International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 10, No.1 (Nov-2021)

http://dx.doi.org/10.12785/ijcds/100197

Biomedical Image Classification using CNN by Exploiting Deep Domain Transfer Learning

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Received 26 March. 2020, Revised 22 March. 2021, Accepted 3 April. 2021, Published 25 Nov. 2021

Abstract: Accurate biomedical image classification is essential for the clinical investigation of different hazardous maladies. A fair diagnosis of the disease is essential to provide proper treatment and to save precious human lives. Classification methods that support handcrafted features and use artificial neural networks trained with restricted data-set cannot viably enhance the precision rate and meet the stipulations for classification of biomedical images End-to-End deep learning machines empowers direct mapping from crude information to the desired output, eliminating the need for handcrafted features. Deep learning has proven as a powerful classification method as evidenced by its success in recent computer vision competitions. A unique deep convolutional neural network (CNN) model for brain tumor classification has been proposed in this paper. The model tested on the OASIS MRI data-set and gives an average accuracy of 90:84%. The present model is based on a pre- trained vgg-19 model on a large Image-Net database. Novel CNN model does not require training from scratch wasting weeks or days, rather uses transfer learning for knowledge distillation. Also to further enhance the training acceleration other optimization methods have been used, weights are initialized by the Gaussian initialization method followed by the ReLu activation function. ADAMS SGD optimization has been used and a drop-out algorithm is implemented to get rid of the overfitting of the model. The model when implemented on the biomedical image dataset has achieved the highest classification accuracy rate, outperforming all existing techniques with lesser training time.

Keywords: CNN, SIFT, HOG, PHT, MRI, OASIS, ADAMS, SGD, CONVONET, ReLu, Soft-max, LRN, FC.

1. INTRODUCTION

Discovering the abnormalities in the brain using MRI is critical for brain tumor detection and treatment. Usually, the information in MRI images is interpreted by medical experts. The manual screening is fairly tedious and experiences a few basic constraints including the subjectivity of the analyzed outcome and the changeability between experts. Early diagnosis of the disease is very important. Delay in the treatment may cost the life of the patient. The automatic biomedical image analysis and classification methods help in reducing subjectivity and improving the diagnosis and treatment. Different technologies have been proposed for the order of various kinds of brain tumors in the literature. Some hand-engineered methods were proposed for feature extraction process like local binary pattern(LBP), scale-invariant feature transform(SIFT), and histogram of gradients (HOG), etc. But they were not able to meet the requirement of medical image analysis where accuracy is one of the critical parameters. Most of these schemes follow three main steps feature extraction, dimension reduction, and classification. The method of choice for feature extraction is the wavelet transform. Dimension reduction is done using Principle Component Analysis (PCA). Chaplot et al. 2006[1], Benkelman et al. 2011 [2], Maitra and Chatterjee 2011 [3]. Zhang and Wu 2012 [4]. The commonly used classifiers in medical image analysis are based on SVM (Singular value decomposition) Zhang and Wu 2012 [4]. Kumar et al. 2017 [5] and ANN (Artificial Neural Network) Natteshan et al. 2015 [6], Ibrahim et al. 2013 [7]. The conventional statistical classification approaches result in misclassification because of strictly convex boundaries. Textural features can be incorporated for higher-order. However, they are inconvenient for traditional techniques.

Artificial neural networks cater to non-convex selections. however, sort of unresolved problems still exists in the field of ANNs, like the significant hypothetical reason for

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ANNs, the drawback of choosing the foremost effective architecture, and the black box problem. Additionally, for improving classification, result features from multiple descriptors must be combined. Some studies recommend that CNN is much better than conventional ANN algorithms for image classification. CNN's can eliminate the requirement for feature extraction by directly inputting the normalized images as input to the network Felzenszwalb et al. 2010 [8], Krizhevsky et al. 2017 [9]. Employing deep learning technology in the automatic classification of biomedical images can help radiologists and doctors by diminishing the tedious screening time and extraordinarily enhancing the efficiency of diagnosis. After conducting the comprehension of the literature review, it is observed that a large number of neural network systems have been developed for the classification of the biomedical image to properly diagnose the life-threatening diseases of the patients. All the methods are good at their place but face some critical limitations. This paper aims to employ the deep classification model with greater accuracy, a lesser number of parameters, fast convergence speed, and reduced training time in the classification of biomedical images to properly diagnose the disease.

