MR Image based Brain Tumor Classification with Deep Learning Neural Networks

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Abstract: - The unique combination of Artificial Intelligence and Machine Learning, which helps the computer to imitate the ways and behaviour of human beings can be termed as deep learning. The field of deep learning is an emerging field that has gained a lot of interest toward past years. The Deep Learning have proven already to solve the complex problem using the powerful machine learning tools. One of the best deep learning algorithm is used to classify the brain tumor data set in this paper. The deep learning architecture is able to classify the brain tumor into 4 categories of images. The first being no tumor, the second being pituitary tumor, the third is meningioma and the last one classified as glioma. As we are well aware, the training datasets for the medical imaging scenario are very few. This is a challenging task to apply the deep learning that is obtained from a trained CNN model to dig up the small data set to attain the result. A pre trained CNN model is used here to solve the problem. The obtained results are good over all Performance is measured.

Key-words: - Artificial Intelligence, Machine Learning, Brain Tumor, CNN, Kaggle database, MRI.

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1 Introduction

The complete nervous system of human body is commanded and controlled by the very sensitive and crucial organ of human being called brain. Alone in United States of America, according to the survey conducted by national Brain tumor society, 7,00,000 people live with brain tumors, the chances of increasing the cases might be beyond 7.8 lakhs by the end of 2021[1]. Breast cancers and lung cancer are the most widely found cancers on the planet. Even though the brain tumors are little uncommon, but still, it ranks as a 10^{th} leading cause for death. Brain is the organ that controls the activity of a human, If the patient is suffering from brain tumor, definitely it will impact on the patient's life psychological behavior. As the other cancers, even the brain tumor, is caused by the tissue abnormalities. These abnormalities are found in the central spine that interrupts the proper functionality of the brain. In current date we can have several methods to identify the tumor, few of them are MRI scanning, EEG, CT scanning and others[8]. The figure:1, shows the healthy brain and the brain with a tumor disorder when taken with MRI images.

The major improvement of the MRI based imaging when compared with the CT scan technique is the capturing of the all-possible information in the test sample under consideration with minimized effect of the radiation on the medical subject under investigation.

While capturing the image with MRI technique a specific dye will be utilized for the classification among brain tumor cells and healthy brain cells under investigation. In conventional approach of brain image analysis which can be named as white matter, cerebrospinal liquid and grey matter, but for detailing analysis which are done using the three-dimensional planar analysis such as axial, coronal and sagittal planes respectively as depicted in Fig. 2.

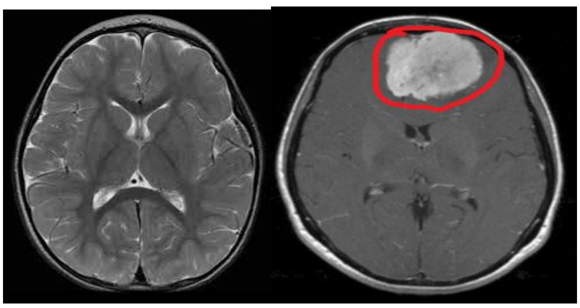

Fig. 1: Healthy brain and Brain with Tumor

The axial planar based analysis of images are captured from head to chin as shown in Fig. 2 (c), sagittal planar images are utilized for the right to left ear as represented in Fig. 2 (b) and with respect to Fig. 2 (a) coronal image based analysis. Similarly, the few weights are considered individually for the analysis such as T1, T2 and Proton density weights for MRI analysis.

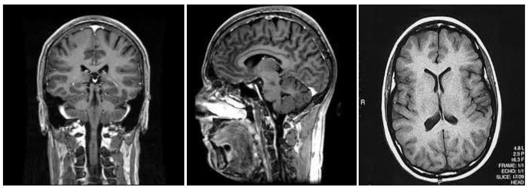

Fig. 2: (a) Coronal image; (b) Sagittal image; (c) Axial image [5]

Based on the classification that has been described by World Health Organization (WHO), there are about 120 types of brain tumors. These brain tumors differ in characteristics, location, size and origin. Among these types of brain tumors, here in this paper, only three types are considered, which are:

1. The tumor that grows in the area of spinal cord and glia tissue, which is called as glioma.
2. The tumor that can grow in the area of membrane called as Meningioma.
3. The tumor that grows in the pituitary gland area, which is called as pituitary tumor.

