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PREDICTIVE MODELLING OF BRAIN TUMOR DETECTION USING DEEP LEARNING

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Abstract. : In recent years, prediction and analysis of human brain tumor have become one of the most challenging issues in healthcare science. Various machine learning algorithms are designed to automate the process of detection of brain tumor. Because of the popularity of computer vision in AI, the segmentation of tumor in unstructured data set such as brain MRI and its analysis as become an important part of the diagnosis of cancer at an early stage. The correct diagnosis is a very crucial and critical step and depends on the expertise of doctors and radiologists. The deep learning models are getting a lot of popularity in the detection of tumors because its accuracy. In this paper, we designed deep learning architectures for detection of tumors in Magnetic Resonance Imaging (MRI) image. In the proposed architecture, firstly, the convolution neural network (CNN) architecture was designed from scratch using Keras library; secondly, the architecture of CNN was tuned by adjusting hyper parameter and increasing number of layers, and finally the transfer learning mechanism was implemented by using weights of VGG16 architecture. The performance of all models was evaluated using confusion matrix on validation and the test data set. The result shows that adjusting hyper parameter and transfer learning the accuracy of detection of tumor can be improved. In addition, this deep learning model detects human brain tumors within seconds as compared to other machine learn- ing algorithm.
Keywords: Magnetic Resonance Imaging(MRI), hyper parameter, CNN, VGG16, Ke- ras,transfer learning.

1. Introduction

Artificial Intelligence in the healthcare domain is used to estimate the power of human cognition to simplify the analysis of complicated medical data by using complex algorithms and decision support systems. As the computing power of medical data is increasing in terms of velocity, volume, and variability, finding meaningful insight from medical data has become a challenging task. Health care data come in structured and unstructured format [1]. The structured data is in the form of textual information containing different features of specific diseases were as unstructureddata are in the form of signals and medical images. Because of the popularity of computer vision in AI, the segmentation of tumor in unstructured dataset such as brain MRI and its analysis as become an important part of the diagnosis of cancer at an early stage. The correct diagnosis is a very crucial and critical step and depends on the expertise of doctors and radiologists. In such cases, the computer-aided diagnosis system is used as the second option for diagnosis [2]. The problem with the traditional computer-aided system is of false positive and false negative predictions done, concerning the classification of tumor which can be life-threatening. Also,due tothe heterogeneous and diffusive shapes of human organs such a liver, brain, tumor, etc., the segmentation of these organs as become challenging task because a lot of overlapping and low clearance ratio is seen between these organs. The physicians are finding it difficult and thus need a second option to come the final conclusion of treatment therapy for patient before any surgical operation decision. So there is a need to design an algorithm which can process 2D medical images of CT scan devices or MRI efficiently and classify weather given image contains tumor or not. The motivation is to design a robust model using deep learning techniques to improve performance of the proposed model in terms computation processing, overfitting,learning mechanism and accuracy. The most popular framework of deep learning is a convolution neural net-

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work architecture for medical image analysis. The transfer learning mechanism can be used to reduce the cost of high computation to train a classifier for medical images [3].

The organization of the paper is as follows: The second section describes various approaches used for tumor detection and differences between them. The methodology of designing deep learning model is given in the third section. The fourth section explains about experimental setup and dataset used for model building. The fifth section summarizes results analysis and tuning of parameters of the deep learning model. The last section highlights the research scope which can be extended as future work.

2. Literature Review

Various machine learning techniques for automatic detection and segmentation of brain tumor are described in literature and their performance are evaluated to check-

accuracy [4]. Deep learning shows the great performance in the healthcare domain of medical image analysis such as MRI, CT scan etc [5] and more in image-based cancer detection and diagnosis [6]. The following table describes the various techniques applied on images of brain tumor with datasets, techniques used and with their performance measure.

Table1. Literature review Overview

Author	Title	Dataset used	Techniques used	Performance Measure	Journal or publisher	Year
Pereira S et al.	Brain tumor segmentation using CNN in MRI images	BRATS 2013	Deeper CNN with LReLu as activation function	BRATS dice scores of 88%, 83% and 77% for whole tumor, core tumor and active tumor regions respectively	IEEE Transaction Medical Imaging	2016
Lina Chato et.al	Machine and deep learning techniques to predict overall survival of brain tumor patients using MRI images	BRATS 2017	SVM,KNN Linear Discriminant, Decision Tree, Ensemble and Logistic Regression,CNN	Accracy=68.8%	In Proceedings of the 2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE), Washington	2017
Amin J. et. al.	Detection of Brain Tumor based on Features Fusion and Machine Learning	BRATS 2012	Gabor Wavelet Features ,Histogramsof Oriented Gradient , Local Binary Pattern and segmentation based Fractal Texture Analysis (SFTA) features -Random forest calssifier	DiceScores Complete = 0.91 Non-Enhancing = 0.89 Enhancing = 0.90	J. Ambient. Intell.	2018
Abiwinanda et. al.	Brain tumor classification using convolutional neural network	figshare Cheng (Brain Tumor	CNN,AlexNet,VGG16,ResNet	Validation Accuracy 84.19%	InWorld Conress on In medical physics and	2018

