

Benign and Malignant Tumor Classification from MRI Images using Modified Convolution Neural Network Approach

HarendraSingh^a, RajeevRatan^b, J.V.Desai^c, Poonam G.Kohli^d

^{a,b,c}Department of Electronics and communication Engineering, MVN University, Palwal 121102,India.

^dDepartment of physiology, Punjab Institute of Medical Science, Jalandhar (Punjab),144006, India

^aharendramvn2010@gmail.com

Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: Globally, according to the World Health Organization (W.H.O) report, a secondary major factor for the death of human beings is cancer. Due to the uncontrolled growth of abnormal tissues, it can start in any organ of the body and after some time spreads to the other parts of the body through the bloodstream. So, for effective treatment of a cancer patient, it is very necessary to diagnose the tumor/cancer cells in the early stage. In this proposed work a 12 layered Convolution Neural Network (CNN) model has been implemented for the classification of benign and malignant tumors in brain tumor MRI images. To avoid the shortage of data during model training, data augmentation and data shuffling have been used. A 10% and 20% dropout of neurons is used to avoid the overfitting of the model. This proposed model can predict the type of tumor (benign or malignant) is comparatively in less computational time with 99.22% of accuracy..

Keywords: Brain Tumor, Convolution Neural Network (CNN), Deep Learning, Data Augmentation, Magnetic resonance image (MRI)

1. Introduction

Nowadays, cancer has become one of the most life-threatening disease. According to World Health Organization(WHO) survey, every year approximately 12.7 million new cancer cases are diagnosed and approximately 7.6 million deaths are recorded due to cancer[1]. The generation of uncontrolled and unnatural brain cells in any part of the brain after gaining mass is known as a brain tumor [2,3]. The brain tumor is classified as benign and malignant. The benign tumor is non-cancerous and can easily be removed by a small surgery known as a biopsy. when benign tumor gains some mass and starts to spread through the bloodstream in other parts of the body, known as malignant. If the tumorous cells are diagnosed in an early stage without segmentation, then chances of survival may be increased[4]. In this paper, a CNN model is proposed using a deep learning approach. This model can classify the brain tumor images with its labels without image segmentation.

Mohsen et al [5] proposed an MRI image classifier model based on deep learning techniques. The model can classify the four classes of brain tumor e.g. normal, sarcoma, glioblastoma, and metastatic bronchogenic carcinoma. The performance of the classifier was quite good when it was combined with Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) tools for features extraction and noise level control as well as dimension.

Sultan et al [6] proposed a model for the classification of brain tumor images using computer vision algorithms. This model can classify brain tumor images with 96.13% as mean accuracy. The model is trained by 3064 T1-weighted contrast-enhanced brain tumor MRI images for Meningioma, Glioma, and Pituitary tumors.

Kumar et al [7] proposed a multiclass deep learning model for nutrients deficiency of apple fruit. This model can classify as well as recognize the types of deficiency present in apple fruit with 98.24 % of accuracy with a collection of the dataset of size 1000 of 4-types of deficiency as Boron, Calcium, Iron, Manganese and Healthy fruit.

Deepak et al [8]have developed a fully automatic brain tumor classification model for glioma, meningioma, and pituitary brain tumor using transfer learning with a higher order of accuracy. The proposed model is based on transfer learning means a pre-trained GoogLeNet model is used for feature extraction and the system records a 98% as a mean classification accuracy.

Ouseph et al [9] proposed a new technique based on CNN for brain tumor detection from MRI images with a higher order of accuracy with less computational time and also able to extract abnormal tissues by using biochemical features.

Jmour et al [10] proposed a convolution neural network (CNN) model using deep learning for traffic sign classification. This model is developed to classify four classes "Stop Sign", "Non-Stop Sign", "Greenlight", and "Red light" with 92 % accuracy using transfer learning or fine-tuning techniques i.e. Alex Net.

