	0.349801	0.214067	0.903672	00:20
8	0.361034	0.164895	0.945126	00:21
9	0.348611	0.184670	0.962845	00:21

The model re-training is done for 3 cycles and for each cycle optimized learning rate is used. The next step involves the final fine-tuning of the improved model.

3.3. Step 3: Fine-Tune and unfreezing for model enhancement

Finally, in this step the model is re-trained. Learner curve is plotted after unfreezing using learner.unfreeze() function. This helps in finding the new optimal learning rate. The Fig. 9 below depicts the same where Dataset-253 and Dataset-205 of brain images are re-trained with new optimized learning rates. Learning rates are set as 1e-04 and 1e-05 respectively for both the datasets.

After re-training the model accuracy for both brain MR scans datasets is validated to 97% and 96% respectively. The model is not causing over-fitting, since at each epoch cycle validation loss is lesser than training loss. The Fig. 10 below depicts the validation accuracy and gives the losses plot graph for both the Dataset-253 and Dataset-205. Also, if the model is under-fitting then it can be improved by incrementing epoch count while performing model training.

Table 4
Validation Accuracy and Losses Plot Table for Dataset-253

epoch	train loss	Valid loss	Accuracy	Time
0	0.223470	0.173160	0.9678245	00:20
1	0.237084	0.171897	0.9523487	00:21
2	0.385604	0.157545	0.976190	00:20
3	0.384724	0.118425	0.985126	00:20
4	0.286101	0.108415	0.954238	00:21
5	0.216819	0.153427	0.947619	00:21
6	0.254501	0.109394	0.967825	00:20
7	0.273091	0.110689	0.983125	00:21
8	0.245608	0.117646	0.984137	00:20
9	0.256968	0.114028	0.976280	00:20

Table 5
Validation Accuracy and Losses Plot Table for Dataset-205

epoch	train loss	Valid loss	Accuracy	Time
0	0.301714	0.174721	0.967198	00:20
1	0.270159	0.157456	0.960418	00:21
2	0.245118	0.163542	0.968153	00:20
3	0.259398	0.170465	0.983127	00:20
4	0.294214	0.164812	0.960418	00:21
5	0.236383	0.164325	0.985126	00:21
6	0.214028	0.167803	0.988254	00:20
7	0.272825	0.152948	0.968475	00:21
8	0.229586	0.163245	0.983127	00:20
9	0.285567	0.163634	0.969253	00:20

The improved model performs tumor classification for both the Datasets. The confusion matrix for both Dataset-253 and Dataset-205 is given below in Fig. 11 and Fig. 12 respectively.

The Confusion Matrix defines:

True-Positive(TP) as: brain MR scan is tumorous and predicted tumorous as well.

True-Negative(TN) as: predicted image is non-tumorous and is actually the same.

False-Positive(FP) as: image is tumorous but predicted non-tumorous.

False-Negative(FN) as: image is non-tumorous but predicted tumorous.

Accuracy: is calculated as total number of true predicted values divided by total predicted values.

The Table 1 below gives the performance criteria of ResNet152 for both the brain MR scans datasets used.

Table 1
Performance evaluation of ResNet152 for both Datasets

Dataset-253			**Dataset-205**		
Confusion Matrix	46	0	Confusion Matrix	47	2
	3	77		2	75
Accuracy	97.61		Accuracy	96.82	
Precision	100		Precision	97.4	
Sensitivity	96.25		Sensitivity	97.4	

The Fig. 13 and Fig. 14 below shows few correct and few incorrect classification predictions for both Dataset-253 and Dataset-205 after final fine-tuning and unfreezing of the model layers. It involves predicted labels which is true output of model. Actual label is the true ground truth class label of MR image.

4. Conclusion

In this paper, ResNet152 architecture which is a pre-trained FastAI CNN model is used. The ResNet152 architecture is taken as base model and improved by modifying the last 3 layers. The dense layer, followed by softmax layer and binary cross-entropy layers are improved with new layers. After that improved ResNet152 deep learning model was trained on 2 different brain Datasets collected from Kaggle and BRATS2015. Fine-tuning of the model is performed. The accuracy percent of improved model is 97% and 96% respectively when verified on Dataset-253 and Dataset-205. The improved model when compared with other deep learning models gives best results with 2 different brain MRI Datasets. The accuracy percent comparison is given in the Fig. 15 below. Data augmentation applied to increment MR images of brain dataset. The developed improved model can be helpful in finding other brain diseases as

well such as brain stroke, haemorrhage, Alzheimer's etc. Also further, other pre-trained architectures can also be improved by modifying the layers of the network.

5. Declarations

ETHICAL APPROVE: The script does not contain any type of material or data which is unethical.

CONSENT OF PARTICIPANT: No consent was needed for writing this research paper.

CONSENT TO PUBLISH: I, the undersigned, give my consent for the publication of identifiable details, which can include photograph(s) and/or videos and/or case history and/or details within the text ("Material") to be published in the above Journal and Article.

