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Magnetic Resonance Image Based Brain Tumor Multi-classification Using Histogram Equalization and Deep Learning

[1]Dhanashri Joshi and [2]Hemlata Channe

[1,2]Department of Computer Engineering,

SCTR'S Pune Institute of Computer Technology,

Savitribai Phule Pune University,Pune, Maharashtra,Pune,411043.

E-mail: [1]j.dhanashri@gmail.com, [2]hpchanne@pict.edu

ABSTRACT

Automatic classification of brain tumors is a challenging task to develop a computer-aided diagnosis system. Identifying a tumor of correct type leads to better treatment decisions and survival of the patient. Magnetic Resonance Imaging (MRI) technique is commonly used in brain tumor classification. It gives structural details of the brain and does not use any ionizing radiations for imaging. The manual classification of a brain tumor depends upon the availability of expert radiologists. Deep learning has shown significant performance for medical image segmentation and classification problems. This paper presents a brain tumor multi-classification system to classify brain tumors into three different types Glioma, Meningioma, and Pituitary tumors, using CNN based deep learning architecture. The model is evaluated on a publicly available dataset that contains 3064 T1 weighted MRI images of 233 patients. MRI images are pre-processed, augmented, and given to the proposed system with the CNN model for classification. It achieves remarkable performance with an average accuracy of 97 % and outperforms many existing methods. This can be used as a decision support system for clinical experts for brain tumor multi-classification.

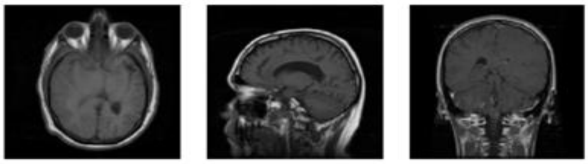
Keywords: *Magnetic Resonance Images, image processing, deep learning, histogram equalization, brain tumor classification.*

1. INTRODUCTION

The brain plays a critical role in the human body controlling all voluntary and involuntary processes. It is highly necessary to maintain a healthy brain to live longer. But due to causes like age, family history, chemical exposure, exposure to radiation, excessive use of gadgets like cell phones, computer tumors can be developed in the brain. A tumor can interrupt the normal functionality and cause an increase in pressure in the brain. As a result, some tissues may get pushed against the skull, thus damaging the healthy brain tissues. Depending upon the tissue origin and its behavior, tumors are classified as benign and malignant tumors. Benign tumors are non-cancerous, whereas malignant tumors are cancerous ones.

There are different types of medical imaging modalities used for brain tumor classification like PET (Positron Emission Tomography), CT (Computerized Tomography), MRI (Magnetic Resonance Imaging). MRI is a non-invasive test most commonly used in neurology and neurosurgery. MRI provides detail of the brain, spinal cord, and vascular anatomy and has the advantage of being able to visualize anatomy in all three planes: axial, sagittal, and coronal. Axial starts from chin towards the head, sagittal is taken from side moving from one ear to another, and Coronal is taken from the back of the head towards the face.

Sample MRI images in three different planes are given in figure 1.



(a) (b) (c)

Figure 1 (a): Axial Plane (b): Sagittal Plane (c): Coronal Plane

Glioma is the type of malignant brain tumor observed more frequently in humans. According to WHO, Glioma is classified into four grades [1]. Grade, I, and II tumors are lower levels of tumors and can be benign while grade III and IV types of tumors are more severe and can cause serious damage to brain tissues. Meningioma tumors are mostly benign tumors and formed on a membrane that covers the brain. These are slow-growing tumors, and if not diagnosed at an early stage, can cause permanent damage to brain cells [2]. Pituitary tumors are developed in pituitary glands, which are responsible for hormone controls in the body. They are considered benign tumors; however, complexities can cause hormonal deficiency and vision loss [3].

Classifying the tumor into the correct type is a very crucial task which leads to better treatment decision and survival of the patient. MRI images are complex in nature, and its quality depends upon the artifact used for imaging. Manual classification is challenging in several cases because lesions in the brain are small in size, and there exist variations in texture, shape, and intensity. Hence Computer Aided Diagnostic

(CAD) system can be used for automatic classification of brain tumors. Machine learning techniques have been used by many researchers for brain tumor classification. Machine learning methods include mainly four stages: pre-processing, segmentation, feature extraction, and classification. Figure 2 shows the general architecture of the brain tumor classification system.

