A Project Report

On

# BRAIN TUMOR CLASSIFICATION USING CNN

*Submitted in partial fulfillment of*
*the requirement for the reward of the degree of*

Bachelor of Technology in Computer Sciences and Engineering


Under The Supervision of
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# CANDIDATE'S DECLARATION

We hereby certify that the work which is being presented in the project, entitled "BRAIN TUMOR CLASSIFICATION USING CNN" in partial fulfillment of the requirements for the award of the Btech submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of july 2021 to dec 2021, under the supervision of Mr Ravi Sharma Assistant Professor, Department of Computer Science and Engineering/Computer Application and Information and Science, of School of Computing Science and Engineering , Galgotias University, Greater Noida.

The matter presented in the thesis/project/dissertation has not been submitted by us for the award of any other degree of this or any other places.

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This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Supervisor

(Mr. Ravi Sharma, Assistant Professor)

# Abstract

The brain tumors, are the most common and aggressive disease, leading to a really short life prospect in their uppermost grade. So, treatment planning is a vital stage to refine the quality of life of cases. Generally, various image techniques resembling as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and ultrasound image are used to valuate the

tumor in a brain, lung, liver, inside, prostate … etc. Especially, in this work MRI images are used to diagnose tumor in the brain.

Notwithstanding the huge volume of data generated by MRI check thwarts automatic set of tumor vs non-tumor in a particular time. But it having some limitation (i.e) accurate quantitative measures is handed for limited number of images. Hence trusted and automatic set scheme are essential to prevent the death rate of natural. The automatic brain tumor set is really challenging task in large spatial and structural variability of surrounding region of brain tumor.

In this, automatic brain tumor finding is proposed by using Convolutional Neural Networks (CNN) classification. The deeper shell design is performed by using small kernels. The weight of the neuron is given as small. Experimental results show that the CNN libraries rate of97.5 accuracy with low complexity and compared with the all other state of arts methods.

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## Acronyms

| | |
|---|---|
| B.Tech. | Bachelor of Technology |
| M.Tech. | Master of Technology |
| BCA | Bachelor of Computer Applications |
| MCA | Master of Computer Applications |
| B.Sc. (CS) | Bachelor of Science in Computer Science |
| M.Sc. (CS) | Master of Science in Computer Science |
| SCSE | School of Computing Science and Engineering |

## CHAPTER-1 Introduction

Brain tumor is one of the vital organs in the natural body, which consists of billions of cells. The abnormal group of cell is formed from the abandoned division of cells, which is also called as lump. Brain tumor are divided into two types matching low grade (grade1 and grade2) and high grade (grade3 and grade4) tumor. Low grade brain tumor is called as benign. Likewise, the high grade tumor is also called as malignant. Benign tumor isn't cancerous tumor. Hence it doesn’t spread other region of the brains. Notwithstanding the malignant tumor is a cancerous tumor. So it spreads fast with indefinite boundaries to other region of the body freely. It leads to immediate death.

Brain MRI image is generally used to dig out the tumor and tumor progress modeling process. This information is generally used for growth spotting and treatment processes. MRI image gives farther information about given medical image than the CT or ultrasound image. MRI image provides detailed information about brain structure and anomaly spotting in brain tissue. Actually, Scholars offered unlike automated strategies for brain growths finding and type cataloging using brain MRI images from the time when it ran possible to overlook and freight medical images to the computer. Conversely, Neural Networks (NN) and Support Vector Machine (SVM) are the

usually used techniques for their good enactment over the most recent untold years. Not with standing new, Deep Learning (DL) models fixed a stirring trend in machine learning as the underground architecture can efficiently represent complex relationships without wanting a large number of nodes like in the superficial skeletons e.g. K- Nearest Neighbor (KNN) and Support Vector Machine (SVM). Therefore, they grew fast to become the state of the art in other health informatics areas for example medical image analysis, medical informatics and bioinformatics.

