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Brain Tumor Classification using Improved Gray Level Co-occurrence Matrix and CNN

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ABSTRACT

Automated tumor detection in medical imaging has been one of the developing fields in medical diagnostic applications. Anomalies of the human body are captured using different imaging techniques. The captured images must be understood and processed for further diagnosis and treatment planning of these anomalies. Although there are skilled medical professionals who will be able to understand the medical images and detect the anomalies. The limited availability of human experts and a large amount of data will cause a problem. In addition to that, there are chances that the diagnosis is prone to human error. This decreases the effectiveness of the diagnosis. Since Convolutional Neural Networks (CNN) is one of the best methods for image analysis, it is proved to be more effective. Therefore, CNN can be used for classification purposes. Automated tumor detection through MRI has become very informative as it provides information about abnormal tissues. This information becomes a necessity for planning treatment. To provide this information we have come up with CNN architecture for brain tumor classification consisting of three tumor types as well as no tumor. The analysis of brain Magnetic Resonance Imaging (MRI) is done mainly focusing on feature extraction and classification. A model is created using improved Gray Level Co-occurrence Matrix (GLCM) for Feature Extraction and CNN for Classification, which will help to classify the tumors with almost 100% accuracy.

Keywords:*-Convolutional Neural Networks (CNN), Gray Level Co-occurrence Matrix (GLCM), Magnetic Resonance Imaging (MRI)*

INTRODUCTION

Cancer is a kind of disease that starts with abnormal cells that grow uncontrollably and abnormally inside the body. It can start in any tissue or any organ of the body. They actually grow beyond their usual boundaries and affect the adjoining parts of the body. The process of these cells growing is called metastasizing and can also lead to death. The other common names for cancer are malignant tumor and neoplasm. According to the research from World Health Organization (WHO) [1] the death caused by cancer is the second-largest globally, which is estimated to be 9.6 million deaths. In 2018, it was reported that one in six deaths was caused due to cancer. Throughout the world, cancer has an impact on the lives of people who are suffering from it. It also exerts a huge amount of physical, emotional, and financial strain on individual families, communities, and health systems. A large number of cancer patients are dying because of insufficient or lack of timely treatments. Survival rates can be increased by early detection and quality treatment. According to the classification method that WHO came up with, brain tumors can be classified, from the least aggressive (benign) to the most aggressive (malignant). A grading method has been

introduced, ranging from Grade I (least malignant) to Grade IV. (Most malignant), which tells the rate of growth of the tumor cells [2].

The brain tumor is one of the most complicated diseases and a key concern for the radiologist in the premature phase of tumor growth as requires an effective and efficient analysis. There are more than 150 different types of brain tumors they are mainly grouped as primary and metastatic. The tumors that are considered for this system are Gliomas, Meningiomas, and Pituitary Tumors. Glioma [3,4] is a type of tumor that occurs in the brain and spinal cord. The Gliomas surround the nerve cells and help in their functioning. The tumor starts in this gluey supportive cell (glial cells). Every year approximately 12,000 new cases of Glioma are reported [5]. MRI is the most common method for diagnostics [6]. However, it proves to be a problem for a human to observe and analyze the MRI scan when given a large amount of data. The experience of the radiologist in early brain–tumor detection plays a major role in the further process [7]. A biopsy is the most common method that many doctors use to diagnose many types of cancer. Other tests can only tell if the cancer is present or not but only a biopsy can confirm its presence. During a biopsy, a small amount of tissue is removed to examine under a microscope. As tumor biopsy is tough an imaging technique such as Magnetic Resonance Imaging (MRI) plays an important role in diagnosing brain tumors. Thus, a system for detection and prediction of the grade of tumors based on MRI has become necessary. In radiology and other medical science fields, machine learning-based approaches like Deep ConvNets play an important role to detect a disease. It is much simpler and provides a feasible alternative to surgical biopsy for brain tumors [8,9].

Glioma Tumor | Meningioma Tumor | No Tumor | Pituitary Tumor

Fig.1:- *MR images of different types of tumors.*

The number of images in the dataset is the biggest problem in feature extraction and classification of the MRI images with some neural networks [10,11]. As all the MRI images used in the dataset are in different planes, using all the available planes could increase complications in the database. Figure 1, a representation of the tumors is shown which are used for training purposes. Using CNN we can classify a tumor, based on the dataset used for training.