AUTHORS CONTRIBUTION: In this work, pre-trained weights transfer learning FastAI architecture is employed. The ResNet152 [24] deep neural network pre-trained architecture is selected for Dataset-253 and Dataset-205 for predicting tumorous and non-tumorous brain images. The motivation for using ResNet152 improved model is to avoid conventional approaches. The new improved model is full automatic system and its major details are given in experiment and discussion section. The model worked on classifying raw brain MR scans from start-to-end structure unlike any manual-crafted feature extraction technique. The model is an improved version which validates 97% and 96% accuracy rate for 2 different brain MR images datasets. ResNet152 architecture is a three layer deep neural network architecture and the pre-trained weights fetched from ImageNet repository. ResNet152 deep NN architecture reports 3.57% of validation error which is least when compared with other pre-trained models on ImageNet that is, VGG16 [22] with 8.43% error rate, ResNet34 [24] having 5.71% error rate and ResNet50 and ResNet101 [24] with 5.25% and 4.60% error rate respectively. With being 8 times deeper than VGG16 CNN architecture yet has lesser complexity [23].

FUNDING: No funding received.

COMPETING INTEREST: there are no relevant financial or non-financial competing interests to report.

AVAILABILTY OF DATA AND MATERIAL: The dataset "BRATS 2015" is available free for research on the internet and the institution has MATLAB software licence on which the code was tested.

AUTHORSHIP

I, the undersigned author(s), certify that:

1. I have read and approved the final version of the manuscript.
2. I have made substantial contributions to the submitted work, which may include study design, data acquisition and/or analysis, and data interpretation.

3. I have made significant contributions to the preparation of the manuscript and/or critical revisions for important intellectual content.
4. I will be accountable for all aspects of the submitted work.
5. I agree to help investigate and resolve any issues/questions that may arise regarding the accuracy and integrity of the submitted work.

I understand that if necessary, the Editor-in-Chief of *Brain Imaging and Behavior* or designate may request deidentified data that has been submitted as part of the manuscript. In this event, I agree to produce the data.

I certify that this manuscript is not under consideration for publication in any other journal, nor has it been accepted for publication in any form, and no rights have been assigned to a third party.

I certify that all individuals who have made specific contributions to this manuscript but who do not fulfill the authorship criteria are listed with their specific contributions in the Acknowledgments section of the manuscript.

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I understand that after the initial submission, authorship changes are strongly discouraged unless clearly warranted. If a major revision is submitted and authors have been added, removed or reordered, a rationale must be clearly indicated on the authorship change form, and all authors, prior and newly proposed, must sign the form indicating their agreement. Original signatures are required. Changes are subject to approval by the Editor-in-Chief.

CONFLICT OF INTEREST AND FINANCIAL DISCLOSURE

“None of the authors have a conflict of interest to declare.”

By signing this document, I agree to accept full responsibility for the work submitted in the manuscript, including the accuracy and integrity of the data and data analyses.

Additionally, I assert that there are no conflicts of interest, either personal or institutional, that have compromised the integrity of the work reported in this manuscript.

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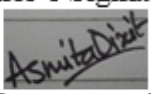