A). Concept of Transfer Learning: The concept of transfer learning is using already gained knowledge while solving one problem to solve the other related problem. Vgg-19 model is the pre-trained model on the large image-net database. Knowledge distillation is used to train our proposed model for learning generic features which include learning edges curvatures and lines. While learning the generic features from the pre-trained vgg-9 model the first part of the proposed model is free-zed then another part of the network is trained by fine-tuning the hyper-parameters to learn more specific and abstract features. The use of the concept of transfer learning has eliminated the use of training of model from scratch and has reduced the computational time from days to even minutes.

The entire paper is divided into 7 sections in which the section gives a brief introduction, section 2 describes related work, the problem statement is given in section 3, and section 4 describes the detailed architecture of the proposed model its layers, and hyper parameters. Training of proposed model, results and discussions, and future scope of the paper are given in the last sections.

2- RELATED WORK

Deep neural networks have been applied successfully to several real-world computer vision problems. Many researchers have explored it for medical image analysis Litjens et al. 2017 [10]. Razzak et al. 2018 discuss the challenges in deep learning-based methods for medical imaging. The authors also elaborate on the open challenges in this area [11]. The applications of CNN in MRI image analysis can be traced to the 1990's Neubauer (1998). The networks were initially used for mammographic images and have further been used in other biomedical images with the development of GPU computing units [12]. Shen et al. 2017 in his papers suggest that CNN gives better classification results than ANN like multilayer perceptron's [13]. The end-to-end CNN was proposed by Bengio et al. 2013 [14]. In recent years' various authors have proposed CNN-based classifiers for medical image classification Ertas et al. 2008 [15], Sampaio et al. 2011 [16], Anthimopoulos et al. 2016 [17], Taj bakhsh and Suzuki 2017 [18]. Some of the works that concentrated on brain tumor classification using deep neural networks are discussed next Heba Mohsen et al. 2018 proposed a technique to classify four classes of malignant brain tumors. This architecture of a deep neural network resembles CNN but requires fewer hardware specifications and is time-efficient [19]. Another technique is proposed for the detection of Glioma, a type of brain tumor based on CNN Hussain et al. 2017 [20]. They achieved a good accuracy rate using CNN. A three-step strategy using the pre-processing stage, classification stage, and post-processing stage is given in Antony et al. 2017 for detection of the brain tumor and classification using CNN [21]. In Milletari et al. 2017 the authors provide a systematic study of the use of CNN for the segmentation of MRI and ultrasound brain images [22].