METHODOLOGY

The proposed system consists of 3 stages: Pre-processing, Feature extraction, and Classification of brain MR images. Our system based on convolution neural network architecture is combined with GLCM for feature extraction and classification.

Classification of brain tumors was performed using the following steps:

Step1: Preprocessing and segmentation of MRI data set

Step2: Feature extraction using GLCM

Step3: Classification of brain MR images using CNN classifier

Input Images Dataset

The dataset of 4 classes of brain tumors: Glioma Tumor, Meningioma Tumor, No tumor and Pituitary Tumor, is obtained from Kaggle [12]. From Figure 1 we observe the MRI scans of the 4 classes of the tumors used. Table 1 and Table 2 show how many images were used for training and testing respectively. The dataset consists of images in different planes for each class which helps in better training and getting accurate results.

Table 1:- *Illustration of how many images of each class were used for training.*

Class	Type of Tumor	No. of images
0.	Glioma Tumor	826
1.	Meningioma Tumor	822
2.	No Tumor	395
3.	Pituitary tumor	827

Table 2:- *Illustration of how many images of each class were used for testing.*

Class	Type of Tumor	No. of images
0.	Glioma Tumor	200
1.	Meningioma Tumor	215
2.	No Tumor	205
3.	Pituitary tumor	144

IMAGE PRE-PROCESSING

MR images of different types of brain tumors are pre-processed using Region of interest, Inverse method and boundary detection methods to enhance the images for the segmentation process [13]. After pre-processing the MR images are segmented using Fuzzy C Mean (FCM) algorithm for further processing called feature extraction. Figure2 shows the block diagram of pre-processing methods used along with its operation to filter the images for segmentation.

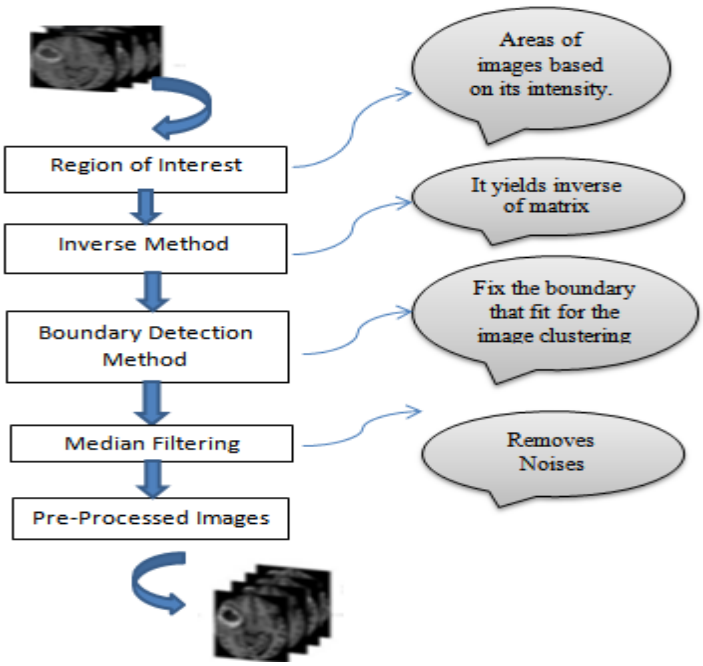

Fig.2*:- Block diagram of Pre-processing of input MR images.*

FEATURE EXTRACTION USING IMPROVED GLCM TECHNIQUE

GLCM is a statistical method to extract texture properties from the pixel ratio by analyzing the spatial distribution of the gray levels in an image. The GLCM property is based on the intensity and ratio of pixels separated by the distance d. This technique follows two steps in extracting features from medical images. Calculate GLCM and calculate the texture properties [14].

The representation of the co-occurrence matrix of the texture features originally proposed by R. Hara lick examines the spatial dependence of the gravel level texture. The co-occurrence matrix is characterized by an image through the method of partitioning simultaneously occurring ideas at a given displacement. Whether taking into account the gray values of the image or various color measurements, the gray scale co-occurrence matrix is mainly used to measure the image texture. The formulas for the statistical functions are shown below [15-17].