Kaldera et al [11] have developed a fully automated model for brain tumor classification and segmentation for both benign and malignant tumor in MRI images. A Convolution Neural Network (CNN) model is used for classification and the Faster R-CNN model is used for brain tumor segmentation. when the model is trained with 218 MRI images then the model shows 100% accuracy for Meningioma and 87.5 % for glioma classification of brain tumor and the average confidence level for segmentation of brain tumor is 94.6 %.

2. Convolution Neural Network

Nowadays Convolution Neural Network (CNN) plays a major role in medical science for image classification, denoising, registration, segmentation, medical image analysis, and brain-computer interface. The computer vision means cascade connection of Convolution Neural Network (CNN) and Artificial Neural Network (ANN)[12]. The CNN is used to extract the features from an unlabeled dataset, like images, audio/video signals and feeds to ANN for prediction. The CNN is a multi-layered architecture and each layer of CNN has a specific number of feature extraction filters, so features extracted by each layer are represented in three parameters like height, width, and depth [10], and these extracted features are used to train the prediction model. The CNN model consists of four layers; Convolution layer, Relu layer, Maxpooling or Average Pooling layer, and Flattening layer.

3. Convolution Layer

The output of convolution operation is based on three parameters; filter size, stride, and padding. How many shifts at a time taken by the filter to the right side during convolution operation is decided by stride? The size of the image is inversely proportional to stride. Padding is used to put the zeros at boundaries in all directions of the binary image to the size of the image is increased [13,14]. Padding is classified as ‘Valid’ and ‘Same’. When valid padding is selected during convolution operation the size of the image is reduced without eliminating the important features but for the same padding, the size of the image is constant. If the size of the input image is $[N_h, N_w, N_c]$ feed to convolution layer then the size of convoluted image $[M_h, M_w, M_c]$ is calculated by using given equations (1), (2), (3) as :

$$M_h = \frac{N_h + 2 * \text{Padding} - \text{filtersize}}{\text{stride}} + 1 \tag{1}$$

$$M_w = \frac{N_w + 2 * \text{Padding} - \text{filtersize}}{\text{stride}} + 1 \tag{2}$$

$$M_c = K \tag{3}$$

With:

N_h, N_w, N_c : Height, Width, and Depth of an input image

M_h, M_w, M_c : Height, Width, and Depth of a Convoluted image

K: No. of filter =No. of input features

Figure 1 (a) &(b) shows an input MRI and convoluted brain tumor MRI image with hyper-parameters: Number of filter=1= no. of features, Size of kernel = (3*3), Padding= ‘valid’ (size of MRI images is reduced), Stride=1 is used. The convolution operation is used to learn the filters without eliminating the most important information which correlated the one pixel to its nearby pixels.

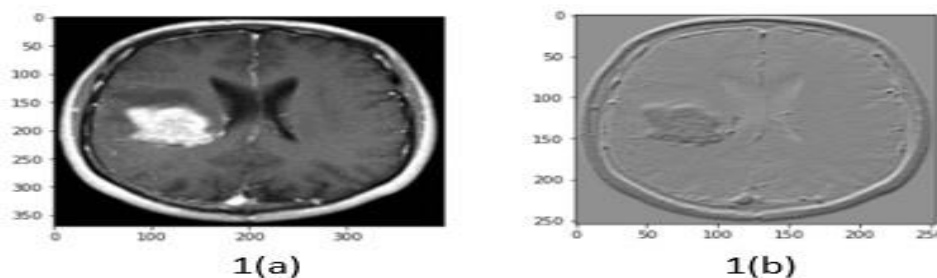


Figure1 (a) Input MRI Image Figure 1 (b) Convoluted MRI Image

Relu Layer

A Rectified Linear unit function (Relu) is a non-linear activation function that performs a threshold operation on each pixel of the input image [10]. All available ‘negative pixels’ values in the MRI image are converted into zeroes after Relu operation so that the number of dark pixels inside the input image is increased without affecting the actual size of the MRI image. If $f(x)$ is a Relu activation function, represented as by equation (4).