Figure 3 shows the different MRI images of tumors are in a different place. In all the three images the tumors are marked with the red outline.

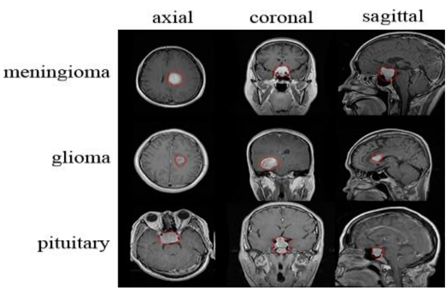

Fig. 3: A normalized MRI image that shows different forms of tumor. In each image, the tumor is marked with red outline.

2 Review of Literature

In image processing techniques, primarily for tumour region spotting in image identification with segmentation it is deployed with the deep learning and AI (Artificial Intelligence). Till date an huge amount of works are carried in the domain of biomedical engineering.

Badza et al. [2] discuss about new architecture of brain tumor classification based on CNN. He proposes a simpler system rather than the existing complicated one. The system is capable of classifying three types of tumors. It was mainly based on T1 weighted contrast enhancement magnetic resonance images. The accuracy obtained for this system was about 96.56%.

Ruba et al., proposes a model for both the CT image and MRI image in [3]. It shows a modified segment semantic network, that is based on the CNN. The paper shows a good accuracy for all the three types of tumors. For glioma being 99.78%, for pituitary tumor being 99.56% and four million men in glioma 99.57% of accuracy.

Kalaiselvi et al., proposes and recurrent neural network in [4]. This paper is based on the extraction of features from the brain image. The results of the experiment conducted in the classification of the tumor gives an accuracy of 98%.

Cinarer et al., mentions about a deep neural network classification [5]. With a technique called Synthetic Minority Oversampling Techniques, considering the data set as Rembrandt images, this technique is used for preprocessing. This method has achieved about 95% of accuracy rate. This method provides an F1 measure of 94.9%. The Precision of 95.4%, and the recall value as 95%.

Sajja et al.[6] proposed a hybridized algorithm on CNN. The open database images are considered from BRATS, These images were based on MRI brain images. The proposed model achieved 96.15% of accuracy.

Khan et al.[7], proposed an automated, multimodal classification method that utilizes the deep learning for classifying the brain tumors. The results obtained are, 97.8%,96.9%, 92.5% for BraTs2015, BraTs2017, and BraTs2018, respectively, was achieved using proposed method.

Khan et al.[8], introduces a new approach using convolutional neural network in the image processing and data acquisition. The cancerous and non cancerous MRI images are used. The results of the experiment shows the model is highly efficient by achieving 100% accuracy. The other parameters like ResNet-50 obtained as 89%, VGG-16 is obtained as 96% and the Inception-V3 achieved 75% of accuracy.

Suganthe et al.[9] tells about a recurrent neural network architecture for the classification of brain tumors that can detect the brain tumors with an accuracy of 90%.

3 Methodology

3.1 Image Acquisition

It is the first step in the proposed methodology, in which this stage of operations are done using the suitable hardware such as mobile phone, digital camera and many other devices for the collection of the data source from unified surface. The image acquisition is the initial step for every image processing system, by the acquisition of the image various available techniques are performed according to the specific need. For the process of image acquisition in particular to the MRI data an high precision devices are deployed for the capturing of the brain data [4].

3.2 Image Pre Processing

This step is next process after image acquisition. MRI data is degraded by several noises like speckle, Gaussian, and Salt and Pepper noise. Through denoising, the corrupted images can be converted to high quality images. The denoising technique used to remove noise is Anisotropic diffusion filter.

