A Deep Learning Technique for classification of tumor present in Brain MRI images

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Abstract: Brain tumor is very dangerous and fatal with high grade type case. If detect and diagnosis early then survival rate of the patient could be extended to some. Conventional classification is done through human expertise in the field. So classification has become an important in Computer Aided Diagnosis (CAD) system. Various imaging technique are used for capturing details structure of human brain such as Computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography(PET). For our worked we consider T2 weighted MRI. In this paper we proposed a model for classification of types of brain tumor base on World Health Organization (WHO) grading system: Low Grade Glioma(LGG) and High Grade Glioma(HGG) and carried out two case studies. **Case I** with Adam optimizers and **Case II** with Rectified Adam (RAdam). Proposed model used Convolutional Neural Network (CNN) with Regularizer. A comparison for two cases in made is also done.

Keyword: Brain tumor, CAD, WHO, Low Grade Glioma, High Grade Glioma , MRI, CT, PET, CNN, Regularizer, Adam, RAdam.

I. INTRODUCTION

Brain is one of the complex organ of human body which is made of different specific area working together. It consists of more than 100 billion neurons that communicate. Brain control most of human body activities. Tumor is abnormal growth of cells under uncontrolled cell division. So brain tumor is abnormal mass inside tissue. Brain tumor can either be benign or malignant. Benign does not contain cancerous cells. Benign tumor can be remove with surgery and not reappear again in future. They have clear boundary and generally do not invade neighboring cells tissue. Malignant tumors contain cancerous cell, rapidly grows invading surrounding cells, threatening to life. Researchers do not exactly outline cause of brain tumor. Some types are believing to occur more to people working in certain industries like oil, rubber, drug manufacturing.

There are more than 120 types of brain and central nervous system tumor. Brain tumor are classified based upon different criteria like origin of cells where tumor occur. WHO broadly provide grading system of tumor to know where different types of tumor fall into: Lower grade (Grade I, Grade II) and High grade (Grade III, Grade IV). Few characteristics charted out by WHO:

- Grade I: least malignant, possibility of curable, long term survival
- Grade II: slow growing, somewhat infiltrative.
- Grade III: malignant, infiltrative and tends to high grade.
- Grade IV: most malignant, rapid growth, aggressive.

World Health Organization (WHO) Brain Tumor Grades

	Grade	Characteristics	Tumor Types
Low Grade	WHO Grade I	• Least malignant (benign) • Possibly curable via surgery alone • Non-infiltrative • Long-term survival • Slow growing	• Pilocytic astrocytoma • Craniopharyngioma • Gangliocytoma • Ganglioglioma
	WHO Grade II	• Relatively slow growing • Somewhat infiltrative • May recur as higher grade	• "Diffuse" Astrocytoma • Pineocytoma • Pure oligodendroglioma
High Grade	WHO Grade III	• Malignant • Infiltrative • Tend to recur as higher grade	• Anaplastic astrocytoma • Anaplastic ependymoma • Anaplastic oligodendroglioma
	WHO Grade IV	• Most malignant • Raid growth, aggressive • Widely infiltrative • Rapid recurrence • Necrosis prone	• Gliobastoma multiforme (GBM) • Pineoblastoma • Medulloblastoma • Ependymoblastoma

Fig 1: WHO tumor grading (American Association of Neurological Surgeons)

According to school of neurosurgical (University of Pittsburg) some symptoms related to brain tumor:

- Headaches (worse in morning ease in daytime)
- Drowsiness, Nausea, Lack of vision
- Lack in body movement coordination
- Weakness in arms and legs movement.

Tumors we consider for this model are Low Grade Glioma (LGG) and High Grade Glioma (HGG). LGG consist of Grade I & II. They are sometimes referring to as “Benign”. These tumors are slow growing but can cause complex problem if its location in brain is at critical area. Normally start in glial cells. Few typical LGG tumors includes: Pilocytic astrocytoma, Pineocytoma, Oligodendroglioma etc. They slowly invade brain areas and can grow gradually and eventually becoming HGG. Some LGG can easily remove with surgery but diffuse types which does not have clear border interface are hard in treatment. HGG includes Grade III & IV. Recently this type of tumor is referred to name “Glioblastoma”. They grow and spread rapidly as compared to LGG and widely infiltrative in nature. Sometimes they are referring to as ‘Malignant’ tumor. Most common Grade III includes Anaplastic astrocytoma, Anaplastic Oligodendroglioma while Grade IV is Glioblastoma multiforme.