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		Dataset, 2017)			Bio medical Engineering;Springer.	
Deepak et.al.	Brain tumor classification with deep CNN features through transfer learning.	figshare	Transferred learned (Google Net),deep CNN-SVM	Accuracy 98%	Computers in biology and medicine	2019
Talo et.al	Application of deep transfer learning for automating brain abnormality classification in MRI images.	Dataset available Harvard Medical School website	pre-trained CNN ResNet34	Accuracy on 613 images is 100%	Cognitive Systems Research	2019

S Kumar et.al has described the hybrid architecture for detection of tumor, in which features are extracted using DWT and a genetic algorithm is used for reducing the numbers of features and finally SVM is applied for classification [13].Dong at.al apply fully automatic segmentation on brain tumor by using U Net Deep learning segmentation on BRATS 2015 datsaet [15]. Nasor et. al. has described the approach by using machine learning techniques for detection of brain tumor at an early stage using a combination of different techniques such as k-means, patch based processing ,object counting and finally tumor evaluation and they got accuracy 0.99 and dice score 0.95[16].

3. Methodology:

The supervised classification modeling is done by designing deep learning CNN architecture and transfer learning mechanism.

Design CNN model for tumor detection:

A convolution neural network is an artificial neural network, which uses convolution tricks to add convolution layers. We use these convolution tricks to preserve the spatial structure in images which helps in classifying tumor. Initially the network was designed with one convolution layer with 32 filters and kernel of size 2 as shown in figure1. The max pooling was done with stride equal to 2 to preserve the spatial

property of brain tumor and 128 neurons were used in fully connected layers for final prediction.

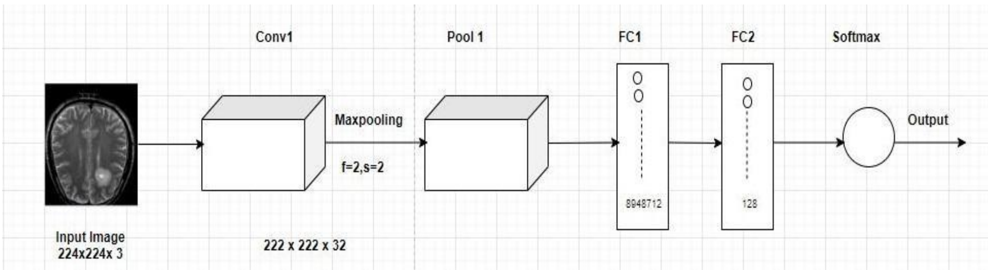

Fig1: CNN model

Since we have been using GPU based system with augmented data set, we modified the above network by adding extra dense layers and adjusted hyper parameters as shown in figure2. The network consist of two layers with convolution filter size of 32 and 64 followed by two fully connected layers with adjusted hyper parameters.

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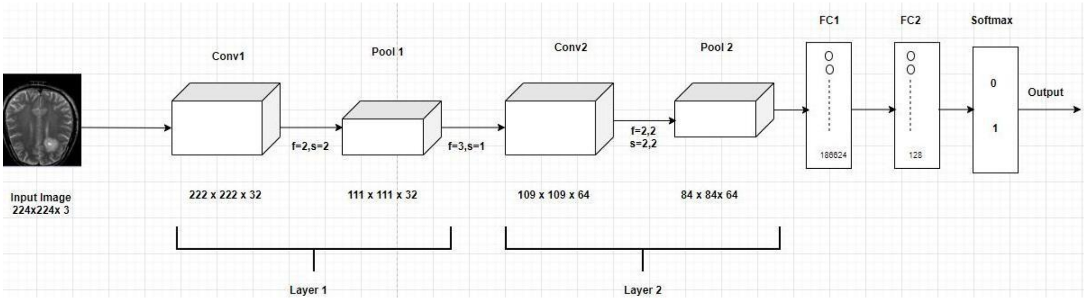

Fig2: CNN model with adjusted hyper parameter

The activation output volume size after applying the convolution operation is given by equation 1.