3.3 Classification of Brain MRI Images

A hybridized convolution neural networks as an healthy brain and pains with A hybridized convolution neural network is used in this paper to classify the brain MRI images as an healthy brain and brains with a tumor.

3.4 Architecture of CNN

The classification capability of CNN model is very high based on the contextual information. There are 4 major layer divisions in CNN model as in Fig 4. The first one is convolution layer, the second is pooling layer, then activation function and the final is fully connected layer. Based on the features extracted from the images classification is done accordingly in the output layer. Based on receptive field, the image local features from the input images are extracted. The neurons of the currently are interconnected with the neurons of the previous layer. This interconnection will generate the weight vector. Based on the neurons that share the same weight, in the different locations of input data image; the classification of the image can be done. In the pooling layer, if the feature has been extracted and detected, it becomes less significant. The pooling layer is also called as subsampling Layer. The number of trainable parameters will be suddenly reduced if pulling layer is used. The pooling function takes the input elements as input and process the data, as a result of which output vector is generated. There are two pooling techniques, Max pooling and average pooling. Among which, Max-Pooling id widely used. The Max pooling reduces the map size. Fully connected layer is very similar to fully connected network. The dot product of input vector and the weight vector is calculated, In order to develop the final output. The functionality cost is reduced when gradient descent is used. There are sevral architectures in CNN few of them are, LeNet Architecture, AlexNet Architecture, GoogleNet Architecture and others.

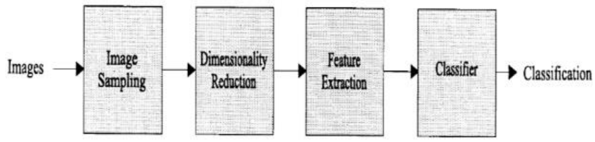

Fig. 4: Architecture of the convolutional neural network

The methods proposed by convolution neural network.
The new method proposed by the convolution neural network is depicted in the figure 5. This complete structure is made out of five layers. The four layers are Max pooling layer, convolution layer, flattened layer, fully connected layer and finally the output layer. We can see a significant change in the improvement of accuracy when the convolution layer is increased. By the increase of convolution layer, even the noise in the input images can also be reduced, this resulting in more interpretability of the system. The pooling layer plays a crucial role. Again, where if the pooling layer size is increased, the features can also be underlined in more precise way. This also improves the training time by reducing the image Size.

a) *Input layer*
This is the primary layer, which is direct interface to fetch the MRI images from the user end for feature extraction at the next layer.

b) Convolutional layer
The very next layer to the input layer is an bi-dimensional layer which is convolutional in nature. In this layer for the orientation of the required amount of filters are employed for the feature extraction from the input MRI image. With the extracted features from the MRI data are utilized for the calculation of the similarity indexes. The convolutional operation is conventionally termed as mutual product of j and I object functions with the interval [0,k] given by (3).

$$[i*j](k)=\int_0^{\tau} \mathrm{f}(\tau)\mathrm{g}(\mathrm{k}-\tau)\mathrm{d}\tau \qquad (3)$$

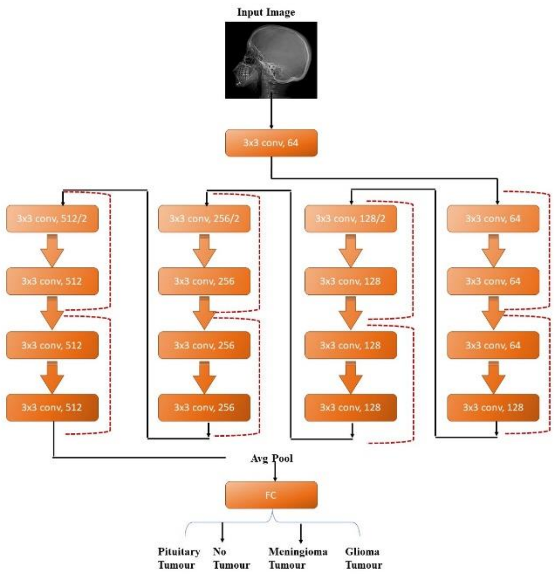

Fig. 5: Proposed convolutional neural networks

A brief explanation of each layer is mentioned below.
The output image of the size 64 X 64 pixels with the performance of the convolution operation with 3 X 3 filters is applied on MRI image of dimension 64 X 64 X 3 , output image is represented in (4).