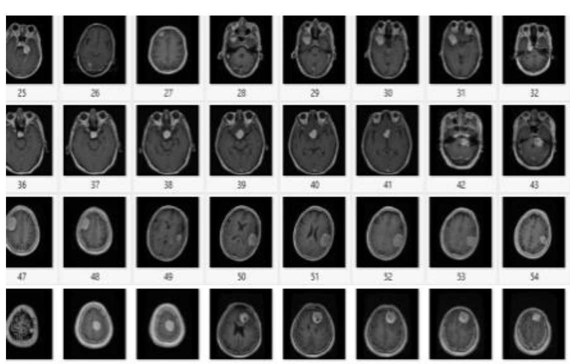
2. PROBLEM STATEMENT

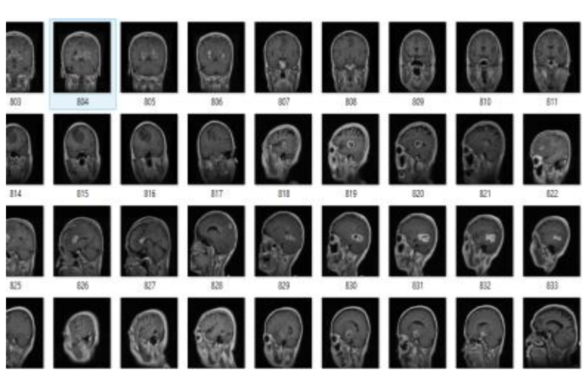
Diagnosis of diseases such as interstitial lung diseases (ILD), brain tumors, spinal problems, etc. for patients using traditional radiological screening techniques and manual identification which is rather time-consuming and suffers from several critical limitations including the subjectivity of diagnosed result and the variability between laboratories. The automatic classification of biomedical images by utilizing deep learning technology has the potential to assist radiologists and physicians by reducing the time-consuming screening time and greatly improving the efficiency of diagnosis. With the recent drastic advances in the biomedical image technology, many types of biomedical images have been generated in a variety of modalities using advanced medical imaging devices, this includes CT (Computed Tomography), X-Ray, MS(Microscopic), US(Ultrasound), and MRI (Magnetic Resonance Imaging). As a result, it has become impractical for specialists to manually label and annotate all the images collected from a very large number of patients every day. So the classification of biomedical images is an essential task in the clinical diagnosis of numerous medical diseases identified from those images. We will apply an end-to-end classifier for the classification of those biomedical images. In our work, the performance of the classifier is improved in terms of convergence speed, training time complexity, and classification accuracy over the existing classifier.

3. PROPOSED METHODOLOGY

A. Dataset Description

A publicly available dataset [23] is used for the analysis of the proposed techniques. This brain tumor dataset contains 3064 T1-weighted contrast-enhanced images from 233 patients with three different types of brain tumor: meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices). The whole data set of 3064 medical images is divided into three categories for training and testing. Training images are divided into class1, class2, and class 3, with each training class, consists of 560 images each. Testing image (420 images) and internally divided into three classes where, each class consists of 140 images, and 964 images are kept for validation purposes. The results of the proposed technique are compared with an existing promising technique using CNN and the same dataset [24]. The snapshot of the dataset is given as in Figure.1.





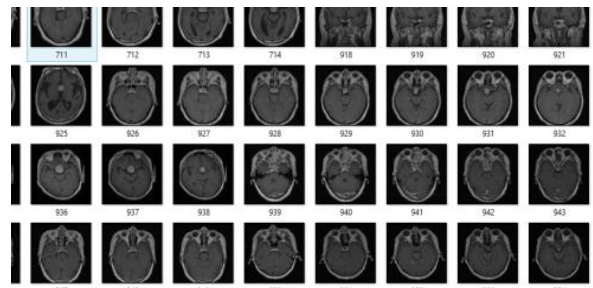


Figure1. Snapshot of brain tumor dataset used consisting of three classes a) meningioma b) Glioma c) pituitary Tumor

a. Pre-Processing of Input

All the input images are subjected to pre-processing step, in which all the images are resized to standard input size of $224*224*3$, and image enhancement technique for noise removal and also for contrast enhancement using a median filter.

b. Architectural details of the Proposed model

Structuring and training a proposed model requires advanced methodologies considering the number of neurons and layer types and the way to match

between the layers, particularly convolutional kernel numbers and size The engineering of the proposed method depends on Imagnet-vgg demonstrate. The proposed model consists of six convolutional layers, three pooling layers, and two fully connected layers. Between every two convolutional layers, the ReLu layer is embedded to introduce the global non-linearity in the network. Two popularly using pooling techniques are average and max pooling, but our model supports a combination of both the techniques to perform spatial dimensionality reduction, leading to cutting down of parameters immensely. Likewise, the drop-out algorithm is implemented with the standard numeric value of 0.5 to decrease the likelihood of overtraining or overfitting the proposed network. Towards the end of the entire network, the soft-max layer is implemented responsibly for generating the probability

score of classification results. The framework of the proposed CNN model is given in fig 2(b). fig 2(a) represents architectural details of the pre-trained VGG-19 model, based on that model proposed model was designed with some

modifications and hyper tuning of the necessary parameters mentioned in detail in Table 1. The framework of the pre-trained VGG- 9, as well as proposed convolutional neural network (CNN), is given as Fig. 2