$$N_{wh}^{[l]} = \frac{N_{wh}^{[l]} + 2P^{[l]} - f^{\,l-1}}{S^{[l]}} + 1 \text{ ....(Eq 1)}$$

Where
$N_h^{[l]}$= Height of input image
$N_w^{[l]}$=Width of input Image
$N_c^{[l]}$=Number of filters

f^l =Filter Size of Kernel
P^l =Padding Size
S^l=Stride Size

The equation1 gives the linear output by applying the convolution operation, the non-linearity is introduced by applying Relu function to the output volume by adding some bias $b_i^{[l]}$. Therfore, net activation size for next layer is given by equation 2

$$a^{[l]}=Relu(N_{wh}^{[l]} + b_i^{[l]}) \text{ .... (2)}$$

Transfer Learning

To improve performance of the deep learning model, the transfer learning technique can be used. In transfer learning pre-trained models are used to build model instead of designing them from scratch. Here we have used VGG16 architecture weights for training the model. In this architecture we have frozen higher layers and trained lower layer using weights of VGG16 architecture. The VGG16 architecture contains 16 layers of which pre-trained weights are used for training. The VGG16 architecture is shown in figure3.

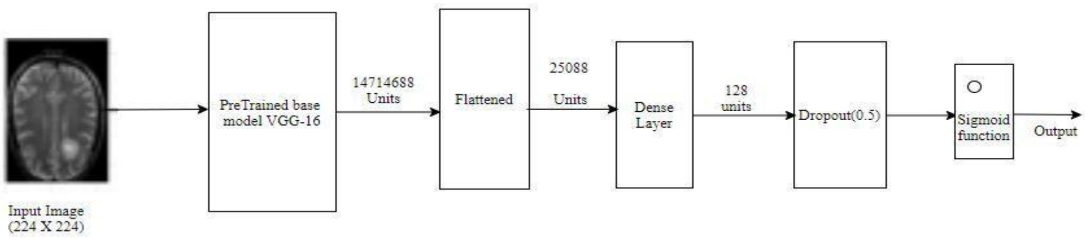

Fig3: CNN model with VGG16 transfer learning mechanism

So one solution to minimize high computation cost is to use deep learning transfer learning mechanism. The transfer learning mechanism uses pertained weights of CNN such as VGG16 and can save time and computational power as well as speed up the learning process. The VGG16 is used as a base model to train early layers of architec-

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ture and only last 4 layers are added during the training process as shown in figure3. The activation units of this model are flattened, which acts as input to rest of layers ofthe model. The dense layer of 128 units is used to take dot product with units of flat- tened layer and generates final activation units by applying ReLu function to gene- rates final activation on which sigmoid function is applied to get binary output of tumor classification The table 2 and table 3 shows the summary of activations units of two deep learning architectures of figure2 and figure3.

Table2.CNN model with adjusted hyper parameter

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 224, 224, 3)]	0
zero_padding2d (ZeroPadding2	(None, 228, 228, 3)	0
conv0 (Conv2D)	(None, 222, 222, 32)	4736
bn0 (BatchNormalization)	(None, 222, 222, 32)	128
activation (Activation)	(None, 222, 222, 32)	0
max_pool0 (MaxPooling2D)	(None, 55, 55, 32)	0
conv1 (Conv2D)	(None, 26, 26, 64)	51264
max_pool1 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
fc2 (Dense)	(None, 1)	2305

Total params: 58,433
Trainable params: 58,369
Non-trainable params: 64

The table3 below shows number of parameters of VGG16 model and layers used for training the sample size using transfer learning mechanism.

Table3.CNN model with transfer learning mechanism

Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 7, 7, 512)	14714688
Flatten (Flatten)	(None, 25088)	0
Dense1 (Dense)	(None, 128)	3211392
dropout_8 (Dropout)	(None, 128)	0
Dense2_Output (Dense)	(None, 1)	129

Total params: 17,926,209
Trainable params: 3,211,521
Non-trainable params: 14,714,688

4. Experimental Setup:

The proposed model is designed and trained on NVIDIA K80 GPU. The model tested and evaluated on brain MRI image dataset [14]. The brain MRI dataset contains 253 MRI images out of which 153 images are tumors and 98 are non tumors. The images are resized to dimension 224 * 224 to fit to the VGG16 model for training. Since we are using transfer learning mechanism to optimize the CNN model, the data augmentation technique is used to increase size of the data set. After data augmentation technique, the tumorous images are 1095 and non-tumorous images are 980. The annotation of the tumorous and non-tumorous images is done and is stored in the form of numpy array. The CNN model with adjusted hyper parameter and CNN model with transfer learning are trained for 25 epochs with batch size of 32 and accuracy and loss is recorded. The batches are normalized to reduce overfitting and covariance shift. The ground truth of validation dataset was done with MRI images from the radiologist.