$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases} \quad (4)$$

Figure 2 (a) &(b) shows an input MRI and Conv2D+Relu operated brain tumor MRI image with hyper-parameters: Number of filter=1= no. of features, Size of kernel = (3*3), Padding= 'valid' (size of MRI images is reduced), activation function= 'Relu' Stride=1 is used. The darkness is increased because all pixel values below zero become zero.

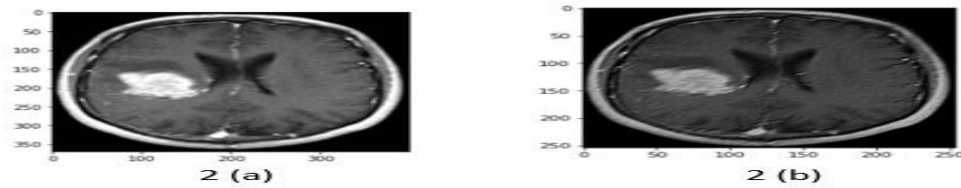


Figure 2 (a) Input MRI Image **Figure 2 (b)** Conv2D+Relu MRI Image

Pool Layer

After two successive Conv2D+Relu layer a pooling layer is used to reduce the dimension of an input image [1-10] Mask size and Stride, two main hyperparameters are responsible for how much spatial co-ordinate numbers are reduced without affecting the depth channel of an input image. Max-pooling and Average pooling are two pool operators. In Max-pooling the maximum value of the pixels is picked to calculate the new image but in average pooling average of all pixels during on stride operation is calculated.

Figure 3 (a) &(b) shows a sample of input MRI and Conv2D, Relu, and Max pool operated brain tumor MRI image. The hyper-parameters for a convolution operation on a brain tumor image are selected as Number of filter=1= no. of features, Size of kernel = (3*3), Padding= 'valid' (size of MRI images is reduced), activation function= 'Relu', Stride=1, size of Max-Pool operator is (2*2) is used.

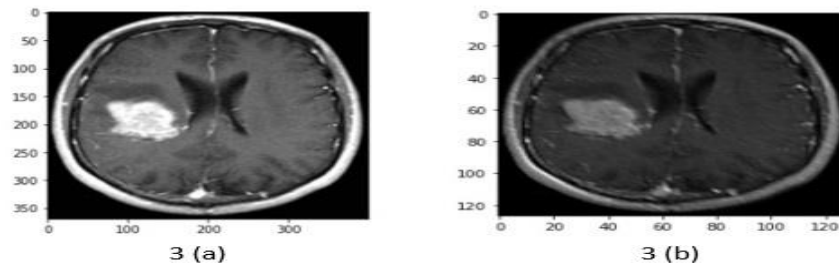


Figure 3 (a) Input MRI Image **Figure 3(b)** Conv2D+Relu+MaxPooling MRI Image

4. Proposed CNN Model for Image Classification

In this work, a Convolution Neural Network (CNN) model is proposed for the classification of a brain tumor in Magnetic Resonance Imaging (MRI) images. **Figure 4** shows the block diagram of the proposed CNN model. The collected unlabeled MRI dataset is preprocessed before splitting into training and, testing sets. To avoid the shortage of data during CNN model training, data augmentation and data shuffling have been used. Finally, the performance of the trained model in terms of prediction accuracy is tested by using tuning of hyperparameters [15].