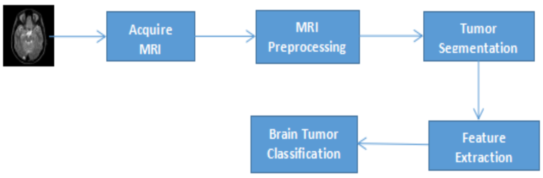


Figure 2: General architecture of the brain tumor classification system.

Recently Deep Learning has shown better performance for segmentation and classification in the field of medical imaging. CNN architecture uses convolutional filters to extract the features. It has the benefit of automatic feature learning and achieves good accuracy as compared to state-of-the-art machine learning methods.

In this paper, a deep learning architecture using Convolution Neural Network is proposed for the multi-classification of brain tumors into three types Glioma, Meningioma, and Pituitary. In section 2,a review of the related work is given. The proposed method and the CNN model is presented in section 3.Section 4 discusses the result and implementation details. The conclusion of the paper is mentioned in section 5.

2. RELATED WORK

Various machine learning and deep learning methods have been proposed for brain tumor classification in recent years.T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (FLAIR) image modalities are used for brain tumor segmentation and classification. Ghassemia et al.[4] introduced a new method for brain tumor classification using a discriminator in a generative adversarial network (GAN) for feature extraction. Six layers deep neural network classifier achieves an accuracy of 95.6% for three types of tumor classifications. The Brain tumor classification system is proposed by E. Goceri using capsule networks [5]. The Dynamic routing algorithm helps the capsule neural networks to retain the spatial relationships among learned features. Sobolev gradient optimization and expectation maximization based dynamic routing algorithms have been utilized for classification. The proposed system is tested for three types of tumor classification with 92.65% of accuracy. K. Kaplan et al.[6] has used modified local binary pattern feature extraction method for brain tumor classification. Two feature extraction methods nLBP and αLBP are introduced. nLBP finds the relationship of each pixel around the neighbours. αLBP operator measures each pixel value from an angle value. The accuracy of 95.56% was achieved for three types of tumor classification.

Sert et al. proposed a brain tumor detection system using fuzzy entropy segmentation and CNN. Single image super-resolution and fuzzy entropy methods are used for segmentation. Automatic feature extraction is achieved by pre-trained Resnet architecture, and SVM is utilized for binary classification with accuracy 95% [7].A new approach using Regularized Extreme Learning Method with hybrid features is proposed by Gumaei et al.[8].A normalized feature descriptor NGIST is applied to resolve the issue of image illumination and shadowing. A Feed-forward RELM neural network is utilized for three-class classification with5-fold cross-validation. The proposed system achieved an accuracy of 94.33%.

A capsule network (CapsNet) is utilized for tumor classification by Afshar et al.[9].The position of the tumor with boundaries is given as input to CapsNet. The system gives an overall accuracy of 90.80%. A model based on the Genetic Algorithm (GA) and Convolutional Neural Network (CNN) is suggested by Anaraki et al. to classify brain tumor images. GA-CNN architecture achieves the accuracy of 94.2% on the CE-MRI dataset for multi-classification.[10].M. Sajjad et al. uses InputCascadeCNN for tumor segmentation in multigrade brain tumor classification [11]. Augmented images are feed to VGG19 architecture. The proposed method achieves 94.58% accuracy for multi-classification.

Feature extraction is a very crucial step for classification using a machine learning technique. Ismael et al.[12] extracted statistical features using the 2D Discrete Wavelet Transform (DWT) and 2D Gabor filter. Classification accuracy of 91.9% is achieved using a multi layer perceptron with back-propagation. Deep learning (DL) is an advanced field used in medical image classification and segmentation, with better results as compared to machine learning methods .LSTM based neural network is used for tumor classification by Zhou et al.[13].An auto-encoder is used for feature extraction from an axial view of images.MRI images are considered as a sequence of images; hence LSTM is utilized for classification with accuracy of 92.13%.Paul et al. suggested a brain tumor multi-classification framework using CNN with two convolutional layers, max-pooling layers, and 2 Fully Connected (FC) layers followed by a softmax layer. The system has achieved 91.43% accuracy for tumor classification into three types-Meningioma, Glioma, and Pituitary. [14]

3. PROPOSED METHODOLOGY

Figure 3 represents a block diagram of the proposed method to perform the classification of brain tumors into three classes-Glioma, Meningioma, and Pituitary.