5. Result Analysis and Discussion

The two different CNN models are trained separately and the performance was recorded. The CNN model architecture shown in figure 2 with adjusted hyper parameter trained for 25 epochs. The layer1 of this model uses the kernel of size 7*7 with 32 filters and layer2 uses kernel of size 5*5 and 64 filters. The max pooling of size 4*4 was applied in two layers to preserve spatial properties of tumors. Finally, all neurons coming from layer2 are flattened into single vector, which acts as an input to artificial neural network. The trainable parameters are 58,369 and non-trainable parameters are 64 out of total parameters 58,433 in the network. The proposed architecture improves accuracy of CNN architecture shown in figure1 from 72% to 80%. The accuracy and loss plots are shown in figure. From plot is seen that model with hyper parameter adjustment improves the accuracy both in validation and testing dataset. There is slightly peak is seen in loss during training because of small sample of test dataset which can be adjusted by increasing size of dataset, but as epoch increases the loss decreases and it is in line with validation loss.

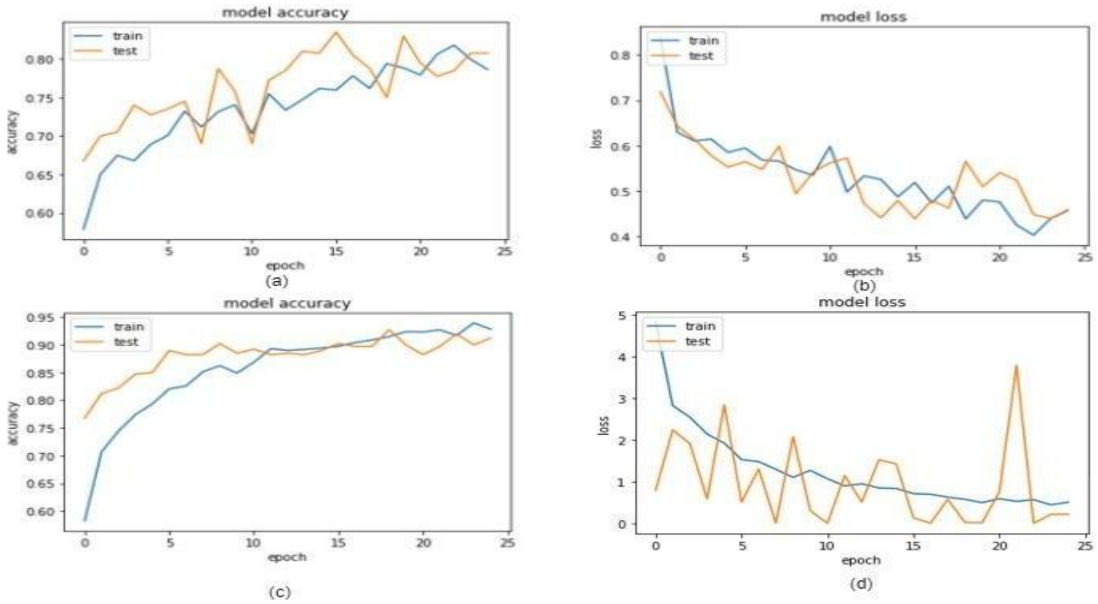

Fig4: CNN model with hyper paramter (a) ModelAccuracy (b) Model Loss
CNN model with Transfer Learning(c) Model Accuracy (d) Model Loss

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The model is further improved by transfer learning mechanism. We have used weights of VGG16 architecture as base model by keeping last few layers intact with kernel size 7*7 and 512 filters. The total trainable parameters are 3,211,521 parameters out of total parameters 17,926,209.It is observed during experiment that by adding more dense layers, the performance of the architecture shown in figure3 is improved. The performance of the CNN architecture with adjusted parameter andVGG16 CNN transfer learning model is evaluated using confusion matrix. The performance of the model is evaluated separately on validation and testing dataset accuracy is plotted as shown in figure5.

The accuracy of the CNN model with adjusted parameters for validation is 80% and for testing it comes to be 89% Fig (a)(b). By applying transfer learning mechanism there is considerable improvement in the accuracy of the CNN model with 88% for validation and 94% for testing. Also the F1 Score of CNN model is .80 and that of CNN using transfer learning model is .85. So by transfer learning mechanism the performance of model has improved.