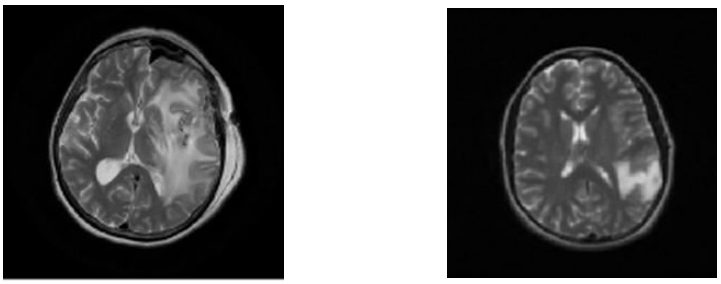


Fig 2: (a) High Grade (b) Low Grade

Many imaging techniques are used for diagnosis of brain tumor. Some of recent advancement techniques include computed tomography(CT), magnetic resonance imaging(MRI), positron emission tomography(PET). MRI uses magnetic field instead of X-rays to provide body details images. Generally, diagnosis of brain tumor starts with MRI and once taken type of tumor is decided by radiologist or human expert by mere looking at tissue after biopsy. MRI is preferring to CT as it gives more deep details structure of brain and does not used ionized

radiations. Unlike CT no physical movement of patient is needed while taking 360 degree of body structure. Different types of MRI sequences: T1,T2 weighted, Axial, FLAIR etc. For this worked only T2 weighted slices are considered.

Based on National brain tumor society an estimation of 7 lakhs American are having brain tumor. Out of these 69.8% account for benign and remaining 30.2% for malignant tumor. An approximately 87000 patients will receive diagnosis for primary brain tumor in 2020. Out of these about 61,000 will be for benign and remaining for malignant [National Brain Tumor society]. Survival rate varies with ages, older the lesser. For malignant brain tumor patient its only 36%. Lastly a prediction is made about 18,000 people dying in 2020 from brain tumor.

II. LITERATURE REVIEW

Researchers across different university uses different approaches in classification of brain tumor. Some classified tumor as benign and malignant, some into specific classes or into grades. S.Deepak use method of transfer learning with pretrained GoogLeNet for classifying tumor into three types: meningioma, pituitary and glioma [1].Three method are performed and compare their results. First, modified GoogLeNet with softmax as classifier achieved 92.3±0.7%. Secondly feature is extracted GoogLeNet with SVM with error correcting output achieving accuracy of 97.8±0.2%. Thirdly KNN as classifier achieved 98.0±0.4%.

In [2] a customized CNN model is used by H.H. Sultan and N.M Salem. Two separate studies carried out using T1 weighted MRI slices. Study I, classifies brain tumor into three types: glioma, meningioma and pituitary. Study II, classifies tumor into three grades, Grade I, Grade II and Grade III.96.16% and 98.7% accuracy are achieved respectively with regularization method. D.Sridhar [3] used DCT and PNN for brain tumor classification. Feature extraction is done through DCT and then PNN classifies the tumor. They classify five tumor types with limited dataset to check reliability of their proposed model.

Four type of classification is performed in [4]. They consider: normal, sarcoma, glioblastoma and metastatic bronchogenic carcinoma. For feature extraction DWT is deployed and reduced dimensionality with Principal Component Analysis(PCA). Then finally in DNN different classifier are used and compare their values as: KNN(k=1) is 95.45%, KNN(k-3) is 86.365, LDA is 95.45% and SMO is 93.94