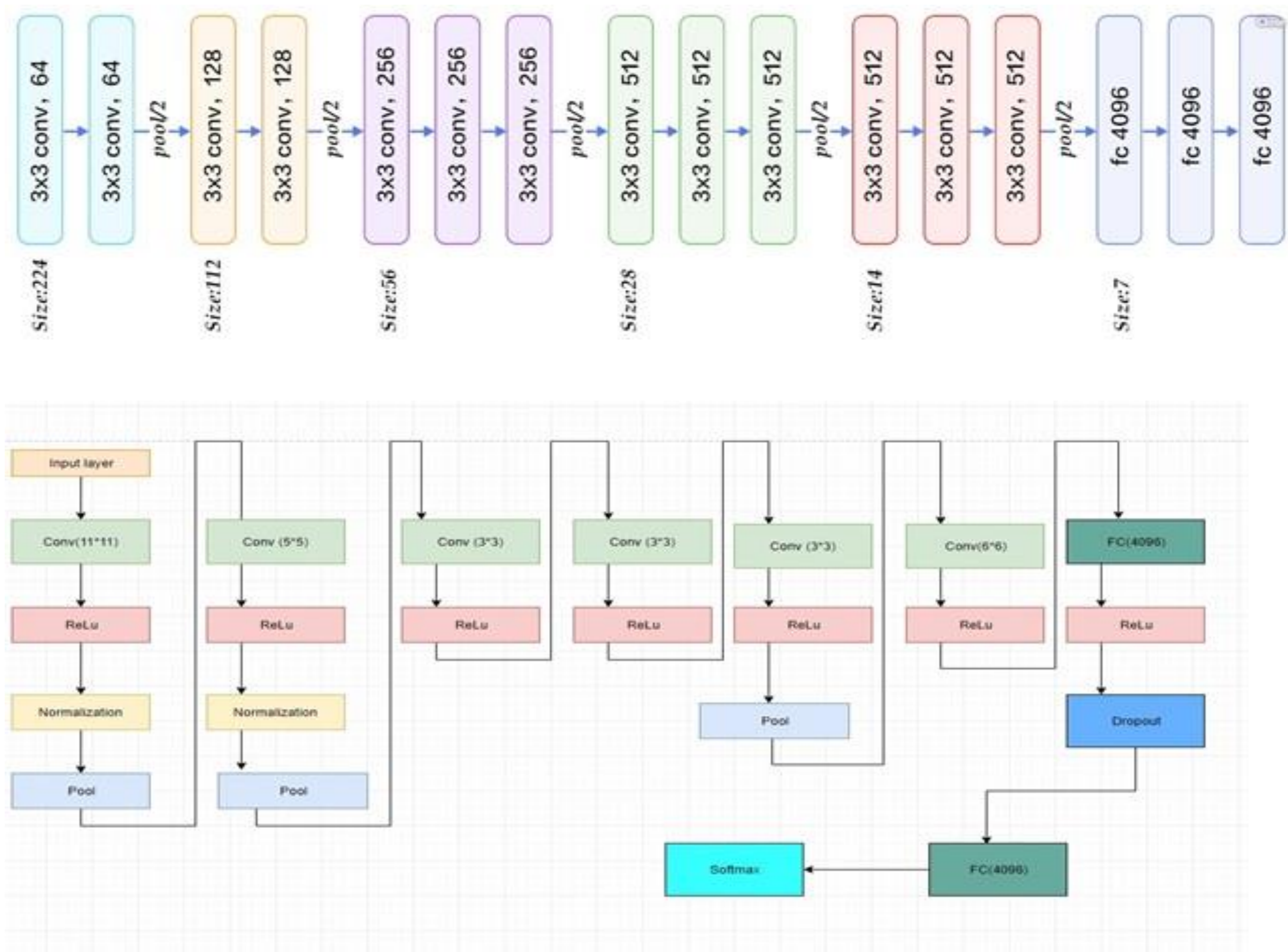


Figure 2. a) Vgg-19 model b) Proposed model based on pre-trained Vgg-19 model.