The CE-MRI dataset contains .mat files of 3064 images. The first step involves converting .mat images to .jpeg format images. The MR images are first pre-processed. Then data augmentation technique is used to increases the size of

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training samples by geometrical transformation and distortion methods.

Dataset is shuffled and split into training, testing, and validation sets.CNN model is built by setting hyper-parameters and optimization parameters like kernel size, no of kernels, learning rate, drop-out rate, etc.Finally, the network is trained, and the performance of the model is evaluated.

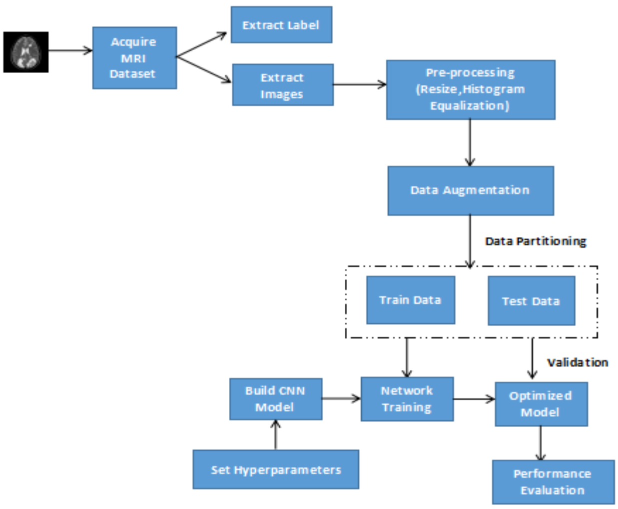

Figure 3: Block diagram of the proposed method.

3.1. DATASET DETIALS

CE-MRI dataset is procured from Nanfang Hospital and General Hospital, Tianjing Medical University, China. It includes 3064 T1 weighted images of 233 patients having three types of tumors-Glioma, Meningioma, and Pituitary [15].The dataset contains MRI images in all three planes: axial, sagittal, and Coronal. A few previous works include MRI images in only one plane; however, this research utilizes MRI images in all three planes. Table 1 shows the detailed descriptions of MRI slices in a dataset. The images are of size 512*512 pixels. Sample MRI images are given in figure 4.

Table 1: CE-MRI dataset details

Tumor Type	Glioma	Meningioma	Pituitary	Total
No of Slices	1426	708	930	3064
No of Patients	91	82	60	233

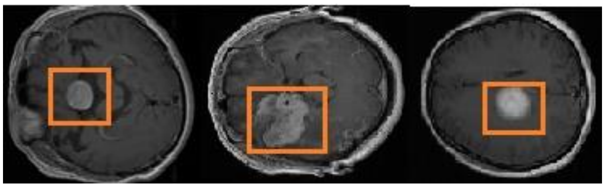

Figure 4: (a) Glioma (b) Meningioma (c) Pituitary tumors marked in an orange box

3.2. PREPROCESSING

Resize: *The f*irst step of the proposed method is, preprocessing of images, which is necessary for better performance of the model. The dataset contains MRI images of size 512*512*1, which are resized to 128*128*1 for dimensionality reduction, better training of the network, and fewer computations.

Histogram Equalization (HE): Magnetic resonance imaging technique produces high-quality images. Contrast enhancement of such images is necessary, so that appropriate result is achieved for a specific application. Image enhancement is done by using histogram equalization. Histogram graphically represents the intensity distribution of images. Histogram equalization adjusts the most frequent intensity values in an image so as to enhance the contrast of images. This technique generally improves the global contrast of images when images are characterized by close contrast values.

The following equation (1) explains the histogram equalization technique.

Let ‘X’ be given image, represented by matrix M_x of integer pixel intensities ranging from value 0 to M-1. Where M is possible intensity values, for gray images, M is 256. Let ‘Y’ be the normalized histogram to represent ‘X’ having a bin for each intensity value.

$$Y_n = \frac{\text{count of pixels having intensity n}}{\text{total count of pixels}} \quad n = 0, 1, 2... M-1$$

The histogram equalized image ‘Z’ will be given by,

$$Z_{i,j} = floor((M-1)\sum_{n=0}^{X_{i,j}} Y_n \quad \text{.....................} (1)$$

Where, floor rounds to the nearest integer value. [16]

Figure 5 shows an example of histogram equalized images.