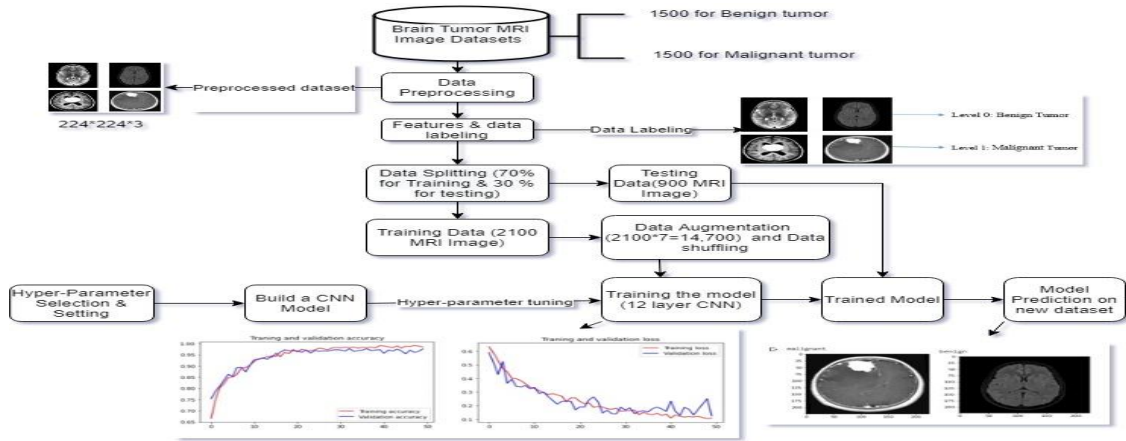


Figure 4 Block diagram of Proposed Model

5. Dataset and Pre-processing

For developing a proposed CNN model, 3000 T-1 weighted contrast-enhanced MRI images (1500 MRI images for Benign tumor and 1500 MRI images for Malignant tumor) are used and collected from “Punjab Institute of Medical Sciences” (PIMS), Jalandhar, Punjab. To check the performance in terms of prediction by the model after training sixty MRI images are used after pre-processing. The downloaded dataset is split into two sets as training and testing with 80/20 percentage ratio after pre-processing. The testing dataset is again divided as 10% for testing and the rest 10% for model validation. The first step in pre-processing is to convert the whole dataset images into a uniform dimension of 224*224*3 so that computation time and complexity of the model is reduced that reflects in terms of better performance with less time[16]. Data shuffling and augmentation steps are also used to avoid the shortage of data during model training. In the data augmentation seven operator; image rotation, width and height shift, image zooming & shearing, and image horizontal & vertical flip are used. Due to the data augmentation process, the original 3000 MRI image dataset is increased by the factor of seven. So, the final MRI Image dataset becomes 21,000 MRI images.

6. Proposed CNN Architecture

In this proposed CNN model, 12 layers are used excluding the input layer, which holds all MRI images of size 224*224*3 after pre-processing and augmentation process. In this model 3, convolution layers with activation function 'Relu' are used with no. of filters; 64,128,128, kernel size; 10,3,2, strides =1, and valid padding respectively. Relu activation function is used to reduce the computation time of the model by replacing all negative pixels' values to zero. Figure 5 shows a convolution operation, in which an input image of 6*6*1 is convoluted with a filter of size 3*3[17].

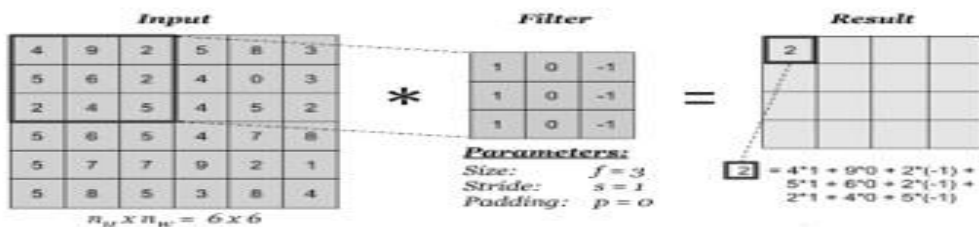


Figure 5 Convolution Operation

Three Maxpooling layers with pool size (2*2) are used to reduce the size of the convoluted image. without eliminating the features by pooling the maximum value out of four as shown in Figure 6.