a. Convolutional layer

In the above figure 2(b) the CONV layer is the delegate part in the entire convolutional neural system. An image $(224\times224\times3)$ is fed to this layer. The main aim of this layer is to do identification local features extraction from the received input channels or grids. To do local feature extraction, each kernel is supposed to perform a convolution operation. The output of the neurons is computed which are connected to the local regions in the input, the dot product is computed between their weights and a small region they are connected in the input volume. The engineered model consists of a total number of 64 kernels in the first convolutional layer, second, third, fourth, and fifth layer contains a total of 256 kernels and in the sixth and seventh layer, and there is a total of 4096 kernels present. Apart from several kernels, in the first layer, the kernel size is (11×11) pixels which are reduced to (5×5) pixels in the second layer and further reduced to (3×3) pixels in the rest of the layers of the convolutional neural network. The last convolutional layer consists of (6×6) pixels kernel size.

b. ReLu activation function

It is necessary to perform ReLu operation after convo and fully connected layer. This function is used to introduce the global non-linearity in the system. Other functions like sigmoid or tanh functions can also be used but when the number of hidden layers is increased in the deep neural network the accuracy decreases most of the time and is not good Hence in place of them, we used the non-saturating nonlinear function as rectified linear units (ReLu). The ReLu function is given as:

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

c. Max pooling layer

Max pooling layer is usually employed to down-sample an input image reduces the dimensionality of the input. It applies the max filer to non-overlapping sub-regions of the initial representation. This helps in avoiding over-fitting by proving the abstract representation of the input, the dimensionality reduction procedure performed by the max-pooling layer shows great improvement in computational efficiency. The present model comprises of pooling layer with a (3×3) grid measure that obtains the most extreme incentive from the subset of 9 components, to get the most noteworthy incentive for the following layer.

d. Normalization layer

The present model employs local response normalization (LRN). LRN usually follows the max-pooling layer and is used to perform the refinement of the pooling layer. The layer eliminates noise captured in feature maps followed by pooling. This layer has the propensity to expel undoing's among the yields of the neighboring kernels.

e. FC layer and soft-max layer

Following the pooling layer, the 256 feature maps are cascaded and fed as an input to the first FC layer that consists of 4096 neurons, and output from this FC layer is fed as an input to the second FC layer which also contains 4096 neurons. A Soft-max regression layer to output probabilities over N classes is implemented at the end of the proposed CNN framework.

Fine-tuning of Hyper-parameters as per the requirements is given by TABLE I.

TABLE I. HYPER-PARAMETERS OF THE PROPOSED MODEL

Layer	Hyperparameter	Description
Convolutional layer1	Kernel size Number of kernels Stride Pad	(11*11*3) 64 4 0
ReLu1	Stride Pad	1 0
ReLu1	Stride Pad	1 0
Normalization layer1	Stride Pad	1 0
Pooling layer 1	Pool size Stride Pad	(3*3) 2 0
Convolutional layer 2	Kernel size Number of kernels Stride Pad	(5*5*64) 256 1 2
ReLu 2	Stride Pad	1 0
Normalization 2	Stride Pad	1 0
Pooling layer 2	Pool size Stride Pad	(3*3) 2 0
Convolutional layer 3	Kernel size Number of kernels Stride Pad	(3*3*256) 256 1 1
ReLu3	Stride Pad	1 0
Convolutional layer 4	Kernel size Number of kernels Stride Pad	(3*3*256) 256 1 1
ReLu4	Stride Pad	1 0
Convolutional layer 5	Kernel size Number of kernels Stride Pad	(6*6*256) 4096 1 0
ReLu5	Stride Pad	1 0
Pooling layer 3	Pool size Stride Pad	(2*2) 2 0
Convolutional layer 6	Kernel size Number of kernels Stride Pad	(6*6*256) 4096 1 0

ReLu6	Stride Pad	1 0
Fully connected layer1	Kernel size Number of kernels Stride Pad	(1*1*4096) 4096 1 0
ReLu6	Stride Pad	1 0
Fully connected layer2	Kernel size Number of kernels Stride Pad	(1*1*4096) 3 1 0
Softmax loss layer	Stride Pad	1 0