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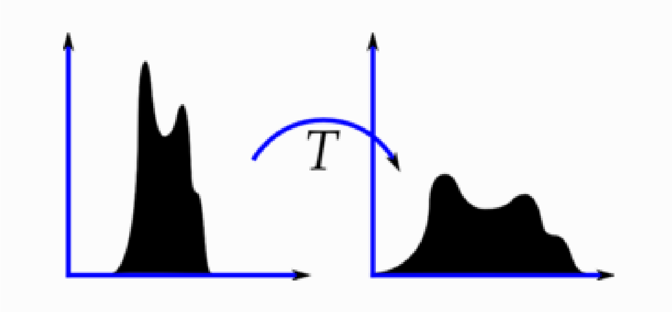
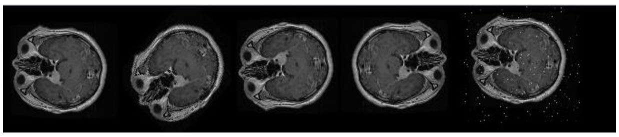


Figure 5: Example of histogram equalization [17].

3.3. DATA AUGMENTATION

To train a deep convolutional neural network, tuning of parameters is necessary for mapping specific input to output. When many parameters are involved, a suitable number of training samples are required to improve the performance of the model. Data augmentation refers to constructing new data points by utilizing the original data. It is used to avoid overfitting. In overfitting, the network learns the function with high variance, so it flawlessly trains the data with limited samples and affects the model's ability to generalize. Domains like medical imaging rarely have access to big data; hence data augmentation can be used to increase the size and quality of training dataset. In this study, data is augmented using a geometrical transformation and distortion method.The Geometrical transformation includes rotation by 45 degrees,up-down flip, left-right mirror,whereas distortion includes the addition of salt noise to images.3064 images are increased by factor 5, so the final dataset constitutes 15320 images. Figure 6 shows a sample of augmented and original images.



(a) (b) (c) (d) (e)

Figure 6: (a) Original image (b) 45 degree rotation (c) up-down flip (d) right-left mirror (e) salt noise added to image.

3.4. PROPOSED CNN MODEL

The proposed CNN model is shown in figure 7. It consists of 16 layers. Augmented images from the pre-processed stage are given to the input layer. Then it is passed through a convolution neural network with Rectified Linear Unit (Relu) activation unit and max-pooling layer. The drop-out layer is used to prevent overfitting. Finally, a fully connected layer is used, followed by the Softmax layer and classification layer to predict the output of the class.

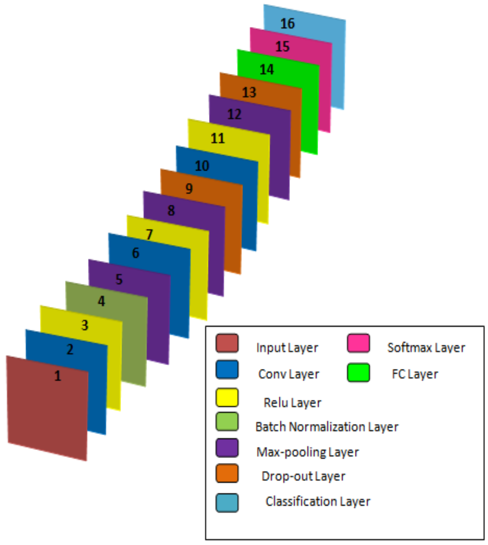


Figure 7: Architecture of the proposed CNN model.

Representation of the CNN model to classify the brain tumor into three types - Meningioma, Glioma, and Pituitary is given in figure 8.

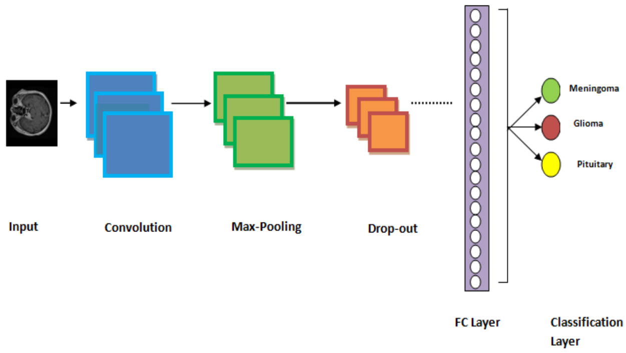


Figure 8: Representation of the CNN model.