A convolutional neural network (CNN) is a class of artificial neural network, uttermost ordinarily applied to analyze visual imagery. They're also known as shift steady or space steady artificial neural networks (SIANN), based on the participated- weight architecture of the convolution kernels or filters that slide along input features and feed translation equivariant responses known as feature charts.

Types of Tumor:

Benign Tumor
Malignant Tumor

- Benign Tumor:

Not Grow
Non Cancerous(Easily remove)

- Malignant Tumor:
  Spread
  Cancerous

### 1.2.1 Tool and Technology Used

Dataset-

This study uses four different data sets that are available in publicly accessible databases. The first data set is called the Reference Image Database for Assessing Response to Therapy [14] The total number of images in this data set is 70,220. The second data set is called The Repository of Molecular Brain Neoplasia Data (REMBRANDT) (Lisa et al. 2015). The REMBRANDT data set contains a multi-sequential magnetic resonance imaging of 130 patients with gliomas grade II, grade III and grade IV. The total number of images in this data set is 110,020. The third set of data is called Cancer Genome Atlas Low-Grade Glioma (TCGALGG) (Pedano et al. The TCGALGG data set contains 241,183 magnetic resonance images of 199 patients with low-grade gliomas (Grade I and Grade II). These three sets of data are from the Cancer Imaging Archive Project (TCIA) (Clark et al. 2013). Each case was multimodal with contrast-enhanced T1 and FLAIR images. Another data set used in this study (Cheng et al. 2015) contains 3064 contrast-weighted T1 images of 233 patients with three types of brain tumors: glioma (1426 sections), meningioma (708 sections) and pituitary gland (930 sections). Total of 2990 images are collected, including 1640 tumor and 1350 non-tumor images. A total of 3950

images are collected for the classification2 task, including 850 normal images, 950 gliomas, 700 meningiomas, 700 pituitary glands and 750 metastases. For the classification3 task, a total of 4,570 images are collected, including 1,676 grade II, 1,218 grade III and 1,676 grade III.

Convolutional Neural Network-

The most widely used deep learning model among neural networks is the CNN model. A typical model consists of two parts: feature extraction and classification. The CNN architecture generally has five main layers: input layer, convolution layer, grouping layer, fully connected layer, and classification. layer. CNN performs feature extraction and classification through trainable layers that are placed sequentially one behind the other. The feature extraction part of CNN generally includes the folding and grouping layers, the classification part includes the fully connected and classification layers. Although CNN has focused on picture classification and accepts pictures as input data in recent years, it has been widely used in many other fields such as audio and video whose input data can be any signal.

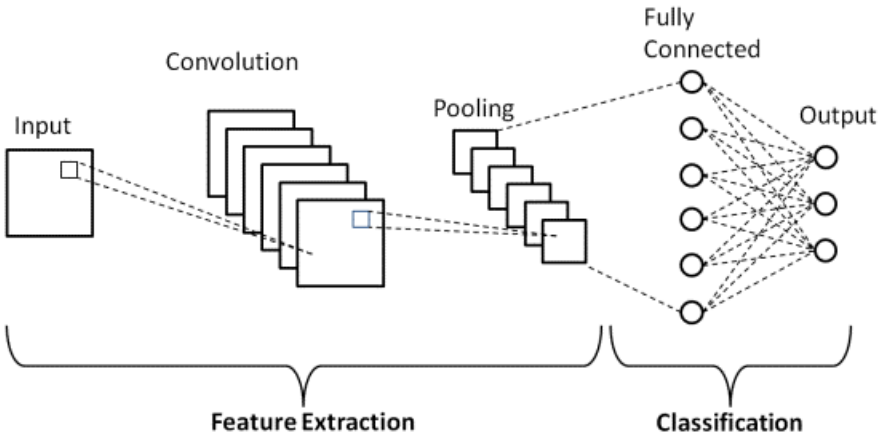


*Figure 1Basic Architecture of CNN model*

## Chapter 2 Literature Survey/Project Design

In recent years, several studies have applied data mining algorithms on different medical datasets to classify Brain Tumor. These algorithms show good classification results and encourage many researchers to apply these kind of algorithms to solve challenging tasks. In a convolutional neural network (CNN) was used to predict and classify the invasive ductal carcinoma in brain histology images with an accuracy of almost 88%. Moreover, data mining is used widely in medical fields to predict and classify abnormal events to create a better understanding of any incurable diseases such as cancer. The outcomes of using data mining in classification are promising for Brain Tumor detection. Therefore, data mining approach is used in this work.