$$[\frac{wi-fi+2pa}{st}]+1 \quad (4)$$

The output image with size of 64x64 is applied to the max-pooling layer. In the similar manner, all convolution layers are estimated in the proposed network.
This is an linear function, where the resultant obtained in accordance with the applied input if and only if it is non-negative. ReLU is a novel and mandatory triggering feature for various types of neural networks as a mannequin utilizes an simpler manner for the instruction to attain improved performance. Its operations are relatively linear for the values non zero, which implies the training of neural network in backward propagation. The other interesting feature of the ReLU function is the normalized values to zero for other intermediate values of non-positive hence it is nonlinear function for the rest of the values which will be given by (5).

$$f(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \quad (5)$$

d) Max pooling layer
The pooling layer is very essential in terms of minimizing the dimension of operation. The minimization of the numbers of neurons in the output of the convolutional layer, the pooling algorithm is the hybrid combination of the adjacent members available in the output convolution matrix. Commonly used pooling algorithms are average and Max Pooling. In this article of research, the two dimensional convolution layer outcome is the feeding input to the max-pooling layer, the max-pooling layer output images can be estimated as shown in (6)

$$[\frac{O+2pa-2}{st}]+1 \quad (6)$$

where, padding (pa) is 0,number of stride (st) is 2, O is 64×64,and size of the filter (fi) is 3×3 .So, the size of the image produced from the max pooling layer is 32×32 ([(64+0−2)/2]+ 1). For the remaining max pooling layers, the same approach has been employed in the proposed architecture.

e) Flatten layer
With the following from the max-pooling and convolution operations and multi-dimensional tensor is mandatory at the output part, an uni dimensional tensor is required. This is attained in the flatten layer which are fully connected to the input layer.

f) Fully connected layer
Similar to that of feedforward neural network, Each node in the fully connected layer is interconnected with the other nodes. The function of activation is much needed for MRI images to be classified.
To train the classifier, the epoch in the CNN are increased to an adequate manner. This resulting in a better performance. The weight updating function is used to update the weights, while moving from epoch to epoch, as mentioned in the equation. 7.

$$w_{ij} = w_{ij} + \Delta w_i \quad (7)$$
$$\text{where} \quad \Delta w_{ij} = (l) Err_j O_i \quad (8)$$

g) Transfer learning of CNN (EfficientNet)
During the process of training, as mentioned in the above, the weights of the CNN is updated after each iteration. In the current design, there are 4,012,672 trainable parameters and 237 layers in EfficientNet architecture. A considerably large data set has to be taken to train and to optimize such DN. To calculate the appropriate local minima, cost function will be very difficult if the data set is smaller, and also resulting in overfitting of the model. So the initialization of the weight will be taken from pre-trained EfficientNet model.

4 Result Analysis

4.1 Classification of Brain MRI Images

In this research article for the testing of the designed architecture of classifier for the brain tumour over the wide range of public available database it is chosen to operate with the KAGGLE dataset, in which 394 test images which is the association of 100 MRI images with glioma tumor,115 Images with Meningioma tumor,74 Images with Pituitary tumor and healthy person MRI images of 105. In the context of the research proposed for the classifier approach it is considered with the 104 MRI images with disorder oriented dataset and 65 normal dataset of MRI images. For the classifier oriented investigation it is done with the 105 usual healthy person MRI data along with the 100 MRI images with glioma,115 images with meningioma and 74 images with pituitary tumor. The distribution table of KAGGLE database is as shown in Table 1.

Table 1. KAGGLE Dataset Distribution.