Author in [5] first classifies the tumor into benign and malignant tumor and then detection system is performed afterward. for classification they used extreme learning machine local

receptive fields (ELM-LRF). Cranial MRI are used; noise is remove by smoothing then classification is done. For final stage i.e. detection watershed segmentation method applies to produce tumor region as output of the model. A multiclass model is proposed by Kruti G. Khambhata and Sandip R. Panchal [6]. Texture (using Gabor transform) and intensity (using color moment) are extracted from MRI images. Then Support vector machine to classify brain tumor based on WHO grading in to five class: Astrocytoma (Grade I), Glioblastoma multiform (Grade IV), Meningioma (Grade II), Medullablastoma (Grade II) and metastatic melanoma (Grade III) with 76.14%, 76.65%, 84.26%, 86.80% and 82.23% respectively. Nilakshi Devi and K. Bhattacharya [7] developed a soft computing framework for tumor detection using ANN. Median filter, histogram equalization, threshold segmentation are preprocessing steps applied in the model. Feature extraction is done with GLCM (gray level concurrence matrix). Finally, ANN is use to detect whether there is tumor or not in MRI images. A modified ResNet-101[8] is used for classification of three tumor types: glioma, pituitary and meningioma. Squeeze and excitation (SE) blocks are stack up one upon another, combine with base ResNet-101 to form SE-ResNet-101 architecture. This model achieved better accuracy of 93.83 as using with SVM (91.14%). [9] uses a three layers CNN model with two fully connected layers with a softmax to classifies images into pituitary, glioma and meningioma. R. Ezihilasi and P. Varalakshmi use Alexnet is used for classification and its output are feed into RPN (Region Proposal Network) and ROI (Region of Interest) to detect tumor region using Faster R-CNN.

III. PROPOSED METHOD

Recognition and classification in medical images has become a big attention in recent years. A deep neural network is thoroughly used by many scholars for research work. CNN is one of the best to use for classification purpose. It sees an image as array of pixel and look to image as HxWxD (height, width and channel). CNN consist Convolutional Layers, activation function, pooling layers, Fully connected layers.

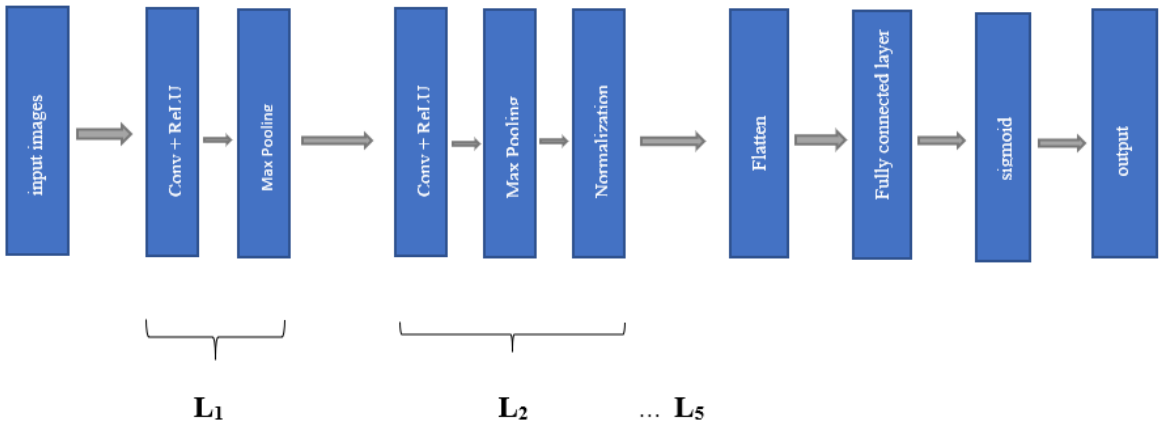


Fig 3: Proposed architecture of CNN (L represent layers).

Fig2 shows the architecture of our model.Five convolutional layers are used.First and second layer consist of 16 units which linearly increase in multiple of 2, with last layer having 128 units. A kernel (filter) of 3x3 with ReLU as activation function. ReLU is rectified linear unit. It is a non-linear operation after convolution layer. Mathematically defined as:

$$f(x) = \max(0, x)$$

It returns zero if receive a negative value but for positive input, return that value back.

Layers	No. parameters
L1	448
L2	4640
L3	9248
L4	18496
L5	73856

Table1: No. of parameter in each layer.