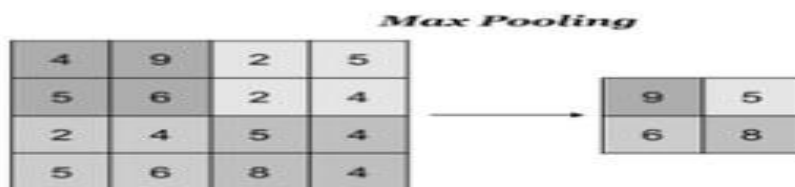


Figure 6 Maxpooling Operation

In figure 6 for Maxpooling operation with pool size 2*2, the value 9 is considered because it is maximum as compared to 4,5,6. In the proposed model, two dropout layers are used with 10% and 20 % respectively to avoid overfitting of the model during training face[12-18]. A flattening layer is used to convert the n-dimensional array into 1-D. So, after flattening the total no. of input parameters or neurons are 80000. The last two fully connected layers are used. In the proposed CNN model is given in which; total no. of trainable parameters for brain tumor classification is 20639682 out of 20,639,810.

7. Results and discussion

The Proposed CNN model for Brain Tumor classification in MRI images is implemented using the online platform 'google colab' with python 3.8. The Experiments are performed on the system having Intel Core i5 7th Gen CPU with 2.5 GHz Processor, 4 GB graphics, and 8 GB RAM. **Figure 7 (a) & (b)**The training and validation accuracy and losses of the proposed CNN model for brain tumor classification. The proposed model gives a training accuracy of model 99.88 % and validation accuracy 99.22 % with a hyper parameter; Batch size=32, Epoch = 50, Step size per epoch=65.

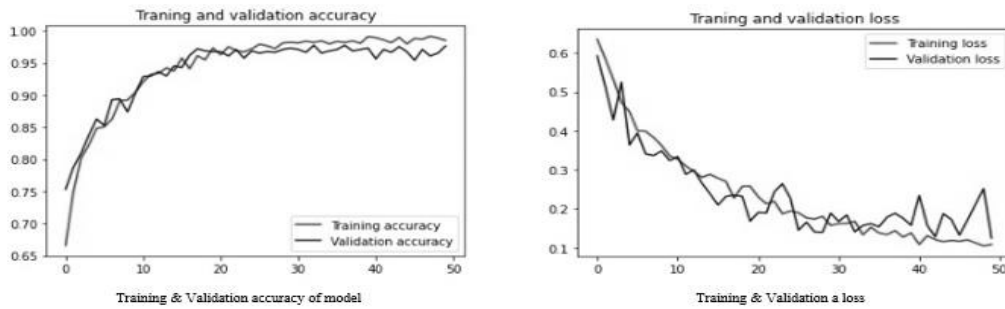


Figure 7 (a) Training accuracy and loss of proposed CNN Model **Figure 7 (b)** Validation accuracy and loss

8. Confusion Matrix

For checking the performance measures of the proposed CNN model a confusion matrix is plotted. **Figure 8** shows a confusion matrix in which, the x-axis of shows the predicted labels (model output) and the y-axis represents the true labels.

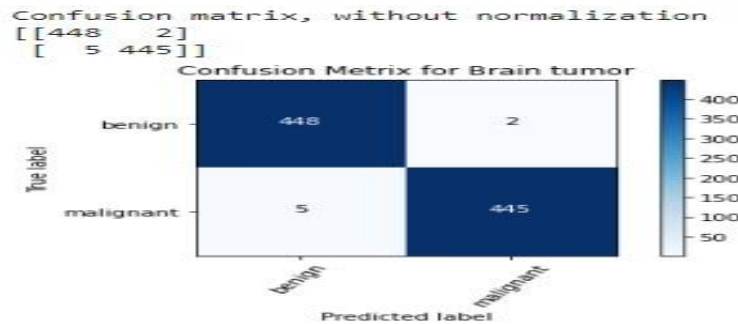


Figure 8 Confusion matrix

Based on confusion matrix parameters, some CNN model performance parameters are calculated is calculated by using given equations (5), (6), (7), (8) as under:

$$\text{Precision} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Positive})} \tag{5}$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True positive} + \text{False Negative})} \tag{6}$$

$$\text{Specificity} = \frac{\text{True Negative}}{(\text{True Negative} + \text{False Negative})} \tag{7}$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{(\text{Positive} + \text{Negative})} \tag{8}$$

$$\text{F - score} = \frac{(2 * \text{True Positive})}{(2 * \text{True positive} + \text{False positive} + \text{False Negative})} \tag{9}$$

The accuracy of different performance parameters like ‘Precision’, ‘Sensitivity’, ‘Specificity’, and ‘Accuracy’ of the proposed CNN model are shown below in **Table 1**.