Kaggle / Tumor Category	**Glioma**	**meningioma**	**Pituitary**	**No tumor**	**Total**
Training	826	822	827	395	2870
Testing	100	115	74	105	394
Total	926	937	901	400	3264

Some of the overall performance metrics considered is accuracy, confusion matrix, precision, recall, and F1 Score. From the matrix of confusion, most performance measurements are calculated.

Performance evaluation metrics of any classifier can be calculated using four basic building blocks. Those are TP, FP, TN and FN. Those building blocks are explained in Table 2 in detail. Predicted values are taken on the X-axis and actual values are taken on the Y-axis.

Table 2.Building blocks of classifier in Confusion matrix

CLASS		**PREDICTED**		**Total**
		Positive	Negative	
Actual	Positive	TP	FN	P
	Negative	FP	TN	N
Total		P	N	P+N

The rate correct identification and incorrect identifications can be categorized as two major segmentations logically viz., True and False respectively. As an sub set to make sure as similar to the confusion matrix for grouping it can be broadly fall into Positive and Negative values making it into four various corners of the confusion matrix such as TP,TN,FP & FN termed as True Positive, True Negative, False Positive and False Negative respectively.

The recall or the sensitivity are the main Para meters to estimate the performance of a true positive values. It analyses the presence of true positive cases correctly and classify the actual positive cases of the data set using (9).

$$Sensitivity = \frac{(TP)}{(TP+FN)} \qquad (9)$$

Precision is the parameter used for the measurement of the exact correct prediction which can be given by (10). it computes the percentage of positive cases that are correctly.

$$Precision = \frac{TP}{FP+TP} \qquad (10)$$

The classifier performance is gauged in terms of percentage for all the cases such as positive and negative in terms of accuracy which can be given by (11).

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} \qquad (11)$$

For the accurate measurement of the recalls and precisions in a single attempt it is employed with calculation of the F1 Score which can be interpreted as shown in (12)

$$\text{F1score (F)} = \frac{\mathbf{2XPrecisionXRecall}}{\mathbf{Precision+Recall}} \qquad (12)$$

The Specifity decides the performance of true negative rate. The percentage of negative cases that are correctly classified from the actual negative cases using the data set is being calculated using (13).

$$Specificity = \frac{TN}{FP+TN} \qquad (13)$$

The complete exercise was conducted using Google Colab notebook, The code was written using Python, and the data set is downloaded from Kaggle. The heatmap of the confusion matrix created by the classifier is mentioned in the figure 6.

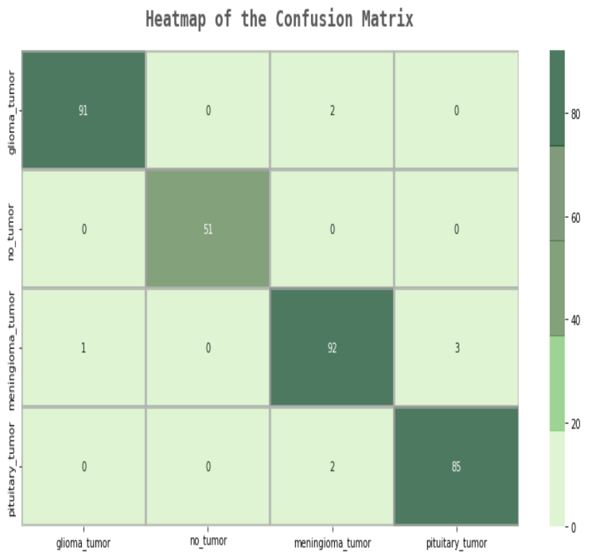

Fig. 6: Contingency matrix for the pre-trained model

Obtained result interpretation is carried out with the confusion matrix, upon the test procedure of 84 different variants of data images with the CNN classifier utilized for training of the 394 data images, in which 91 images were correctly classified as glioma tumor,92 images were classified as meningioma tumor properly,85 images were correctly as pituitary tumor and the 51 images were classified as healthy images. The performance criteria of first model and second model is tabulated in Table 3 and 4 The pre-trained model has reached F1 score of 98%, 98% of precision, 98% of specificity and accuracy as 98% as tabulated in Table 5 and represented in Fig. 6.