4. TRAINING OF CNN

The dataset for the proposed framework includes MRI images of brain tumors divided into three classes as meningioma, Glioma, Pituitary Tumor. The setting of different training parameters for training the CNN model is set as per protocols, the values for different parameters like momentum, learning rate, weight decay for regularization term, and the number of epochs are given as 0.9, 0.00001,1, 40. For each iteration of the training., the training batch size is fixed to 42 each iteration of the training. After setting the parameters as mentioned above for the model, the model is iteratively trained and network parameters are tuned for obtaining an accurate classifier for biomedical images. Overfitting of the model is given by high validation and generalization error which is also shown in fig 3, to avoid this overtraining or overfitting drop out of 0.5 is used which reduces the training error also shown by another fig as below. The training and validation error is shown in Fig. 3(a) and fig. 3(b).

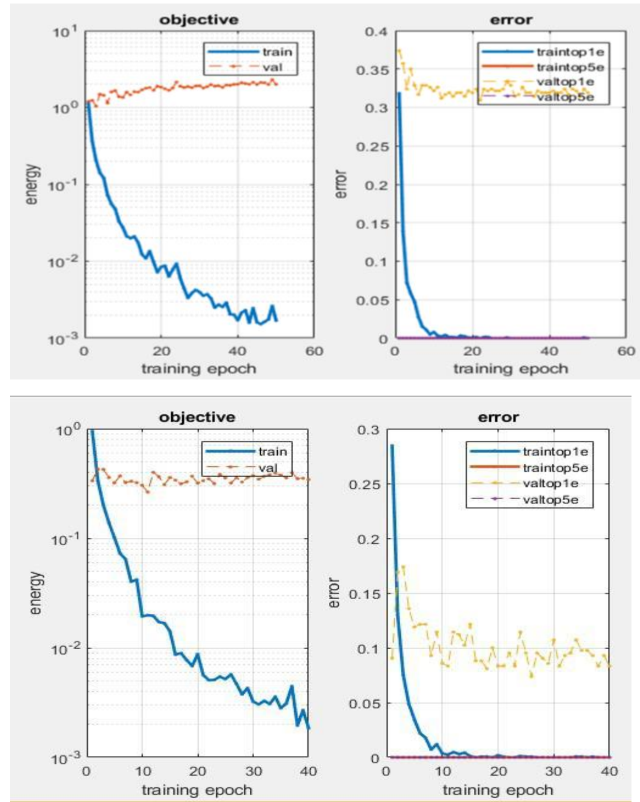


Figure 3. a) Overfitting of model b) Reduced training and validation error (overfitting) due to dropout

a. Drop-out

Doing improvement in the performance and to avoid the overtraining or overfitting of the model, a suitable dropout algorithm is implemented in the proposed framework. The standard value of dropout value 0.5 is used in the proposed CNN model.

5. RESULTS AND DISCUSSION

The CNN model is trained on the matconvonet toolbox and the trained model is obtained and tested. The test images are fed to the network and results in terms of accuracy of the classification are obtained. After testing the images on the trained CNN model the test images are correctly classified into the classes from which they belong. The test images, as well as classification results retrieved, are shown in fig 4. The score of each class is labeled at the top of the classified image. The confusion matrix for both individual classes as well combined confusion matrix is given in Table II and Table III. The computed values of accuracy, recall, precision, and F-Measure are given in Table 3.