Above table shows layers of our model along with number of parameter in each layer in each layer. To down sample, the feature map generated at each layer, max pooling is used. Over fitted model will have low generalization during testing. Dropout, batch normalization and regularizer are used in combine with layers for our model. Dropout makes network learn features more robustly and doubles number of iteration required. But time consumption

becomes less for each epoch. A dropout of 0.2 is used for our model. Batch Normalization standardized input to network. It accelerates training speed, reduced generalization error. For our model it is implemented from second layers to last layer. L2 regularization were used. Regularization is technique of reducing error by fitting appropriate function on training dataset. This help in avoiding over-fitting of model. L2 regularization also called Ridge Regression which adds square magnitude of coefficient as penalty to loss function. Loss function is sum of square difference between actual and predicted value. For example,

$$\text{Loss function , } f(x,y) = \sum_{i=1}^{n}\left(yi - f(xi)\right)^2 + \lambda \sum_{i=1}^{n} \Theta_i{}^2$$

Here the last term lambda is called the regularization term. It gives penalty to some weights. For example if we penalize weight (say) Θ_i and Θ_{i+1} and makes them close to zero, it makes them negligible and hence simplifies the model. Finally, a fully connected layers (FCL) with 32 units. Our model is for binary classification; sigmoid classifier is used for final. Define as:

$$f(x) = \frac{1}{1+e^{-z}}$$

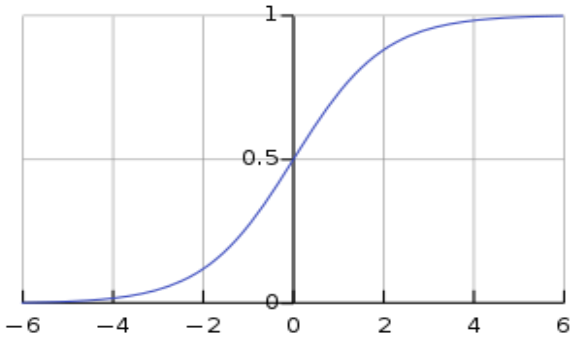


Fig 4: sigmoid curve.

The range of value is (0,1) means high value of x will approach toward 1 but never equals. So this function is used when output has to be predicted as probability (0 or 1).

IV. Experimental Result

Data acquisition: Dataset used in our worked is collected from The Cancer Image Archive (TCIA) using NBIA data retriever. All images are in dicom format, converted into png. Approximately about 200 images are collected for both Low grade and High grade glioma.

Data preprocessing: Images converted to 256x256 dimensions. Then Gaussian smoothing is applied to dataset with the intention of removing noise. It is a 2D convolution operation applies to each pixel. Removing noise from image sample will enhance performance of the model in testing and final accuracy. It is a low pass filter that reduces noise and negligible details of the image. It can be express as:

$$G_{2D}(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma\sigma^2}}$$

x = distance from origin in horizontal axis.

y = distance from origin in vertical axis.

σ = standard deviation of the distribution.

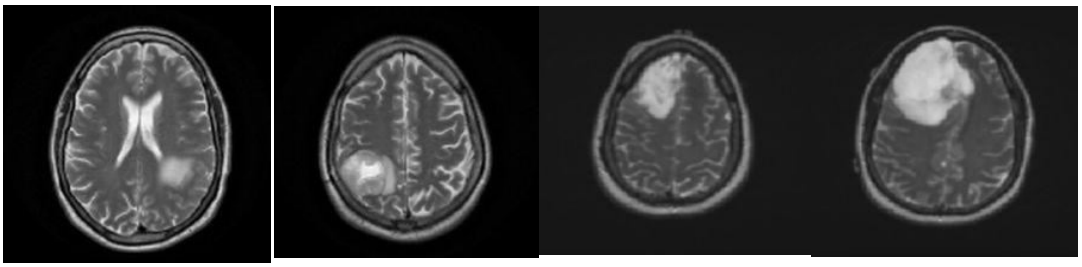


Fig 5: smoothen dataset

Training: Model is trained on images with 50 epochs. Two case study were done with different optimizers. In **Case I** Adam optimizer is used and in **Case II** Rectified Adam (RAdam) optimizers.