Table 1: Accuracy metrics of performance parameters

Type of Tumor	True Positive	True Negative	False Positive	False Negative	Precision	Sensitivity	Specificity	Accuracy	F-score
Benign	448	445	5	2	0.9889	0.9955	0.9955	0.9922	0.9922
Malignant	445	448	2	5	0.9955	0.9888	0.9889	0.9922	0.9921

These performance parameters are extracted from the ‘Confusion Matrix’. The highest performance of ‘precision’, ‘sensitivity’, ‘specificity’, and ‘accuracy’ for the benign and malignant tumor are shown in the table. The overall accuracy of the proposed CNN model for tumor classification is 99.22 %.

Receiver Operating Characteristic (ROC) and Area Under the ROC Curve (AUC)

Receiver Operating Characteristic curve showing the performance of classification model by plotting True Positive Rate (TPR) and False Positive Rate (FPR). Area Under the receiver operating characteristic curve is plotted for a probability model performance measure. **Figure 9** shows a ROC curve of the proposed CNN model with AUC 0.994, which means the proposed model can predict correctly up to 99.4 %.

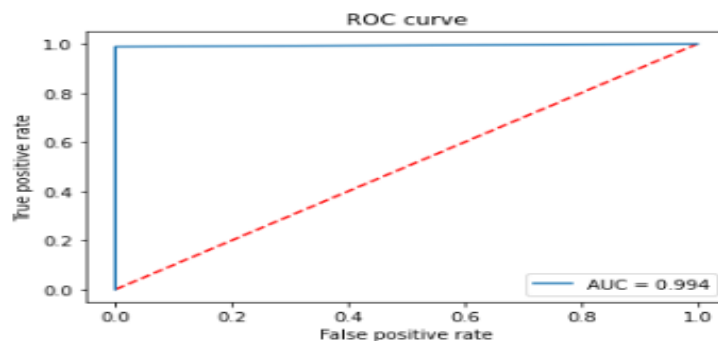


Figure 9 Receiver Operating Characteristic Curve

A sample of predicted Images with a label by Proposed model

Figure 10(a) shows a sample of two input MRI images for tumor prediction. After pre-processing phase, these images are fed to the trained model for prediction. The output predicted by the model with a label is shown in Figure 10 (b).

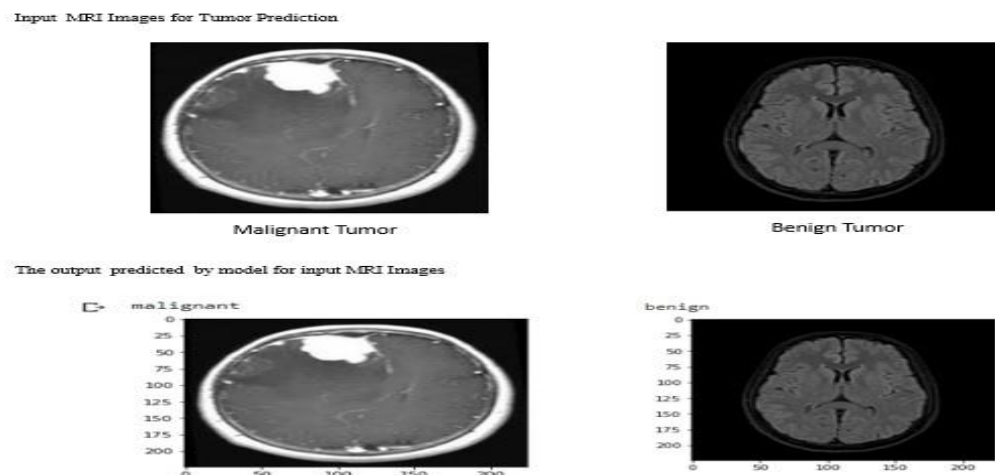


Figure 10 (a) Input MRI Images for Tumor Prediction **Figure 10 (b)** The Output predicted by the model for

input MRI Images.