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Asmita Dixit 30-05-2021

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Figures

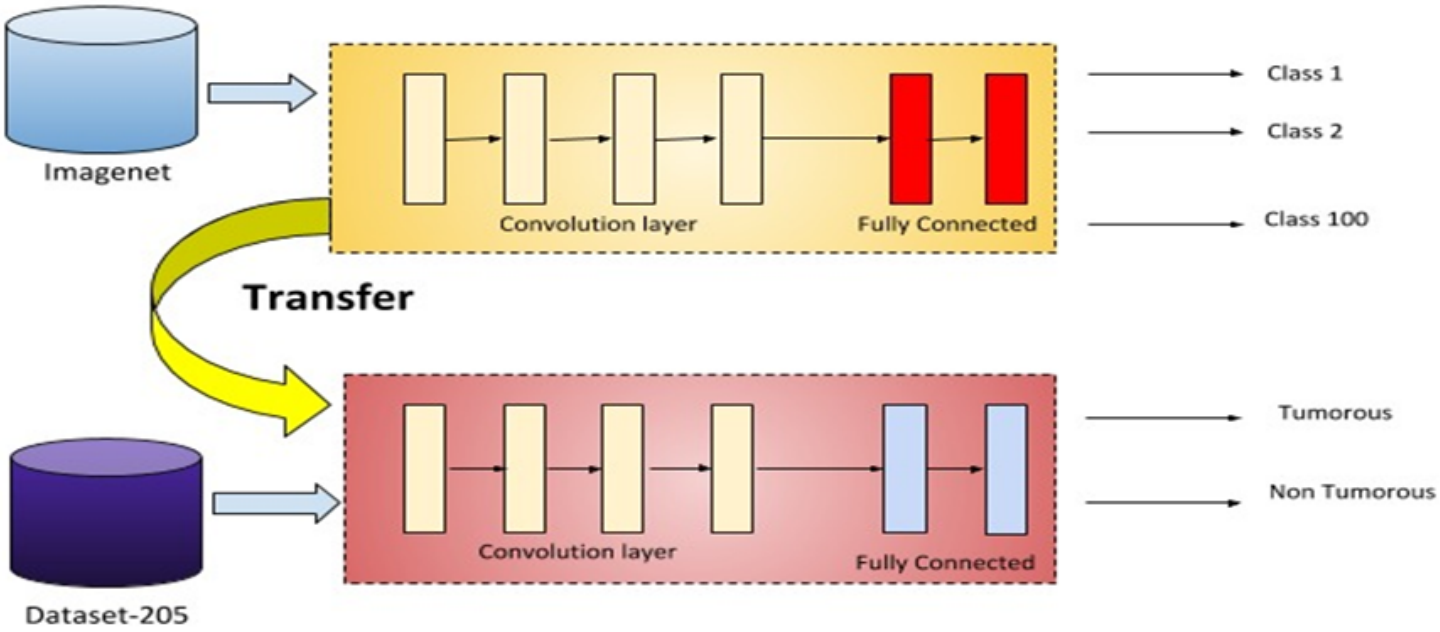

Figure 1

Basic Transfer Learning Concept