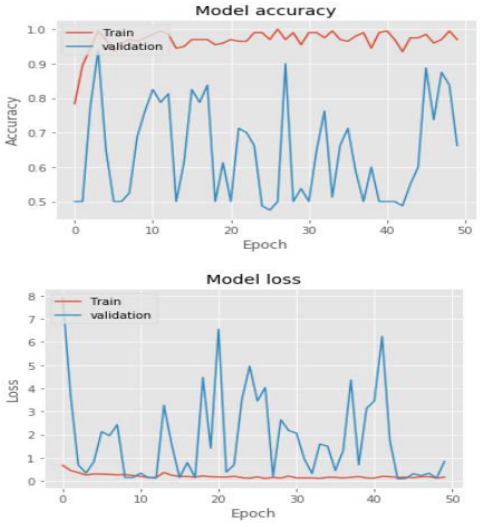
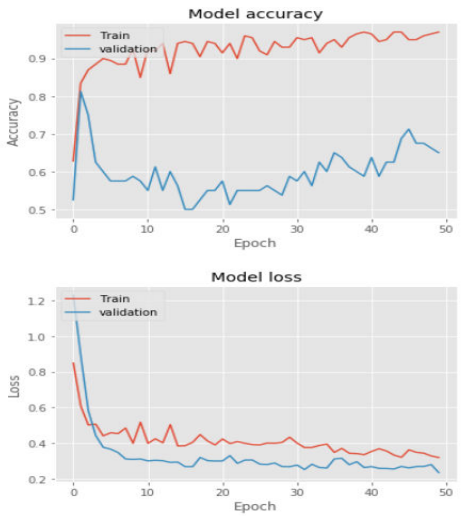


Fig 6: (a) Case I(Adam)



(b) Case II(RAdam)

Fig 5 show graph for training of proposed CNN model with (a) Adam optimizer and (b) Rectified Adam (RAdam) optimizer. RAdam started with low accuracy as compare to Adam optimizer but with gradual increase in number of iteration RAdam catches up with Adam. While in model loss Adam started with much less loss as compare to RAdam. On contrary RAdam attained accuracy in each iteration in very less time in training as show in fig 6. Roughly 25-30% faster than Adam in this worked

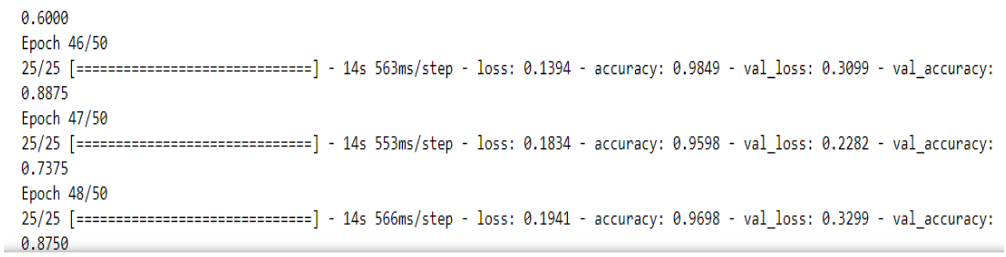
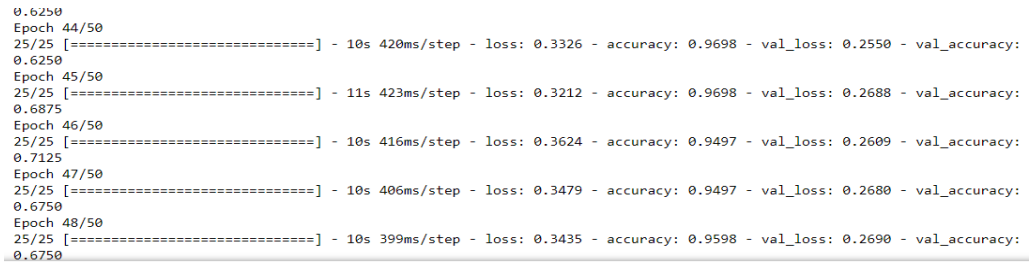


Fig 7: (a) Case I (Adam)



(b) Case II (RAdam

Environment where worked was implemented: windows 10 operating system, 8GB RAM. Python 3.7 with keras and tensorflow libraries.