Few samples of model predicted image are shown in Figure 11, with an actual label.

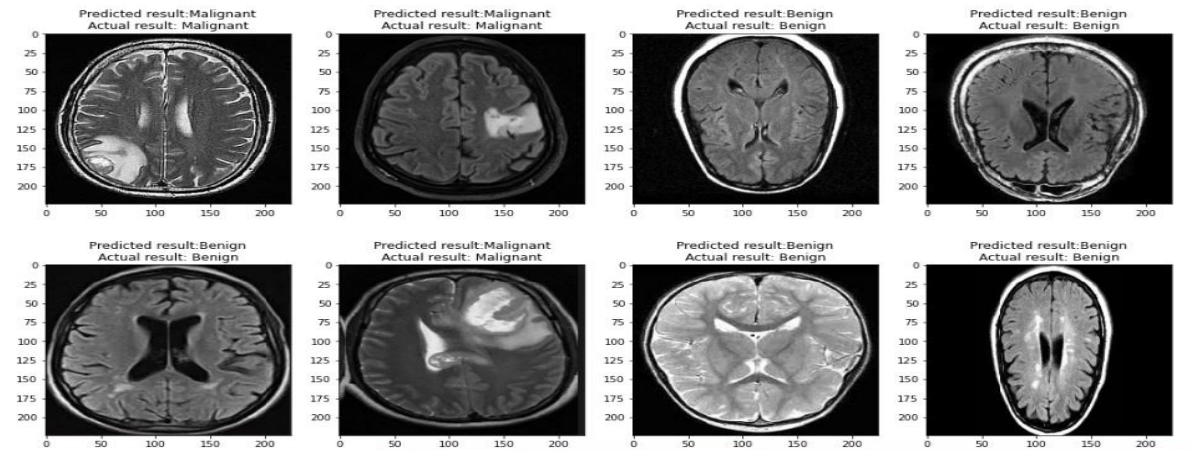


Figure 11 A sample of correctly predicted 8 MRI images with labels by trained CNN Model

Table 2 shows a comparison between the proposed CNN brain tumor classifier and pre-existing. The proposed CNN model gives the best prediction in terms of accuracy as compared to other existing classifiers without segmentation.

Table 2: Comparative study report of proposed CNN model with previous related work

Sr. No.	Model	Model Accuracy	Classification Type	Classification Method
1	H. H. Sultan et al.[6]	96.13%	Multi	CNN
2	Y. Kumar et al.[7]	98.24	Multi	CNN
3	S. Deepak et al.[8]	98%	Binary	Transfer learning (Vgg16)
4	N. Jmour et al.[10]	93.6%	Binary	CNN
5	N. K. El Abbadi et al.[12]	98%	Binary	ANN
6	A. Ari et al.[13]	97.18%	Binary	CNN
7	H. T. Zaw et al.[17]	94%	Binary	Naïve Bayes classifier
8	Proposed CNN Model	99.22%	Binary	CNN

9. Conclusions

In this paper, a 12 layer deep CNN model excluding the input layer has been developed and which can be used to classify the benign and malignant tumor MRI images. First, the proposed CNN model is trained with 70 percent of whole dataset after applying seven data augmentation operators to avoid the shortage of dataset during training face. The model is tested with remaining 30 percent of whole dataset that gives better accuracy of 99.22 %. This proposed classification model can be used in medical imaging to classify the benign and malignant tumor MRI images with better accuracy in less computation time. In the future, brain tumor localization and segmentation algorithms may be developed for detecting the brain tumor in MRI images.

10. Acknowledgements

I would like to thank Dr. Poonam G. Kohli, (Associate Professor), Department of physiology, Punjab Institute of Medical Science(PIMS), Jalandhar (Punjab) for her support in MRI brain tumor data collection. I Harendra Singh specially want to thank my guide Dr. Rajeev Ratan sir (Associate Professor), MVN University for their guidance and constant encouragement towards the work.