3.4.1. CONVOLUTION LAYER

The architecture given in figure 7, has three convolution layers. It is an important block in Convolution Neural Network. Convolution layer applies K convolution filters of size (L×M) to input to produce feature maps. Filters are also called kernels. The filter acts as sliding windows and moves across the input image from left to right .It computes the dot product of kernel weight and input weight. The amount of movement of the filter from one position to another position is defined as Stride (S). Padding (P) is an additional layer added to the border of the image in order to avoid information loss at edges.

The proposed model consists of three convolution layers with no. of filters 64,128,128, having size 10×10, 5×5, and 2×2, respectively. E.g., Let us consider the kernel of size 3×3 applied to an image of size 3×3 with zero padding to produce

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the output of the same shape 3×3.An example is illustrated in figure 9.

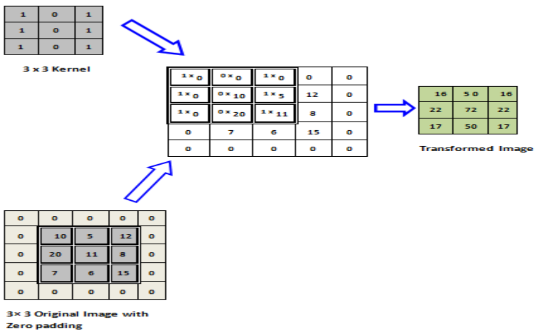

Figure 9: Example of input 3×3, filter with size 3×3, zero-padding, stride 1, and output layer 3×3.

3.4.2. RELU ACTIVATION LAYER

Rectified Linear Unit is a non-linear activation function used to transform the weighted input to a specific output. It is used to overcome the vanishing gradient problem and allows the deep network to perform better by reducing the learning time. It is mainly applicable in neural networks with many layers. It enables the network to learn complex structure data quickly.Equation 2 represents Relu activation function.

$$y = \max(0, x) \quad \text{...} \quad (2)$$

3.4.3. BATCH NORMALIZATION LAYER

A deep neural network is composed of many intermediate layers. When the weights get updated for every layer, the distribution of input to these layers may change after each mini-batch. This causes the training process to slow down. Batch normalization is used to reduce this effect. It is the process that standardizes the input distribution to intermediate layers for each mini-batch. Batch normalization helps the learning algorithm to get stabilized and to converge quickly with less number of epochs. In the proposed model, one batch normalization layer is used after the Relu activation of the first convolution layer.

3.4.4. POOLING LAYER

The pooling layer is applied to down-sample the input data. It reduces the number of parameters to learn for network and hence reduces the computations required to train the network. The model becomes more robust to variations in features by using the pooling layer. There exist two types of pooling Max-pooling and Average pooling. Max-pooling selects the maximum element present in the feature map region acquired by the filter. Average pooling selects an average of the element present in the feature map region covered by the filter. In the presented model, the Max-pooling layer is used. It is explained in figure 10.

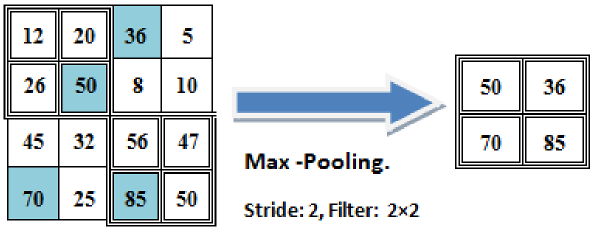

Figure 10: Example of Max-pooling.

3.4.5. DROP-OUT LAYER

Training a deep neural network with few numbers of samples leads to overfitting. In overfitting, the network also learns the noisy input in the training dataset and fails to give good performance for testing/validation data. Drop-out is a regularization technique used to minimize overfitting and overcome generalization. In this method, some numbers of the output of layers are randomly dropped out. The network learns on a few nodes, and statistical noise gets avoided. A hyper-parameter drop-out rate is defined, which gives the probability at which outputs of the layer are dropped. In the proposed method, two drop-out layers are used with a rate of 0.1 and 0.2, respectively, to avoid overfitting.

3.4.6. FULLY CONNECTED AND SOFTMAX LAYER

In the end, the Fully Connected (FC) layer and softmax layer are used. Softmax converts the real values to probabilities. The probabilities exist in the range 0 to 1.Summation of all probabilities is equal to 1. It is used in a multiclass classification problem. Equation (3) represents the softmax calculation.

$$y(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{k} e^{z_k}} \quad \text{......................} (3)$$

Probability is calculated for k different classes as function y, and its sum is equal to 1.Cross-entropy classification layer is used, which gives prediction about the label of an input image.