Result: After the model is successfully trained we tested on separate 40 images (20 for each class) that are not part of training. An accuracy of 97% was achieved in **Case I** and 95% in **Case II**.

Classification Report

	precision	recall	f1-score	support
High Grade	1.00	0.95	0.97	20
Low Grade	0.95	1.00	0.98	20
accuracy			0.97	40
macro avg	0.98	0.97	0.97	40
weighted avg	0.98	0.97	0.97	40

sensitivity: 0.95
specificity: 1.00

Fig 8 (a): Case I

Classification Report

	precision	recall	f1-score	support
High Grade	1.00	0.90	0.95	20
Low Grade	0.91	1.00	0.95	20
accuracy			0.95	40
macro avg	0.95	0.95	0.95	40
weighted avg	0.95	0.95	0.95	40

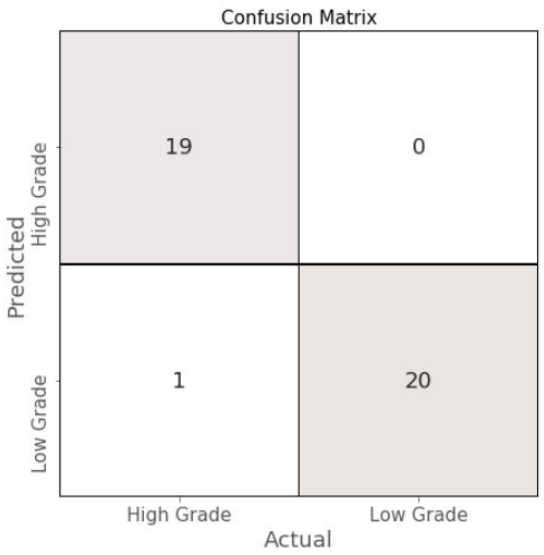
sensitivity: 0.90
specificity: 1.00

Fig 8(b): Case II

Study	Optimizers	Class	Precision	Recall	F1 score	Sensitivity	Specificity	Accuracy
Case I	Adam	High	1.00	0.95	0.97	0.95	1.00	97%
		Low	0.95	1.00	0.98			
Case II	RAdam	High	1.00	0.90	0.95	0.90	1.00	95%
		Low	0.91	1.00	0.95			

Table 2: A comparison of Case I and Case II

Performance: Different metrics can be drawn to check model's performance in regard to each class. Confusion matrix is table which describe a classifier's performance on a set of test data which value are known. It can predict where the model got wrong and mispredicited. Since our problem consist of two classes we got a 2 x 2 confusion matrix.



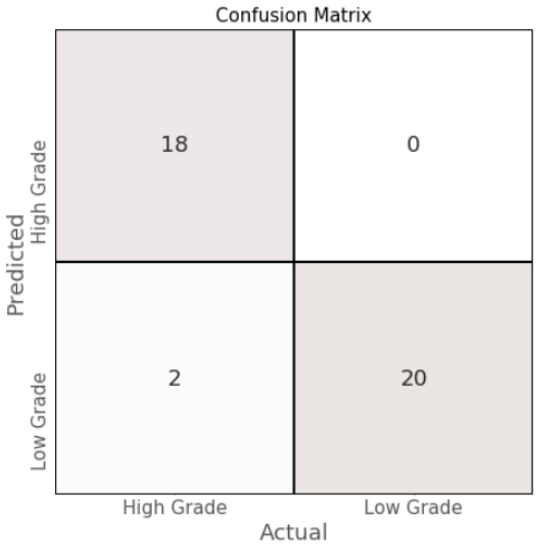


Fig 9: (a) Case I confusion matrix (b) Case II confusion matrix

Different metrics can be drawn to check model's performance in regard to each class. Few essential metrics are sensitivity, specificity etc. they are calculated as:

Sensitivity: Measure the proportion of predicting positive cases as positive (true positive). A value of 0.95 sensitivity is achieved. In healthcare domain a model with higher sensitivity is desired. Mathematically defined as:

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Specificity: Measures the proportion of predicting actual negative cases as negative (true negative). A value of 1.0 specificity is achieved. This means that there is also false negative. Mathematically,

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive}$$

ROC curve: ROC stands for "receiver operating characteristics ". It is graph that shows a classification model's performance at all possible threshold. Usually it plots two parameters:

- True positive rate (TPR): similar to sensitivity/recall. So defined as

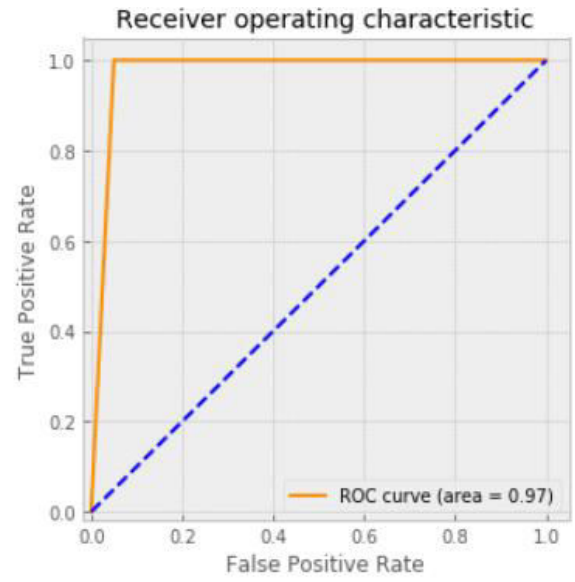
$$TPR = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

- False positive rate (FPR): Defined as

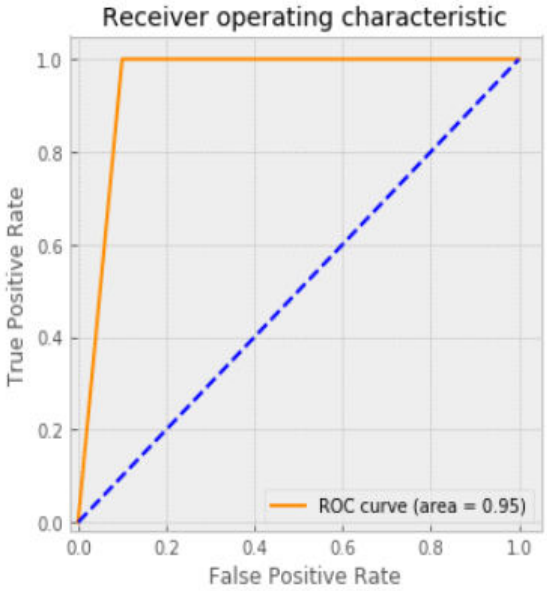
$$FPR = \frac{False\ positive}{False\ Positive + True\ Negative}$$

So, ROC curve plot FPR vs. TPR at different threshold of classification. Fig 9 shows ROC curve and AUC of our classification model.

Area under curve (AUC): This measures the entire area under the ROC curve from (0,0) to (1,1). It provides an aggregate of performance across all classification thresholds. AUC gives rate of success of the model's classification. More AUC value more the better. ROC curve for Case I and Case II ae shown in fig.10.



ROC AUC=0.97



ROC AUC=0.95

Fig 10: (a) Case I (b) Case II

V. CONCLUSION

In this paper we proposed a deep neural network model with L2 regularization that can efficiently classifies brain tumor of two classes: Low Grade and High Grade Glioma. The purposed of the work is to carried out two case studies with different state of art optimizers: - Adam and RAdam and compare their result. The model is simple but yet take less time to train and process MRI images. In this worked we found out both state of art optimizers achieved accuracy with slight higher with Adam but RAdam achieved more stability and less time training the model, hoping RAdam will have more generalization stability in future. If we concerned for more stability and efficient time we can go for RAdam. Future work can be on expanding number of class including different MRI slices. These will help radiologist or expert to save time in deciding tumor type and help in treatment at the earliest.

References:

[1] Brain tumor classification using deep CNN features via transfer learning S. Deepak, P.M. Ameer. Computers in Biology and Medicine 111 (2019) 103345. doi 10.1016/j.compbiomed.2019.103345.