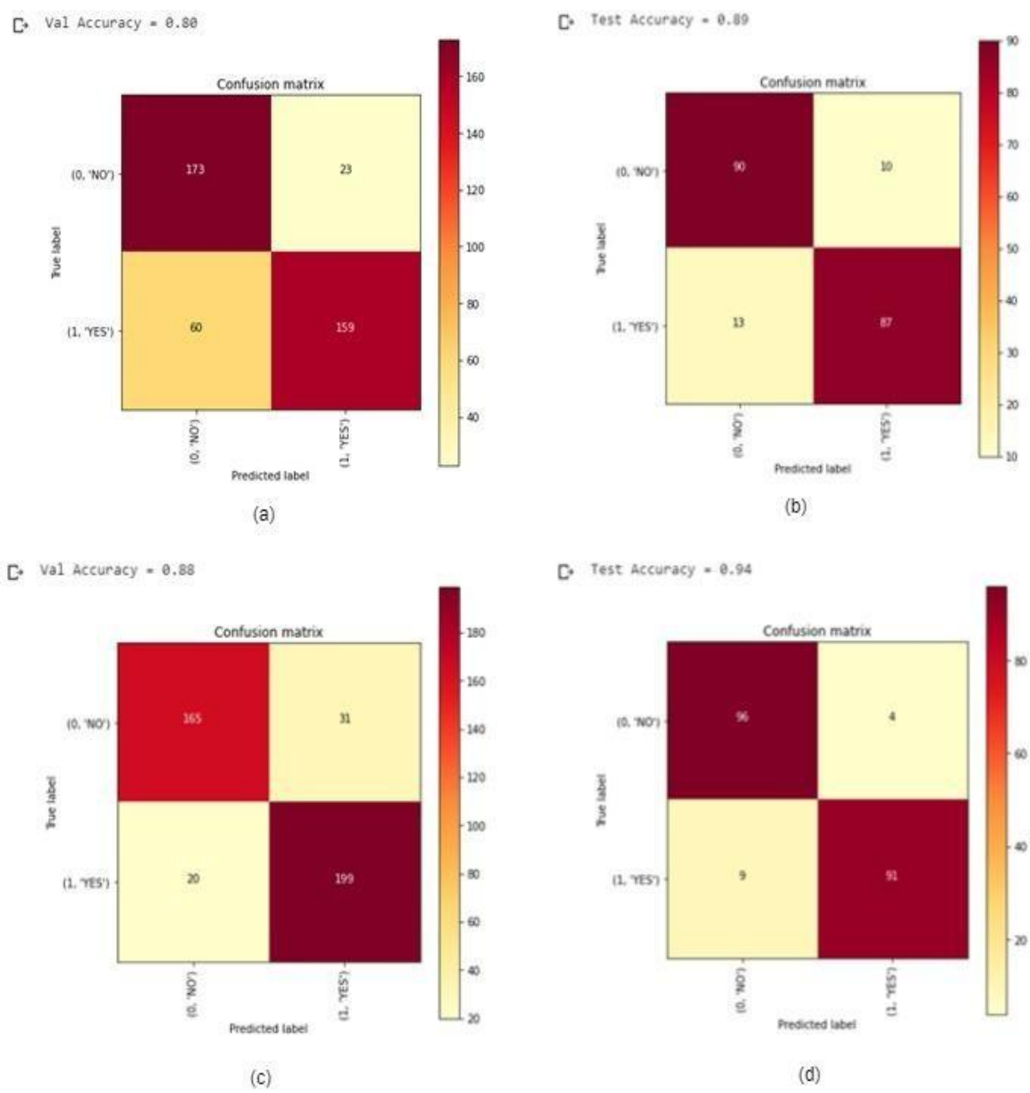

Fig5: **Confusion matrix for CNN model with hyper paramter**
(a)Validation Accuracy (b) Test Accuracy
Confusion matrix for CNN model with Transfer Learning
(c)Validation Accuracy (d) Test Accuracy

6. Conclusion and Future Work

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In this paper, we have proposed different styles of CNN architectures and compared their performance for brain tumor detection. First we started with very simple architecture and recorded its accuracy and then the model is tuned by adjusting hyper parameter and increasing number of filters and layers. The results show that adjustment of hyper parameters increases the accuracy of CNN model. Further model accuracy was increased by using VGG16 has base model and keeping other layers of the model has intact. The use of transfer learning mechanism shows significant improvement in accuracy and F1 score of tumor detection model. The future work will be to design a CNN model for 3D brain MRI images to get geometrical spatial properties of tumor. Also further research work can be extended for selecting optimal weights from the set of ensemble architectures, so that learning and prediction time can be reduced. The different approaches of hybrid architectures such as cascading of different CNN architectures, ensemble of CNN with other machine learning models can be explored to improve the accuracy of deep learning models.

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