3.4.7. OPTIMIZATION TECHNIQUE

An optimization algorithm is used to minimize the cost function. The cost function quantifies error between predicted and actual values. It is shown by the following equation. [18]

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$$Cost\ function' = Cost\ function\ (Loss) + \lambda \sum_{i=1}^{k} u \quad \ldots\ldots\ (4)$$

λ is the hyper-parameter, and w is respective weights for i=1,2,3,……k It is observed that stochastic gradient descent(SGD) with momentum gives better performance for the proposed method.

Gradient Descent (GD) is an iterative technique used to find hyper-parameters like learning rate, batch size in order to optimize the cost function.GD is applied to the whole dataset, whereas Stochastic Gradient Descent (SGD) is applied to randomly selected samples for each iteration. Momentum guides the gradient vector in the right direction to converge fast. Momentum retains the gradient of the last step.It decides the direction for further improvement in the cost function. It is generally defined as a coefficient of momentum, which gives the percentage of gradient retained in every iteration. We have used SGD with 0.9 momentum for the suggested model.

4. RESULTS AND IMPLEMENTATION

The proposed CNN model is trained on Nvidia Tesla K80 GPU, 13 GB RAM, Intel CPU with 2.3 GHz hardware architecture, and python programming language. Dataset is divided into 60:20:20 where 60% training, 20%validation, and 20%testing is used. It is observed that the training after 100 epochs with mini-batch size 10 gives better average accuracy of 97%. We have used three kernels 64,128,128 with size 10×10, 5×5, and 2×2, respectively.SGD with momentum has shown good performance. Table 2 represents the different parameters tested in order to reach the proposed structure with the best possible result.

Table 2: Various parameters and architectures are tested before the best result is obtained.

Parameters	Values
Input image dimensions	512×512,256×256,128×128,64×64
Number of Convolution and Relu Layers	1,2,3,4
Number of Drop-out Layers	1,2,3
Number of Batch-normalization Layers	1,2,3
Kernel size	2,3,5,7,10,19
Number of kernels	32,64,128,256
Number of FC layers	1,2,3
Number of neurons in FC layer	128,256,500
Mini-Batch size	10,16,32,64,128
Number of Epochs	25,50,75,100
Optimization Algorithms	Adam,SGD,RMSprop
Pooling layer	Maxpooling,Average
Drop-out rate	0.1,0.2,0.5
Learning rate	0.1,0.01,0.001,0.0001

Accuracy and loss across the testing and training phase are given in figure 11. It is observed that as the number of epochs gets increased, accuracy increases while loss gets decreased. At 100th epoch, maximum accuracy and minimum loss are achieved.

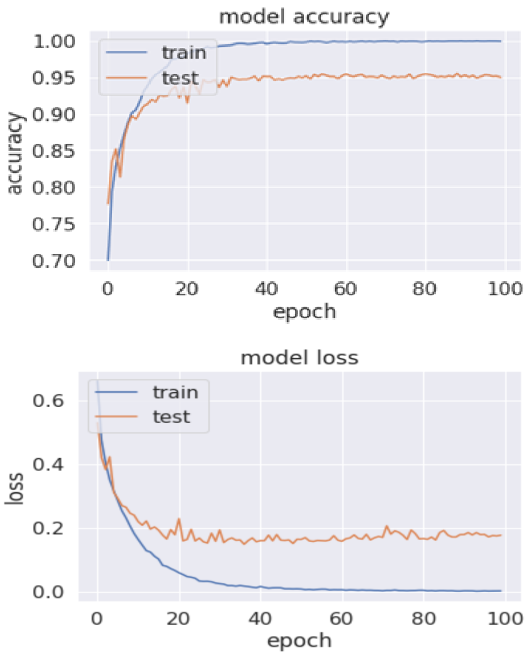

Figure 11: Accuracy and loss during the training and testing phase.

The confusion matrix, which gives a summary of the performance of the model, is represented in figure 12.True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values are evaluated from the confusion matrix.