[2] Multi-Classification of Brain Tumor Images Using Deep Neural Network. Hossam H. Sultan, Nancy M. Salem and Walid Al-Atabany. IEEE Access (Volume: 7) SPECIAL SECTION ON DEEP LEARNING FOR COMPUTER-AIDED MEDICAL DIAGNOSIS. Doi: 10.1109/ACCESS.2019.2919122.

[3] Brain Tumor Classification Using Discrete Cosine Transform and Probabilistic Neural Network. D. SRIDHAR and MURALI KRISHNA. 2013 International Conference on Signal Processing, Image Processing and Pattern Recognition [ICSIPR].Doi: 10.1109/ICSIPR.2013.6497966.

[4] Classification using deep learning neural networks for brain tumors. Heba Mohsen, El-Sayed A. El-Dahshan, El-Sayed M. El-Horbaty, Abdel-Badeeh M. Salem. Future Computing and Informatics Journal Volume 3, Issue 1, June 2018, Pages 68-71. Doi:10.1016/j.fcij.2017.12.001

[5] Deep learning based brain tumor classification and detection system. Ali ARI, Davut HANBAY. Turkish Journal of Electrical Engineering & Computer Sciences. Doi: 10.3906/elk-1801-8

[6] Multiclass Classification of Brain Tumor in MR Images. Kruti G. Khambhata, Sandip R. Panchal. International Journal of Innovative Research in Computerand Communication Engineering. Vol. 4, Issue 5, May 2016. DOI: 10.15680/IJIRCCE.2016. 0405189.

[7] A Soft Computing Framework for Brain Tumor Detection through MRI Images. Nilakshi Devi, Kaustubh Bhattacharyya. ADBU Journal of Engineering Technology (AJET) · February 2018.

[8] Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network. Palash.Ghosal, Lokesh.Nandanwar, Swati.Kanchan, Ashok Bhadra, Jayasree Chakraborty and Debashis Nandi.2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP). DOI: 10.1109/ICACCP.2019.8882973.

[9] Brain Tumor Classification Using Convolutional Neural Network. Sunanda Das, O.F.M. Riaz Rahman Aranya, Nishat Nayla Labiba. 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT). Doi: 10.1109/ICASERT.2019.8934603.

[10] Classification of Brain MRI Tumor Images: A Hybrid Approach. Sanjeev Kumar, Chetna Dabas2, Sunila Godara. Procedia Computer Science Volume 122, 2017, Pages 510-517. Doi: 10.1016/j.procs.2017.11.400.

[11] Brain tumor Classification and Segmentation using Faster R-CNN. H.N.T.K.Kaldera, Shanaka Ramesh Gunasekara and Maheshi B. Dissanayake. 2019 Advances in Science and Engineering Technology International Conferences (ASET).Doi: 10.1109/ICASET.2019.8714263.

[11] Brain Tumor Classification Using Convolutional Neural NetworksJ. Seetha and S. Selvakumar Raja. *Biomedical & Pharmacology Journal*, September 2018. Vol. **11**(3), p. 1457-1461 Doi: 10.13005/bpj/1511.

[12] Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface. Hasan Ucuzal, Şeyma YAŞAR and Cemil Çolak. 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT). Doi: 10.1109/ISMSIT.2019.8932761.

[13] Detection and Classification of Brain Tumor in MRI Images PrachiGadpayleand Prof.P.S.Mahajani. International Journal of Emerging Trends in Electrical and Electronics (IJETEE – ISSN: 2320-9569) Vol. 5, Issue. 1, July-2013.

[14] Identification and Classification Of Brain Tumor Images Using Efficient Classifier B.Sathees kumar. International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-8, Issue-6, August 2019.

[15] A Reliable Method for Brain Tumor Detection Using Cnn Technique. Neethu Ouseph C, Mrs.Shruti K. IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE).

[16] An Automatic Classification of Brain Tumors through MRI Using Support Vector Machine Marco Alfonse and Abdel-Badeeh M. Salem. Egyptian Computer Science Journal (ISSN: 1110 – 2586) Volume 40 – Issue 03, September 2016.