Table 3. Performance criteria of first model

First model				
	Precision	**Recall**	**F1-score**	**Support**
0	0.56	0.95	0.70	105
1	0.76	0.19	0.30	100
2	0.81	0.83	0.82	115
3	0.82	0.78	0.80	74
AVG	0.73	0.69	0.66	---
Accuracy	0.69			394

Table 4. Performance criteria of second model

Second model				
	Precision	**Recall**	**F1-score**	**Support**
0	0.59	0.96	0.73	105
1	0.95	0.18	0.30	100
2	0.73	0.83	0.78	115
3	0.89	0.88	0.88	74
AVG	0.79	0.71	0.67	---
Accuracy	0.71			394

Table 5. Performance criteria of Pre-trained model

Pre-trained model				
	Precision	**Recall**	**F1-score**	**Support**
0	0.99	0.98	0.98	105
1	1.00	1.00	1.00	100
2	0.96	0.96	0.96	115
3	0.97	0.98	0.97	74
AVG	0.98	0.98	0.98	---
Accuracy	0.98			394

4.2 Performance Analysis of Proposed Model

For the pictorial representation of the accuracy and training data loss rate and testing data using pre-trained model is shown in Fig. 6.With the comparative analysis from Fig. 7 and Table 6, it can be clearly stated that accuracy of first model is improved with the increased number of layers and epochs in second model but it can be greatly increased if a pre-trained model is used for classification. A pre-trained model Efficientnet is used in this paper.

Fig. 6:Accuracy and Loss of Pre-trained Model.

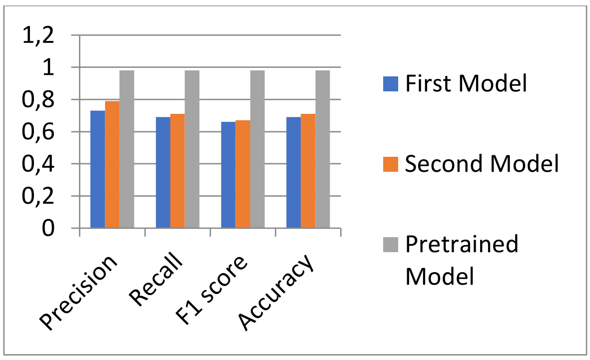

Fig. 7: Comparative analysis of different CNN models

Table 6: Results comparison of different CNN models.

	Precision	**Recall**	**F1 - score**	**Accuracy**
First Model	**0.73**	**0.69**	**0.66**	**0.69**
Second Model	**0.79**	**0.71**	**0.67**	**0.71**
Pre-trained Model	**0.98**	**0.98**	**0.98**	**0.98**

5 Conclusion

In the present research context, it is considered with KAGGLE dataset for the analysis of the classifier performance. Initially, MRI image denoising was done using Anisotropic diffusion filter. In the training phase for CNN classifier it achieved with the almost four hundred normal images, eight hundred images with glioma, eight hundred images with meningioma and eight hundred images with pituitary tumor, in total around three thousand images were considered for the data model. The designed Convolutional Neural Networks were aimed to identify the type of brain tumor from the database under consideration with the classifier approach is carried out with 100 image sets with glioma tumor,115 images with meningioma tumor,74 images with pituitary tumor and 105 normal images making in total of 394 image sets. A hybrid CNN model has been presented, with feed forward neural network as a seed, with the incremental values of epochs, it is assured to have higher accuracy due to higher rate of training states. An individual Epoch is defined as the entire process to reach the output layer from the input layer for the calculation of the Accuracy, Precision, Specificity, Sensitivity and F1 score. It is observed from the results that 69% of accuracy for the first CNN model. When the number of layers and epochs were increased in the second model, the accuracy was increased to 71%. Finally, by using the pre-trained model 98% accuracy was achieved. The major gain in the classifier proposed to the MRI images of the brain was more accurate when a pre-trained model was used. Other factor of improvement as a future scope is to minimize the processing time to process the tumor images as a design constraint.

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