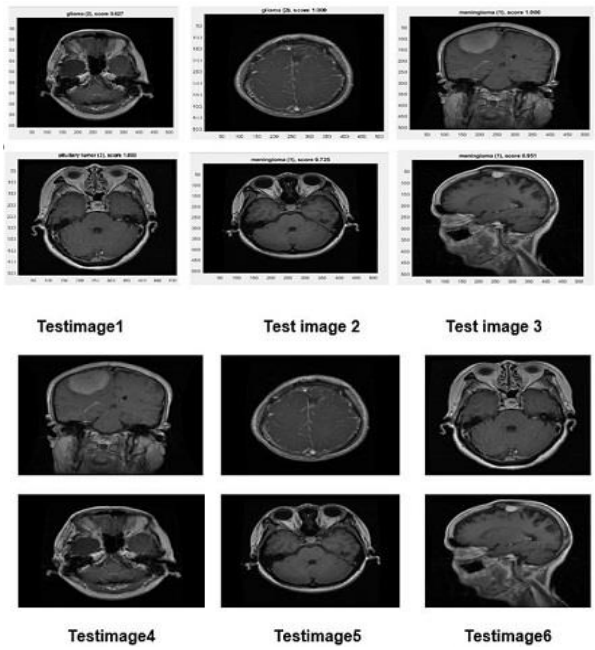


Figure 4. a) Test Images b) Classification Results showing retrieved images from all the three classes

TABLE II. SUMMARIZES THE NUMBER OF IMAGES RETRIEVED CORRECTLY AND MISCLASSIFIED

<table>
<tr><td rowspan="2">Total number of images 3322</td><td>True Positives(TP) 956</td><td>True Negatives (TN) 2062</td></tr>
<tr><td>False Negative (FN) 152</td><td>False Positive (FP) 152</td></tr>
<tr><td>Actual Class</td><td>Meningioma</td><td>Glioma</td></tr>
<tr><td>Meningioma</td><td>136</td><td>7</td></tr>
<tr><td>Glioma</td><td>86</td><td>604</td></tr>
<tr><td>Pituitary Tumor</td><td>16</td><td>1</td></tr>
</table>

Based upon the retrieved total number of training images and retrieved TP, TN, FN, FP. The parameters metric like accuracy precision Recall and Recall are measures as follows:

$$Precision = TP / \mathrm{TP+FP}$$

$$Recall = TP / \mathrm{TP+FN}$$

$$F1 = 2 \times precision \times recall \,/\, \mathrm{precision+recall}$$

$$Accuracy = TP + TN \,/\, \mathrm{TP+FN+TN+FP}$$

TABLE III. THE TABLE BELOW GIVES OVERALL ACCURACY, PRECISION, F-SCORE, AND RECALL OF THE CLASSIFICATION MODEL.

Parameter	**Computed value**
Accuracy	90.85
Recall	79.85
Precision	89.24
F-measure	86.28

The proposed techniques give good recall and precision leading to higher accuracy. The comparison of the results of the proposed technique with other classification techniques is given in Table 4. As can be seen from the results the accuracy of the proposed technique is the highest and there is an improvement of 1:6% over the other promising deep learning technique. It is clear from the below comparison TABLE IV that the technique outperformed all the other techniques in terms of accuracy. But the proposed technique is more computationally complex in terms of training than other similar techniques. The results are graphically plotted in Fig.5 and Fig.6 to visualize the classification and time complexity of the classification methods.

TABLE IV. THE TABLE BELOW GIVES THE OVERALL ACCURACY, PRECISION, F-SCORE, AND RECALL OF THE CLASSIFICATION MODEL.

Classifier	**Accuracy Rate**	**Dataset**
Color + KNN	48.7805	OASIS-MRI
Color +SVM	81.7073	OASIS-MRI
LPB + KNN	45.122	OASIS-MRI
LPB + SVM	57.3171	OASIS-MRI
HOG + KNN	67.0732	OASIS-MRI
HOG + SVM	81.7073	OASIS-MRI
Deepnet1	87.7211	OASIS-MRI
Deepnet3	89.2318	OASIS-MRI
Using LPB +ANN	44.4250	OASIS-MRI
Using HOG+ANN	58.12293	OASIS-MRI
Existing CNN	86.0000	OASIS-MRI
Proposed technique(CNN)	90.84888	OASIS-MRI