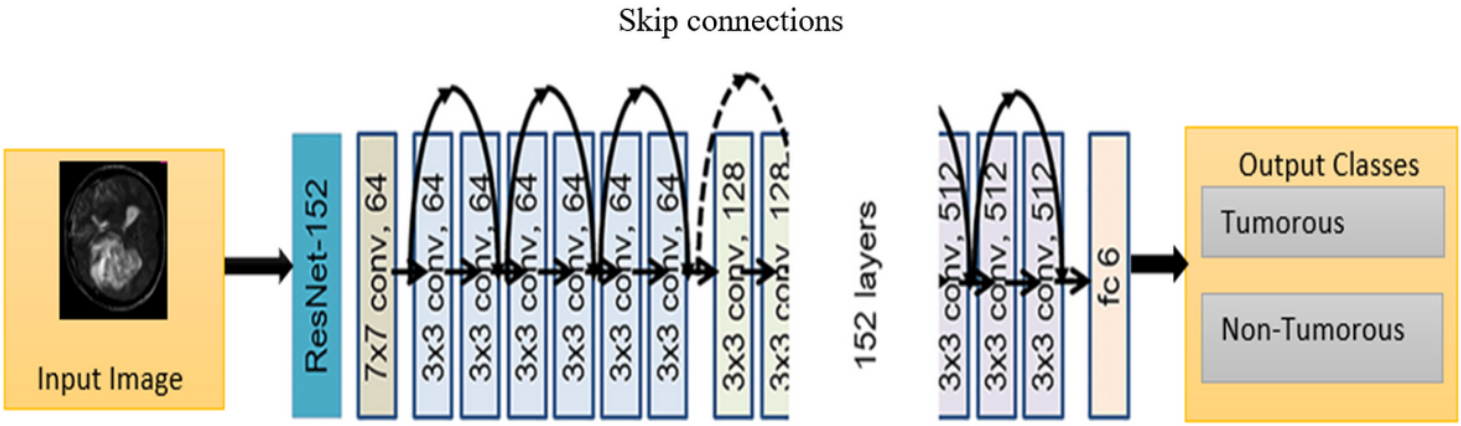

Figure 2

ResNet-152 Architecture

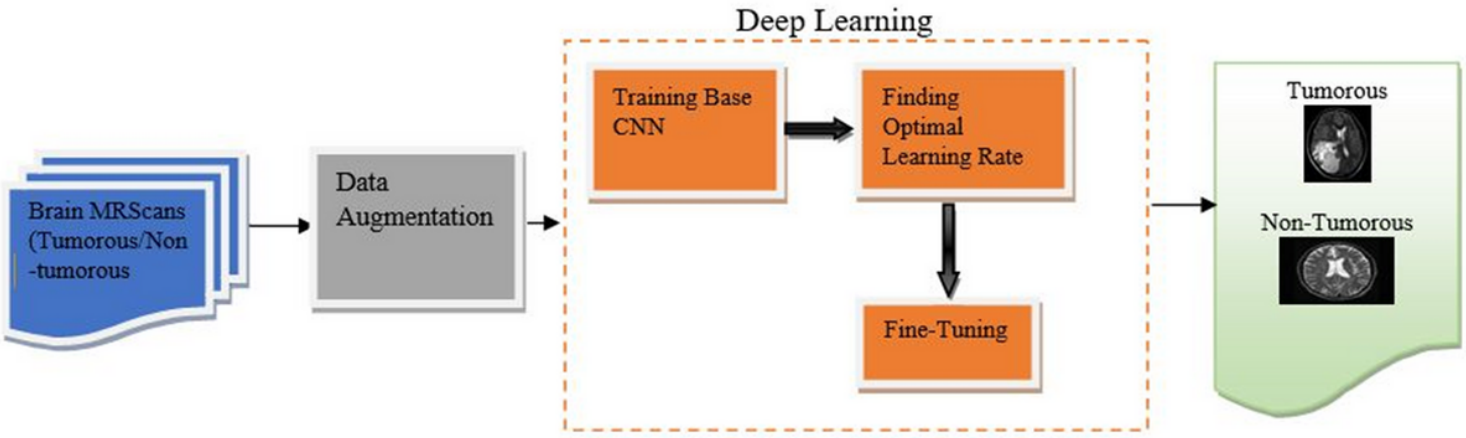

Figure 3

Block Diagram of proposed methodology used

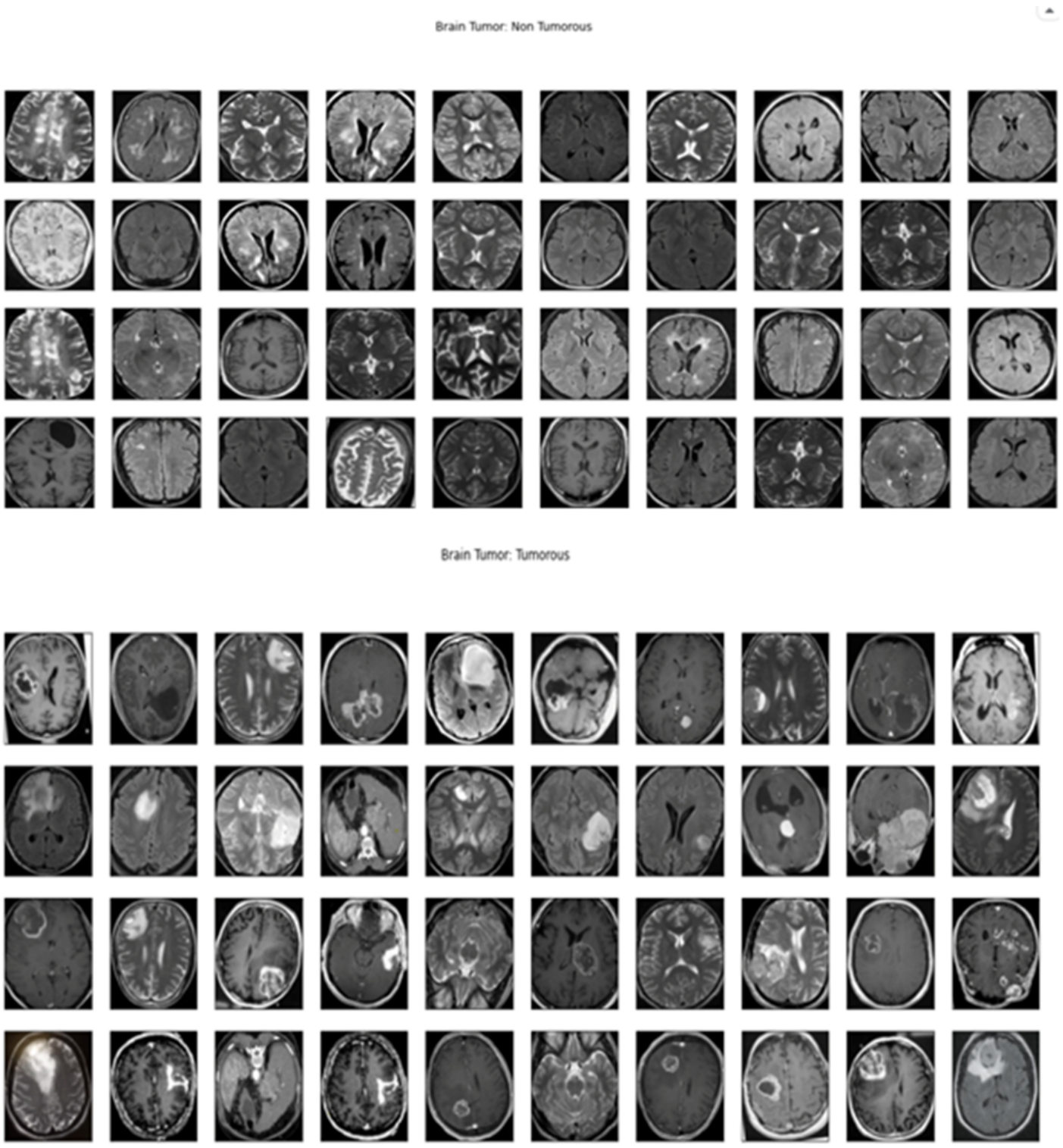