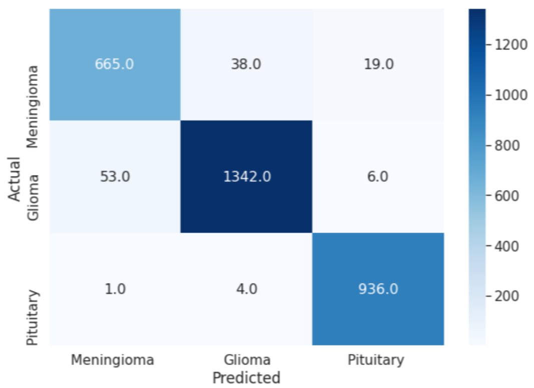

Figure 12: Confusion matrix of the proposed model

True Positive (TP): Number of samples predicted as positive, and actually, they are positive.

True Negative (TN): Number of samples predicted as negative, and actually, they are negative.

False Positive (FP): Number of samples predicted as positive, but actually, they are negative. It is known as type 1error.

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False Negative (FN): Number of samples predicted as negative, but actually, they are positive. It is known as type 2 error.

Precision, Recall, F1-score are calculated from TP, TN, FP, and FN by below formulas.

Precision = TP/TP+FP

Recall= TP/TP+FN

Accuracy = TP+TN/P+N

F1 Score = 2*Precision*Recall/Precision + Recall

Table 3 represents the TP, TN, FP, FN, Accuracy, Precision, Recall, and F1-score of each class in the proposed model. The highest performance in terms of accuracy, precision, recall, and F1-score are shown in bold. It is observed accuracy for Meningioma classification is 96%; for Glioma, it is 97%, while for Pituitary, it is 99%. Best values of precision, recall, and F1-score are obtained for Pituitary tumors.

Table 3: Performance measures in terms of TP, TN, FP, FN, accuracy, precision, recall and F1-score

	Meningioma	Glioma	Pituitary
TP	665	1342	936
TN	2288	1621	2098
FP	54	42	25
FN	57	59	5
Accuracy	0.96	0.97	**0.99**
Precision	0.92	0.97	**0.97**
Recall	0.92	0.95	**0.99**
F1-Score	0.92	0.96	**0.99**

In this paper, the CNN model is presented for the multi-classification of brain tumors. Building and training CNN from scratch is difficult as it may take the number of days to reach a satisfactory result. In existing work in literature, CNN models with different hyperparameters, kernel size, depths are applied to the same dataset for multiclassification. Our proposed model gives better performance as compared with related architectures. A comparison with the existing study is represented in Table 4.

Table 4: Comparison between the proposed model and existing work on the same CE-MRI dataset

Model	Accuracy	Method
Ghassemi et al.[4]	95.6%	GAN-Convnet
Afshar et al.[9]	90.89%	CapsNet
Anaraki et al.[10]	94.2%	GA-CNN
Ismael et al.[12]	91.9%	DWT and Gabor filter features
J.Paul et al.[14]	91.43%	CNN
Cheng et al.[15]	91.28%	KNN and SVM
Pashaei et al.[19]	93.68%	KE-CNN
Proposed Model	**97%**	**HE-CNN**

5. CONCLUSION

In this research paper, deep learning based convolutional neural network model is proposed for the classification of T1-weighted MRI images into three types-Meningioma, Glioma, and Pituitary tumors. Preprocessing includes resize and histogram equalization for image enhancement. The model consists of a total of 16 layers, including three Convolutions, Relu, Max-pooling, one Batch normalization, and two Drop-out layers. Drop-out is used to reduce the effect of overfitting. The model is trained on all three MRI planes axial, sagittal, and coronal. Limited data samples issue is overcome by using data augmentation. By using pre-processing techniques, the performance of the model is enhanced as compared to existing state-of-the-art methods. The given method is a segmentation free approach. Automatic feature extraction is done by using CNN kernels. The proposed model shows 96% classification accuracy for Meningioma, 97% for Glioma, and 99% for Pituitary tumors, with an average accuracy of 97%. This can be used as a decision support system for brain tumor multiclassification and can be tested on a large dataset with multiple MRI modalities.

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AUTHOR PROFILES

Dhanashri Joshi has completed BE in computer science and engineering from Walchand College of Engineering Sangli. She is currently pursuing her Master's degree from Pune Institute of Computer Technology (PICT) in computer engineering. Her area of interests includes deep learning, medical image analysis, image processing.

Hemlata Channe has received BE and ME in computer engineering. She is currently working as assistant professor at Pune Institute of Computer Technology (PICT), Maharashtra. She has more than 16 years of teaching experience. Her research interest includes computer networks, internet of things, cloud computing and security.