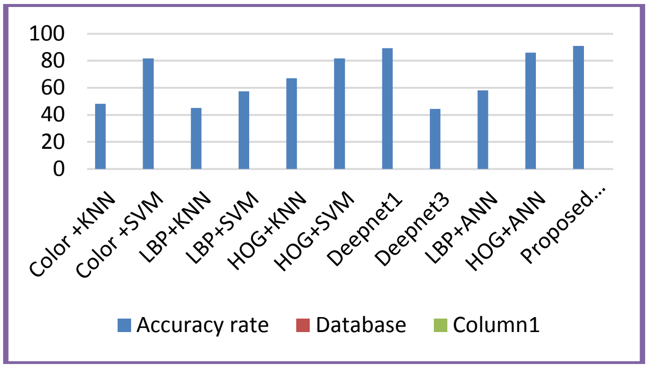


Figure 5. Accuracy comparison graph

From the above table and graph, it is clear that the accuracy of the proposed technique is much higher as compared to all other existing techniques, therefore the proposed technique outperforms all others in terms of accuracy rate. Also, the model requires less training time because of exploitation of the concept of transfer learning, therefore techniques also outperform all others in terms of training complexity as well. The time complexity of all the techniques is given by table V. The proposed technique is compared with Deep net 1 and Deep net 3. The proposed technique is compared with Deep net 1 and Deep net 3in terms of both accuracies as well as time complexity.

The proposed model performs well in terms of accuracy than both the Deep net models, but slightly consumes a few seconds more than these models. Still, the time complexity is comparatively remarkable. The visualization of time complexity is given in Figure 6. below.

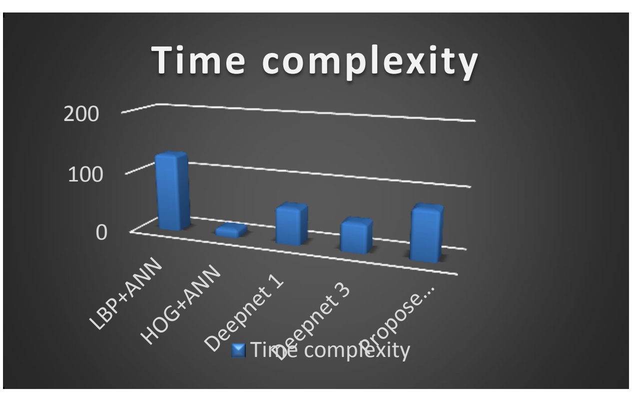


Figure 6. Time complexity comparison graph

The proposed CNN when compared with recent Deep net 3, our method outperformed in terms of classification accuracy which is very low in Deep net 3 and Deep Net 2. Also, the time complexity is not too high in comparison with deep net 3. From the above time complexity graph, it is clear that LBP is used when for feature extraction and then NN is employed for classification, it consumes a lot of time as compared to other mentioned techniques. So the technique is computationally infeasible because of the involvement of the handcrafted feature extraction method.

Limitation: It is clear from the comparison table 3 and 4 and from visual plots representing by fig. 5 and fig. 6 that our proposed techniques outperforms all the existing classification techniques in terms of classification accuracy, but the time complexity of the proposed is quite high as compared to other existing models which need to be optimized in future by using different advanced optimization technique.

6. CONCLUSION AND FUTURE SCOPE

Deep learning architectures are improving computational paradigm for developing predictive models of the disease. In this paper using the concept of deep learning, we have developed an improved classifier using concept deep learning for the classification of biomedical images. The proposed method gives the best performance when it is compared with popular conventional classification models and various recent classification models such as deepnet1 and deepnet3. On doing the comparative analysis of the present proposed technique with these traditional methods it is observed that the present model leads to new and potentially promising results on medical image classification. But cannot compete with the existing methods mentioned in table 4 in terms of time complexity. Therefore, in the future need to address the time complexity issue which is very crucial in real-time data, it is necessary to optimize the model so that time complexity is reduced as well as model size as compared to other existing approaches.

In the future we will be focusing on designing deeper networks and data augmentation will be implemented on all layers of the network for biomedical applications with reduced training time and improved accuracy rate. We can also implement other accelerating and optimizing methods like training acceleration methods like Fourier-based fast convolution methods, by exploiting parallelism, etc.

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