Figure 4

Sample augmented images Dataset-253

Figure 5

Sample augmented images Dataset-205

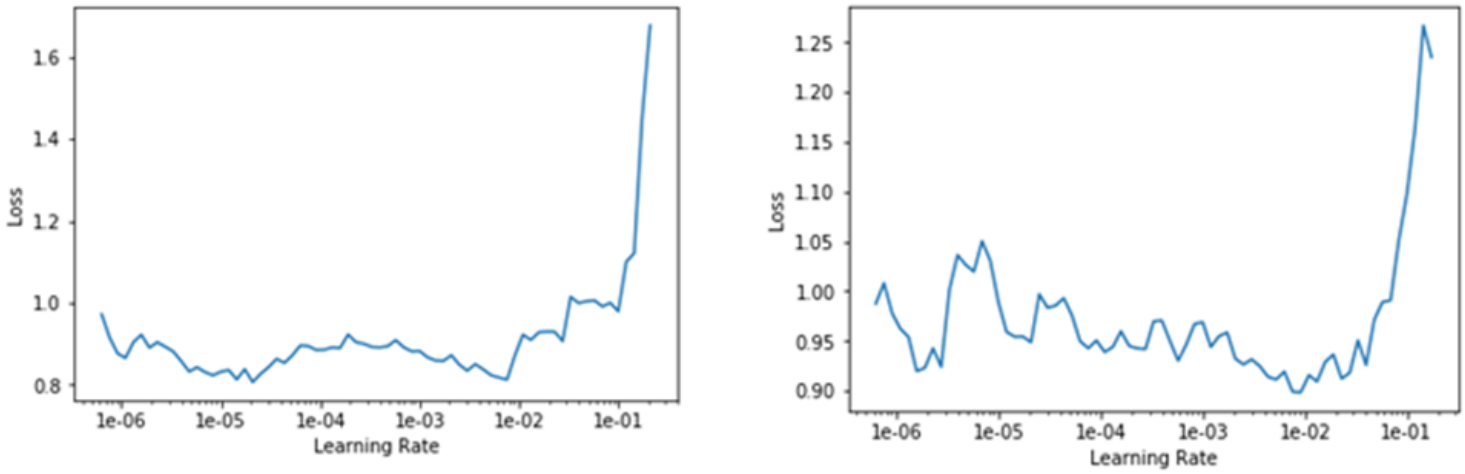

Figure 6

Learning rate curves for Dataset-253 and Dataset-205