Energy is the total number of square of all the GLCM elements, it is also known as second angular momentum or uniformity, which is defined as

$$Energy = \sum_{x=0}^{p-1}\sum_{y=0}^{q-1} f^2(x,y) \quad (1)$$

The inverse moment of the difference (IDM) can be used to measure limited image uniformity of region of interest [18,19].

$$IDM = \sum_{x=0}^{p-1}\sum_{y=0}^{q-1} \frac{1}{1+(x-y)^2} f(x,y) \quad (2)$$

This attribute gives relatively high weight to elements that are different from the average *P (i, j).*

$$Variance = \sum_{x=0}^{p-1}\sum_{y=0}^{q-1} (x-\mu)^2 f(x,y) \quad (3)$$

The higher the standard deviation value, the better the results in terms of intensity levels and edges of high-contrast images.

$$\text{Standard Deviation(SD)} = \sqrt{\frac{1}{(p\times q)}\sum_{x=0}^{p-1}\sum_{y=0}^{q-1}(f(x,y)-\mu)^2} \quad (4)$$

The randomness of texture images can be calculated using entropy, which is defined as

$$Entropy = -\sum_{x=0}^{p-1}\sum_{y=0}^{q-1} f(x,y)\log_2 f(x,y) \quad (5)$$

Skewness is used to define symmetry or asymmetry of the image, which is defined as follows

$$Skewness = \frac{1}{(p \times q)} \sum_{x=0}^{p-1} \frac{(f(x,y) - \mu)^3}{SD^3} \quad (6)$$

The improved GLCM method for feature extraction is based on the gradient of the image and length of the gray level of pixels. Using gradient magnitude and length of the gray level of pixels find the two different co-occurrence matrices, they are named gradient magnitude co-occurrence matrix (GMCM) and gray level run length co-occurrence matrix (GLRCM). The gradient magnitude will give information about strong and weak edges due to frequency variations. GLRLM describes pixels having continuous gray values to find a similar texture.

GMCM feature vectors

For the GMCM matrix, we propose 3 gradient-based features, they represent different measures and denoted them as follows**:**

Strong edges quantity (SEQ): This feature represents voxel pairs with large gradient variations. If neighboring voxels have different gradients then strong edges have been detected.

$$SEQ = \sum_{i=1}^{n} \sum_{j=1}^{n} (i-j)^2 \times \mathrm{GMCMn\ (i,j)} \quad (7)$$

Boundary frequency: This feature assigns higher frequencies voxel pairs with low-frequency variations.

$$BF = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{1}{1 + (i-j)^2} \times \mathrm{GMCMn\ (i,j)} \quad (8)$$

Uniformity (U): Small number of edges and transitions in the images, which indicates uniformity.

$$U = \sum_{i=1}^{n} \sum_{j=1}^{n} (\mathrm{GMCMn\ (i,j)})^2 \quad (9)$$

GLRCM feature vectors

GLRCM matrix defines four features homogeneity, run-length gray level matrix, high similarity pixels, and continuous gray pixels. Figure 3 shows run-length three of voxels in the image matrix and corresponding gray level run length matrix.

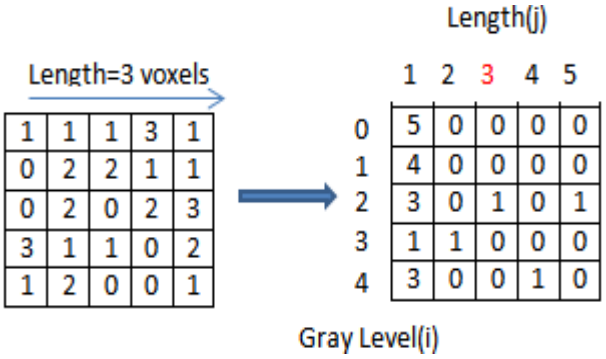

Fig.3:- *Calculation of GLRCM*

Feature in the image is a part of a pattern in an image that helps to identify an object present in an image. Examples of such features are edges, corners, ridges, points in the region of interest, and many more [20,21]. Feature Extraction is identifying abnormalities. We need to extract features from images to do classification using a classifier which is the next step. Using CNN, features are extracted from the images and the model is trained.