References

1. K. Machhale, H. B. Nandpuru, V. Kapur, and L. Kosta. MRI brain cancer classification using hybrid classifier (SVM-KNN). In: 2015 International Conference on Industrial Instrumentation and Control, Pune, India, 2015, p. 60–65.
2. Y. Bhanothu, A. Kamalakannan, and G. Rajamanickam. Detection and classification of brain tumor in MRI images using deep convolutional network. In: 2020 6th International Conference on Advanced Computing & Communication Systems. 2020, p. 248–252.

-
3. E. Avcı and K. Salçın. Detection and classification of brain tumours from MRI images using faster R-CNN. *Teh. Glas.* 2019, 13,337–342.
 4. M. M. Badža and M. C. Barjaktarović. Classification of brain tumors from mri images using a convolutional neural network. *Appl. Sci.*2020;10,1-13.
 5. H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem. Classification using deep learning neural networks for brain tumors. *Futur. Comput. Informatics J.* 2018;3,68–71.
 6. H. H. Sultan, N. M. Salem, and W. Al-Atabany. Multi-Classification of Brain Tumor Images Using Deep Neural Network. *IEEE. Trans. and content mining.*2019; 7, 69215–69225.
 7. Y. Kumar, A. K. Dubey, R. R. Arora, and A. Rocha. Multiclass classification of nutrients deficiency of apple using deep neural network. *Neural Comput. Appl.*2020;20, 1-12.
 8. S. Deepak and P. M. Ameer. Brain tumor classification using deep CNN features via transfer learning. *Comput. Biol. Med.* 2019; 111, 103-345.
 9. N. C. Ouseph and A. K. MrsShruti. A Reliable Method for Brain Tumor Detection Using Cnn Technique. In: *National Conference on Emerging Research Trends in Electrical, Electronics & Instrumentation.* 2015,64, p. 2320–3331.
 10. N. Jmour, S. Zayen, and A. Abdelkrim. Convolutional neural networks for image classification. In: *2018 International Conference on Advanced Systems and Electric Technologies, (IC_ASET 2018).*2018, p. 397–402.
 11. H. N. T. K. Kaldera, S. R. Gunasekara, and M. B. Dissanayake. Brain tumor Classification and Segmentation using Faster R-CNN. In: *2019 Advances in Science and Engineering Technology International Conferences, (ASET 2019).*2019, p. 1–6.
 12. N. K. El Abbadi and N. E. Kadhim. MRI brain cancer classification using hybrid classifier (SVM-KNN). *Ijarcce.* 2017; 6, 123–134.
 - A. Ari and D. Hanbay. Deep learning based brain tumor classification and detection system. *Turkish J. Electr. Eng. Comput. Sci.* 2018;26, 2275–2286.
 13. Q. Yan, B. Wang, D. Gong, C. Luo, and W. Zhao. COVID-19 Chest CT Image Segmentation – A Deep Convolutional Neural Network Solution.2020, p. 1–10.
 - A. Kamboj, R. Rani, and J. Chaudhary. Deep Learning Approaches for Brain Tumor Segmentation: A Review. In: *2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC)2018.* 2018, p. 599–603.
 14. M. B. Ali, R. A. Hamad, and M. Ahmed. Optimizing Convolutional Neural Networks for Brain Tumor Segmentation in MRI Images. In: *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering, (ICCCEEE 2018).* 2018,p. 1–5.
 15. H. T. Zaw, N. Maneerat, and K. Y. Win. Brain tumor detection based on Naïve Bayes classification. In: *Proceeding - 5th Int. Conf. Eng. Appl. Sci. Technol. ICEAST 2019,* p. 1–4.
 16. Zahoor Ahmad. Brain Tumor Detection Features Extraction from MR Images Using Segmentation, Image Optimization Classification Techniques. *Int. J. Eng. Res.* 2018; 10, 182–187
-