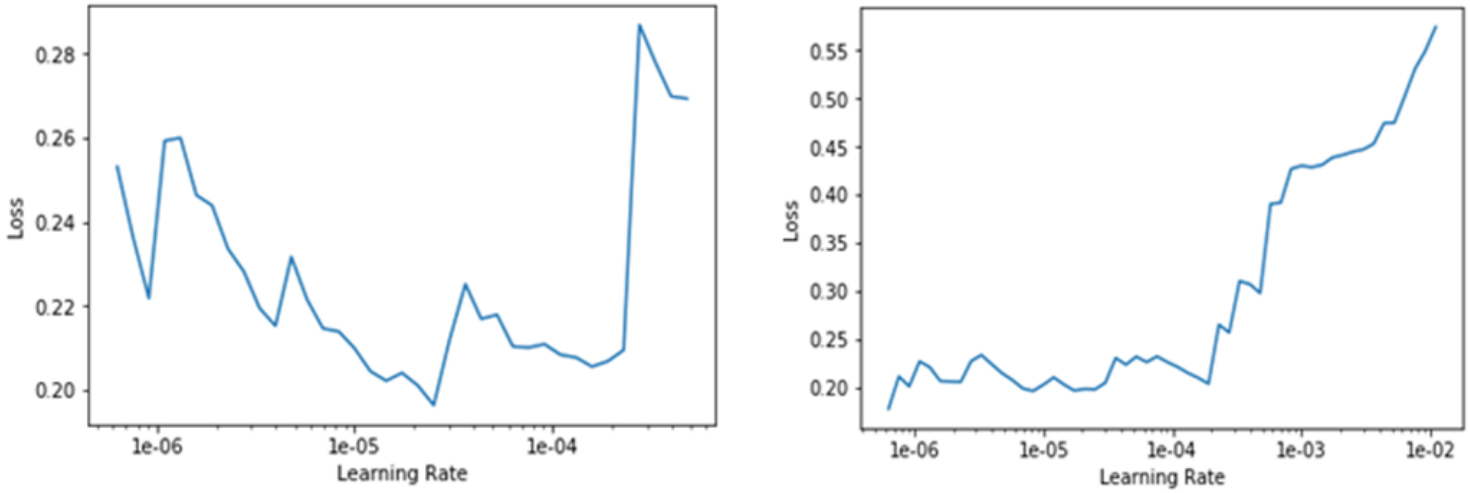

Figure 7

New Optimal Learning rates for fine-tuning of the improved model

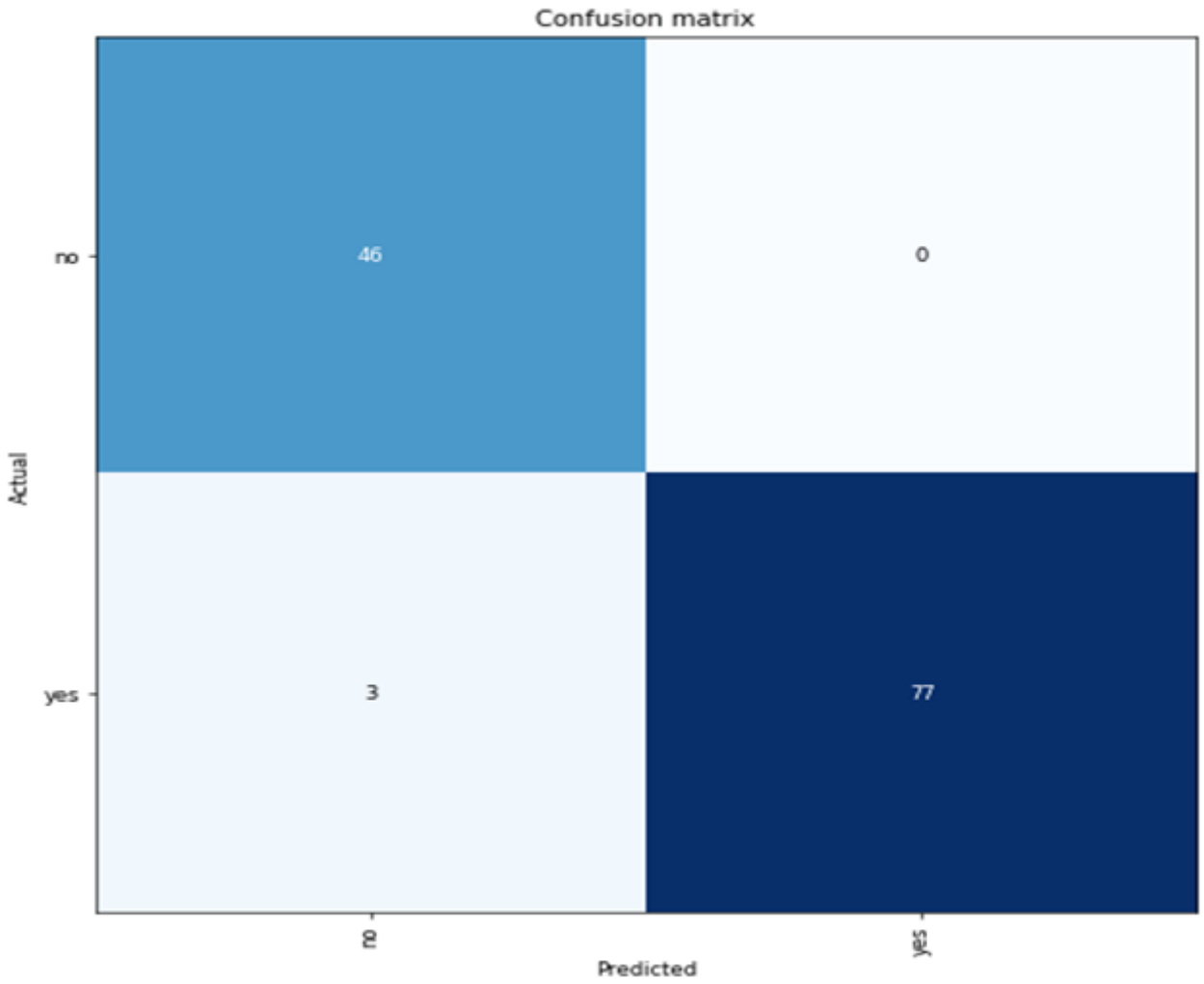

Figure 8

Confusion Matrix Dataset-253