CLASSIFICATION USING CNN

Feature Extraction and classification of tumor cells is an ever-growing technology. Proper diagnosis can only be provided with the correct understanding of the type of tumor. The captured images must be understood and processed for further diagnosis and treatment planning of these anomalies. Although there are skilled medical professionals who will be able to understand the medical images and detect the anomalies. The limited availability of human experts and a large amount of data will cause a problem [22,23].

In our proposed work, we have used the Gradient Magnitude Co-Occurrence Matrix to extract different features. The extracted deep features are then given to convolutional neural networks for the classification of 4 types of brain tumors from brain Magnetic Resonance (MRI) Images. This classifier gets the final predicted output, which is the classified brain tumor.

CNN Architecture

CNN is used for brain tumor classification. An image after pre-processing, of size 150X150X3, is fed as an input to the neural network [24]. A Convolutional Layer is added with 32 filters, a kernel size of 3X3, and a stride of [1,1] using Conv2D class. Rectified Linear Unit (ReLU) activation function is added to bring non-linearity to the model. Max Pooling is done to the output obtained from the previous layer which serves as an input to this layer.

The above steps are repeated again starting from the Convolutional layer till Max Pooling so that the model is very well trained and we get accurate results. All these steps are executed in sequential order. All these steps are represented in Figure 4. Later, Flatten Layer is added along with ReLU with 25% dropout to get a Fully Connected Layer. A Softmax Activation Function is added so that we get the classified output. We get a prediction of the type of tumor along with the accuracy. The detailed representation of these CNN layers and properties are displayed in Table 3.

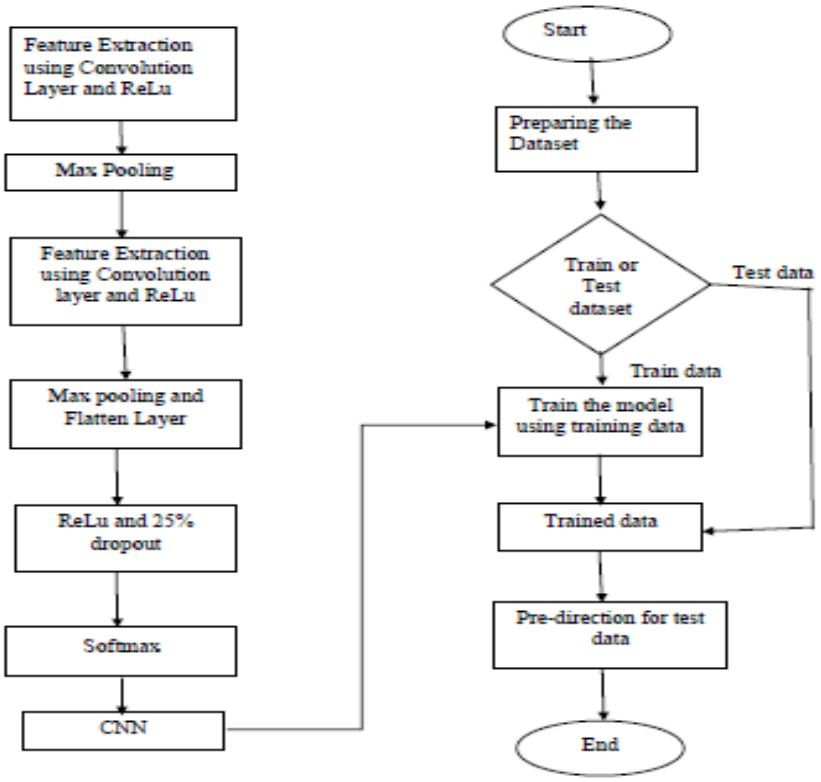

Fig.4:- *Data Flow Diagram of Proposed CNN method.*

Table 3:- *The convolutional neural network layers and layer properties*

Layer No.	**Layer Name**	**Layer Properties**
1.	Image Input	150 X 150 X 3 images
2.	Convolutional	32, 3 X3 convolutions with stride [1,1]
3.	Rectified Linear Unit	Rectified Linear Unit
4.	Max Pooling	2 X 2 max pooling
5.	Convolutional	32, 3 X3 convolutions with stride [1,1]
6.	Rectified Linear Unit	Rectified Linear Unit
7.	Max Pooling	2 X 2 max pooling
8.	Convolutional	32, 3 X3 convolutions with stride [1,1]
9.	Rectified Linear Unit	Rectified Linear Unit
10	Max Pooling	2 X 2 max pooling
11.	Flatten	Converting to single dimension
12.	Fully Connected	32 hidden neurons in fully connected (FC) layer
13.	Rectified Linear Unit	Rectified Linear Unit
14.	Dropout	25% dropout
15.	Fully Connected	4 hidden neurons in fully connected (FC) layer
16.	Softmax	Softmax
17.	Classification Output	4 output classes, “0” for a Glioma Tumor, “1” for a Meningioma Tumor, and “2” for No Tumor, “3” for a Pituitary Tumor

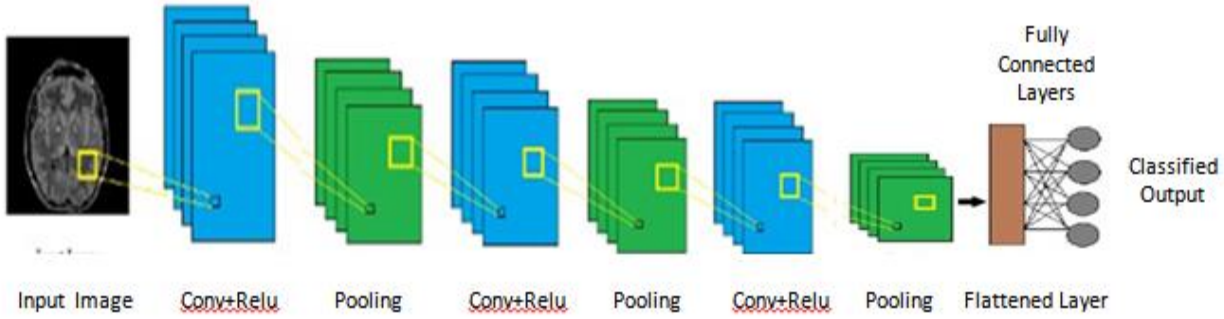

Fig.5:- *Convolutional neural network with layers.*

RESULTS

Results of the developed CNN are represented in Table 4 which shows the average accuracy, precision, sensitivity, specificity, and F-score are obtained when the predictions made were correct. Observations can be made, where the obtained average accuracy from each class was high. We can infer that by using CNN we can classify the tumors into their respective classes with high accuracy. Classification results of four types of tumors with an accuracy of classification are shown in the figures [6-9].

Accuracy: It calculates the total number of images that are correctly classified. It is defined as the sum of correctly classified positive and negative cases, divided by a total number of cases.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

Where,

TP: Correctly classified positive results
FP: Incorrectly classified positive results
TN: Correctly classified negative results
FN: Incorrectly classified negative results

Precision: It calculates the numbers of positive cases are classified, that actually belong to the positive class.

$$Precision = \frac{TP}{TP + FP}$$

Sensitivity: It calculates how many positive cases are correctly classified from the given data.

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity: It calculates how many negative cases are correctly classified from the given data.

$$Specificity = \frac{TN}{TN + FP}$$

F-score: It provides a single score that covers both precision and sensitivity in one number.

$$Fscore = \frac{2 \times TP}{2 \times TP + FP + FN}$$

Table 4:- *Illustration of Accuracy, Precision, Sensitivity, Specificity, and F-score are obtained from each class.*

Types of Tumor	Accuracy	Precision	Sensitivity	Specificity	F-score
Glioma tumor	99.6	97.3	98.3	98.8	98.3
Meningioma tumor	99.3	98.7	97.2	99.4	97.4
Pituitary tumor	99.6	96.7	98.3	97.8	98.7