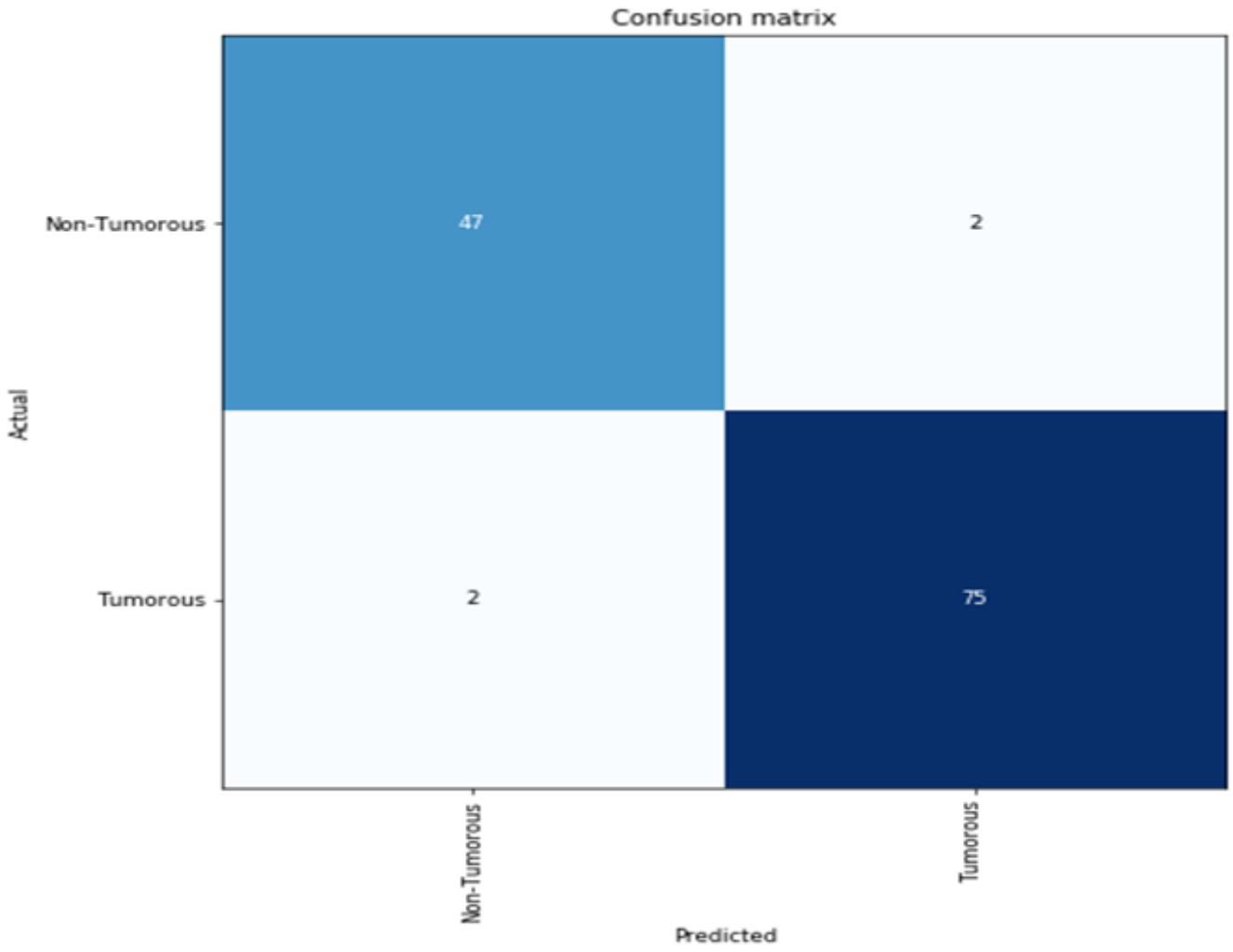

Figure 9

Confusion Matrix Dataset-205

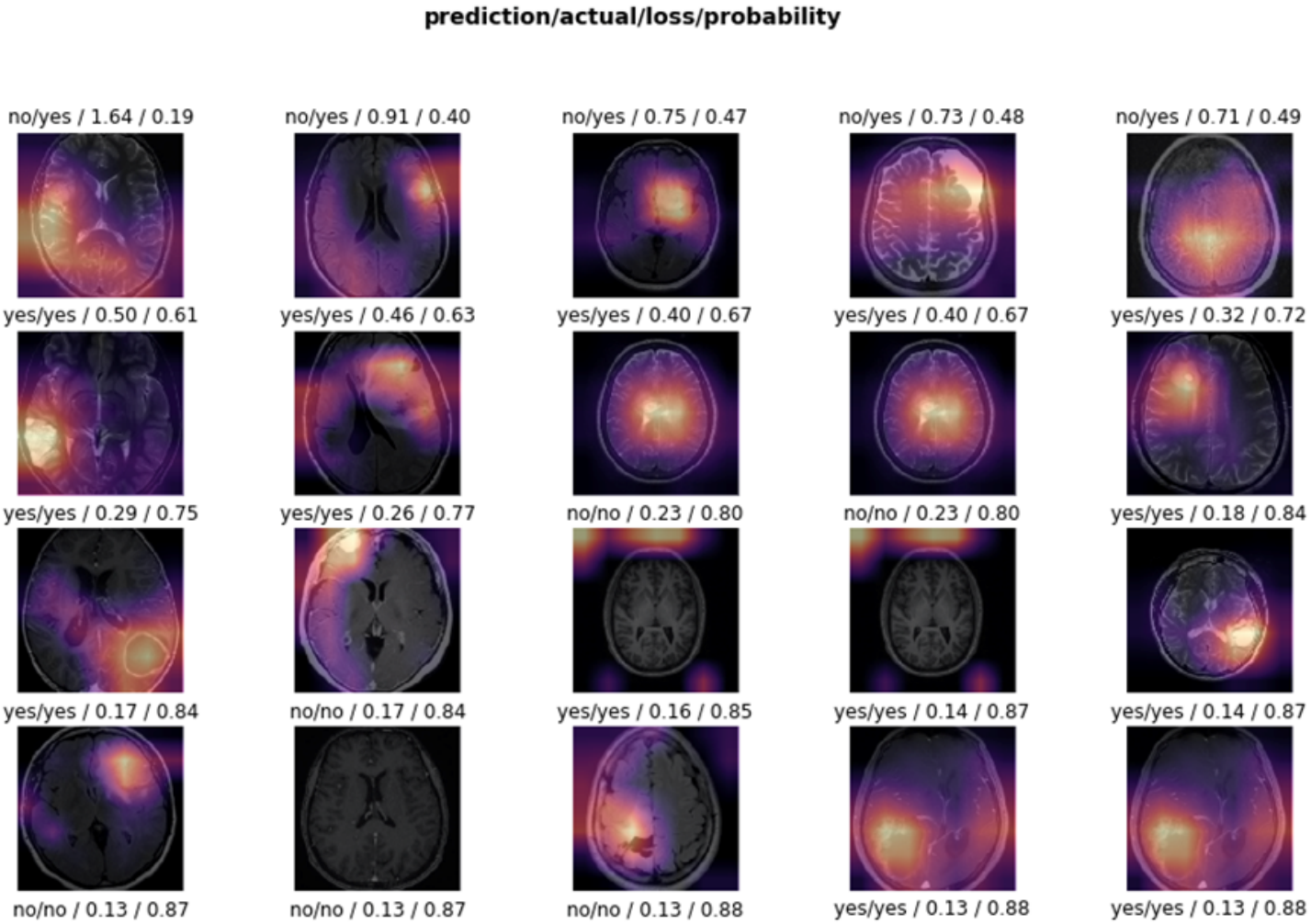

Figure 10

Correct and incorrect predictions Dataset-253

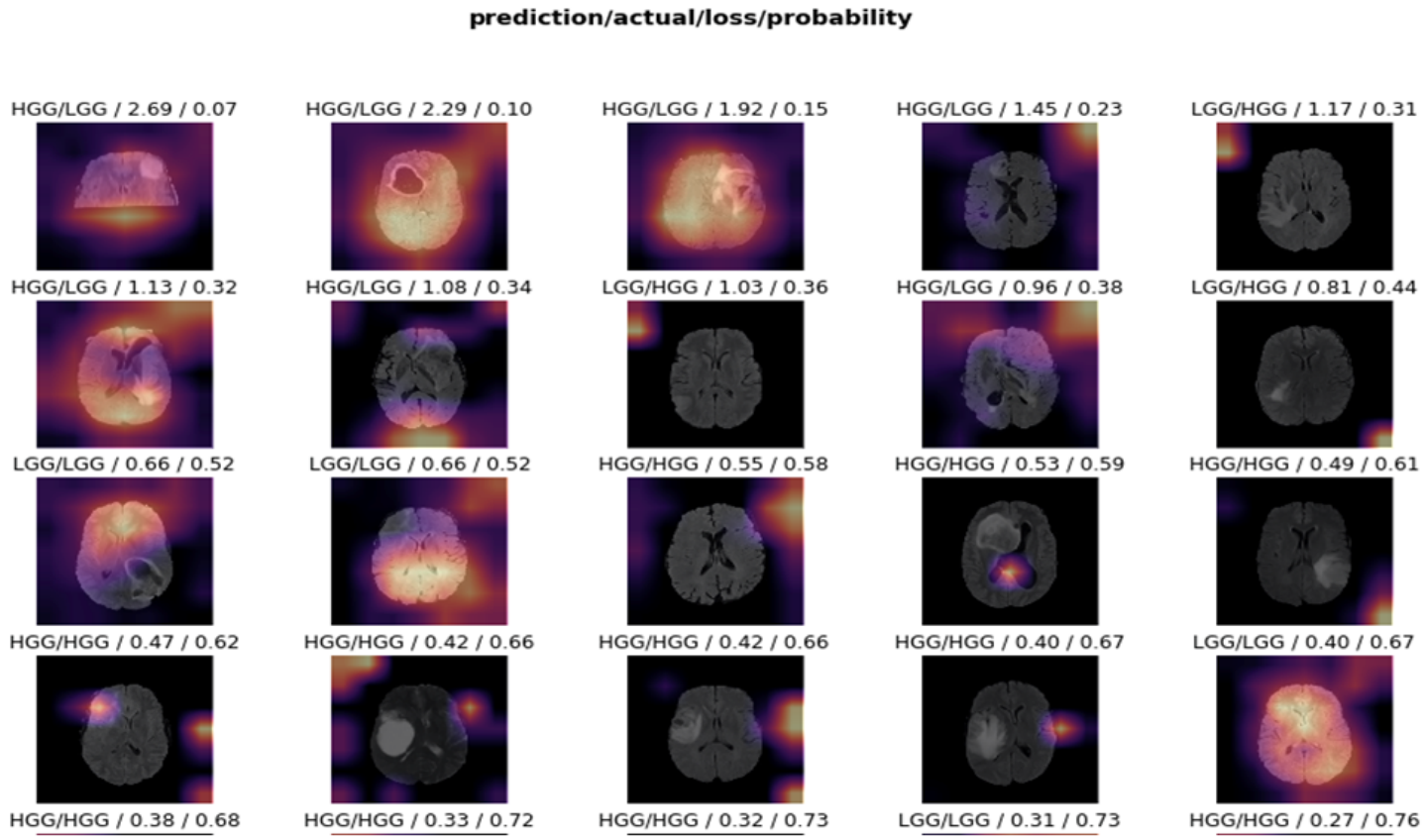

Figure 11