Snapshots of result

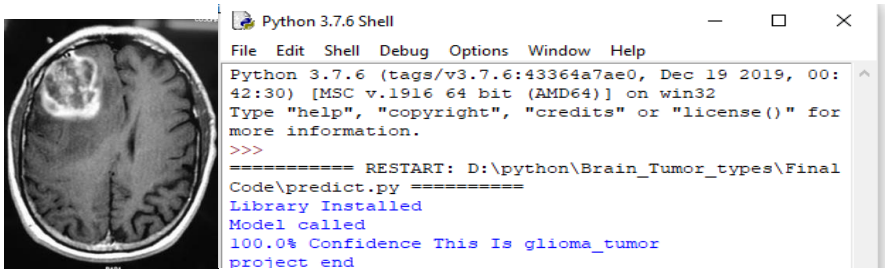

Fig.6:- *Glioma tumor with 100.0% accuracy.*

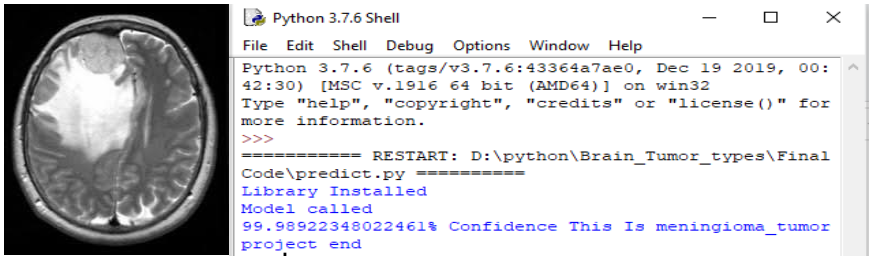

Fig.7:- Meningioma tumor with 99.98% accuracy.

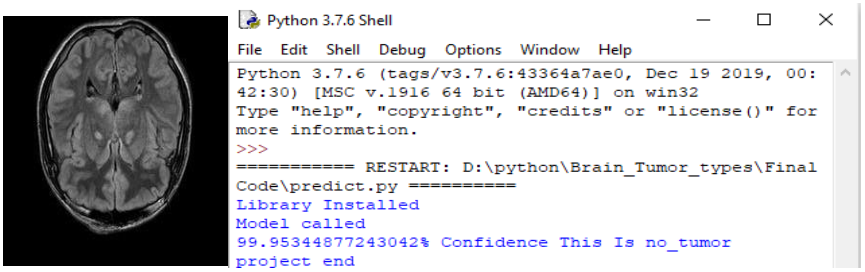

Fig.8:- *No tumor with 100% accuracy.*

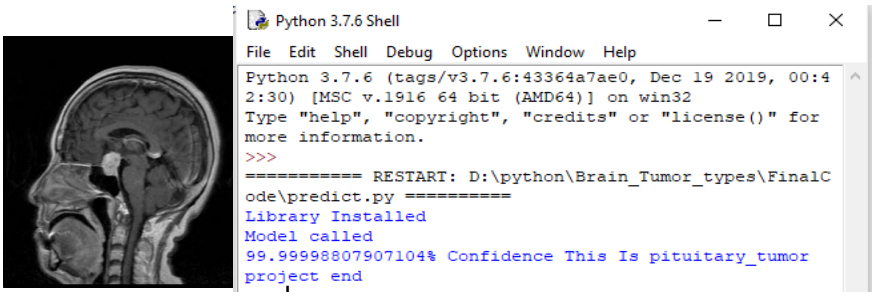

Fig.9:- *Pituitary tumor with 99.99% accuracy.*

CONCLUSION

Convolutional Neural Networks (CNNs) is one of the best techniques for image analysis. Feature extraction and classification of MR images were done using CNN. Four classes of images were used in dataset such as Glioma Tumor, Meningioma Tumor, No Tumor and Pituitary Tumor. Several layers were used such as Convolutional Layers, Max Pooling, Dense Layers and Flatten Layer along with activation functions such as ReLU and Softmax functions. The predicted results were shows almost 100% accuracy. This system can be improved further by training it to detect and classify other types of tumors as well. Outside the brain, the system can be extended to other organs tissues and bones to detect and classify any type of danger. The system can also be updated to give different treatments that could possibly help in treating the detected condition. This can be achieved when huge amount of data is available to train. In future we are planning to work on selective methods of the classifiers by combining two or more feature selection techniques and different classifiers to improve classification time and accuracy. The proposed classifier model may be tuned further to test on real images, to ascertain its applicability as a tool in medical diagnosis.

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