Correct and incorrect predictions Dataset-205

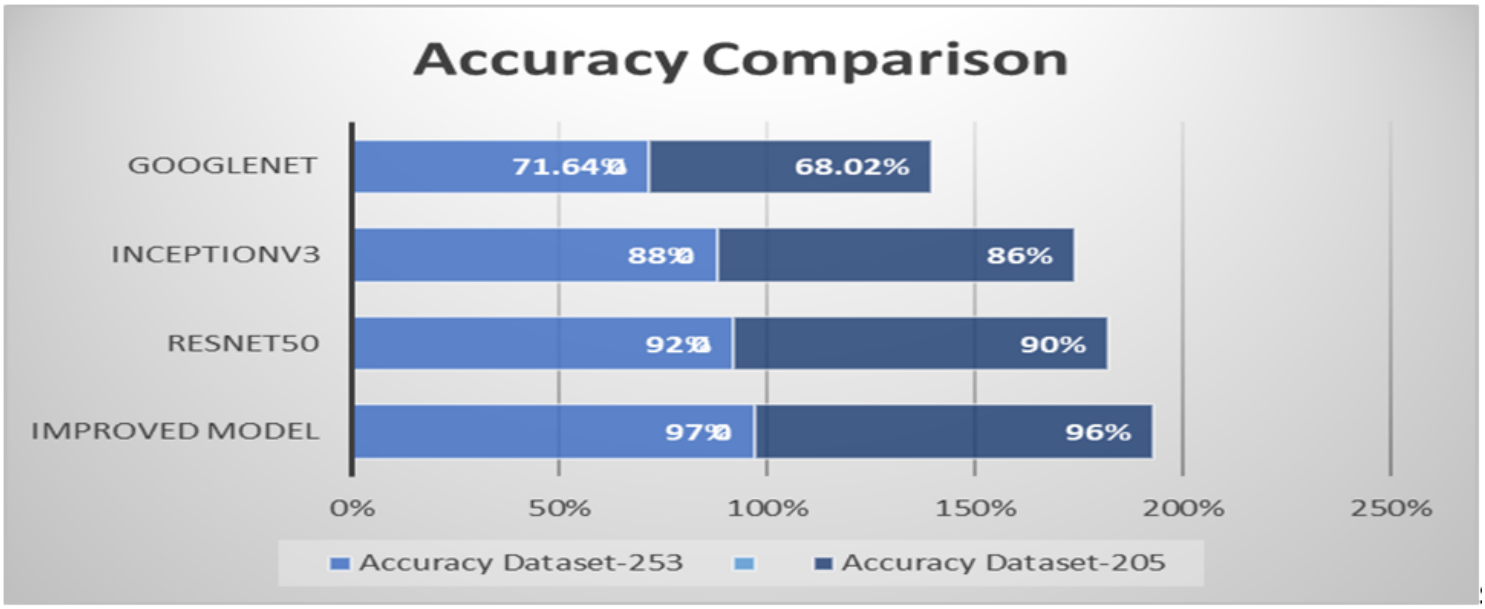

Figure 12

Accuracy Comparison for the two Datasets

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- BIBChecklist.docx