## Proposed System

The human mind is modeled by way of using layout and implementation of neural network. The neural network is especially used for vector
quantization, approximation, statistics clustering, pattern matching, optimization capabilities and classification techniques. The neural network
is split into three kinds based totally on their inter connections. Three type neural networks are comments, feed forward and recurrent community. The
Feed Forward Neural network is in addition divided into unmarried layer community and multilayer community. In the single layer network, the hidden layer is not supplied. But it carries best input and output layer. However, the multilayer includes enter layer, hidden layer and output layer. The closed loop primarily based remarks community is called as recurrent network.In the everyday neural community, photo can not scalable. But in convolution neural network, photograph can scalable (i.E) it'll take 3-D input quantity to 3-d output quantity (length, width, top).The Convolution Neural Network (CNN) includes input layer, convolution layer, Rectified Linear Unit (Re LU) layer, pooling layer and completely related layer. In the convolution layer, the given

enter picture is separated into numerous small areas. Element sensible activation function is finished in ReLU layer. Pooling layer is non-compulsory. We can use or skip. However the pooling layer is mainly used for down sampling. In the final layer (i.E) completely related layer is used to generate the elegance rating
or label rating price based totally at the possibility in among zero to one. The block diagram of mind tumor type primarily based on convolution neural community is proven in fig.1. The CNN based mind tumor
classification is split into levels along with education and testing stages. The quantity of photographs is split into exceptional class by using the use of labels name along with tumor and non-tumor mind picture…and many others. In the schooling segment, preprocessing, characteristic
exaction and class with Loss feature is performed to make a prediction version. Initially, label the schooling picture set. In the preprocessing image resizing is applied to change length of the photo.
Finally, the convolution neural network is used for computerized brain tumor category. The mind image dataset is taken from photo internet. Image internet is a one of the pre-skilled version. If
you need to train from the starting layer, we've to train the entire layer (i.E) up to finishing layer. So time intake may be very excessive. It will have an effect on the performance. To keep away from this type of

trouble,
pre-educated version based brain dataset is used for category steps. In the proposed CNN, we are able to teach best final layer in python implementation. We don’t need to train all of the layers. So computation time is low meanwhile the performance is excessive in the proposed automated brain tumor category scheme.  The loss characteristic is calculated by using gradient descent set of rules. The uncooked image pixel is mapping with class scores by using a score function. The satisfactory of precise set of parameters
is measured by loss function. It is based totally on how properly the caused ratings accredited with the ground truth labels within the training statistics. The loss function calculation may be very essential to enhance the accuracy. If the loss characteristic is excessive, whilst the accuracy is low. Similarly, the accuracy is high, while the loss feature is low. The gradient fee is calculated for loss feature to compute gradient descent set of rules. Repeatly compare the gradient
value to compute the gradient of loss characteristic.
In this research, we applied Image Processing and Data Augmentation techniques on a small dataset of 253 brain MRI images . We trained them through a simple 8 Convolutional layers CNN model and compared our scratched CNN model accuracy with pre-trained VGG-16, ResNet-50, and Inception-v3 models using transfer learning approach. The dataset includes 155 images of malignant cancer and 98

of benign non-cancerous tumors. We split our dataset into 3 separate segments for training, validation, and testing. The training data is for model learning, validation data is sample data for model evaluation and model parameters tuning. Test data is for the final evaluation of our model. Our proposed method is composed of various phases.

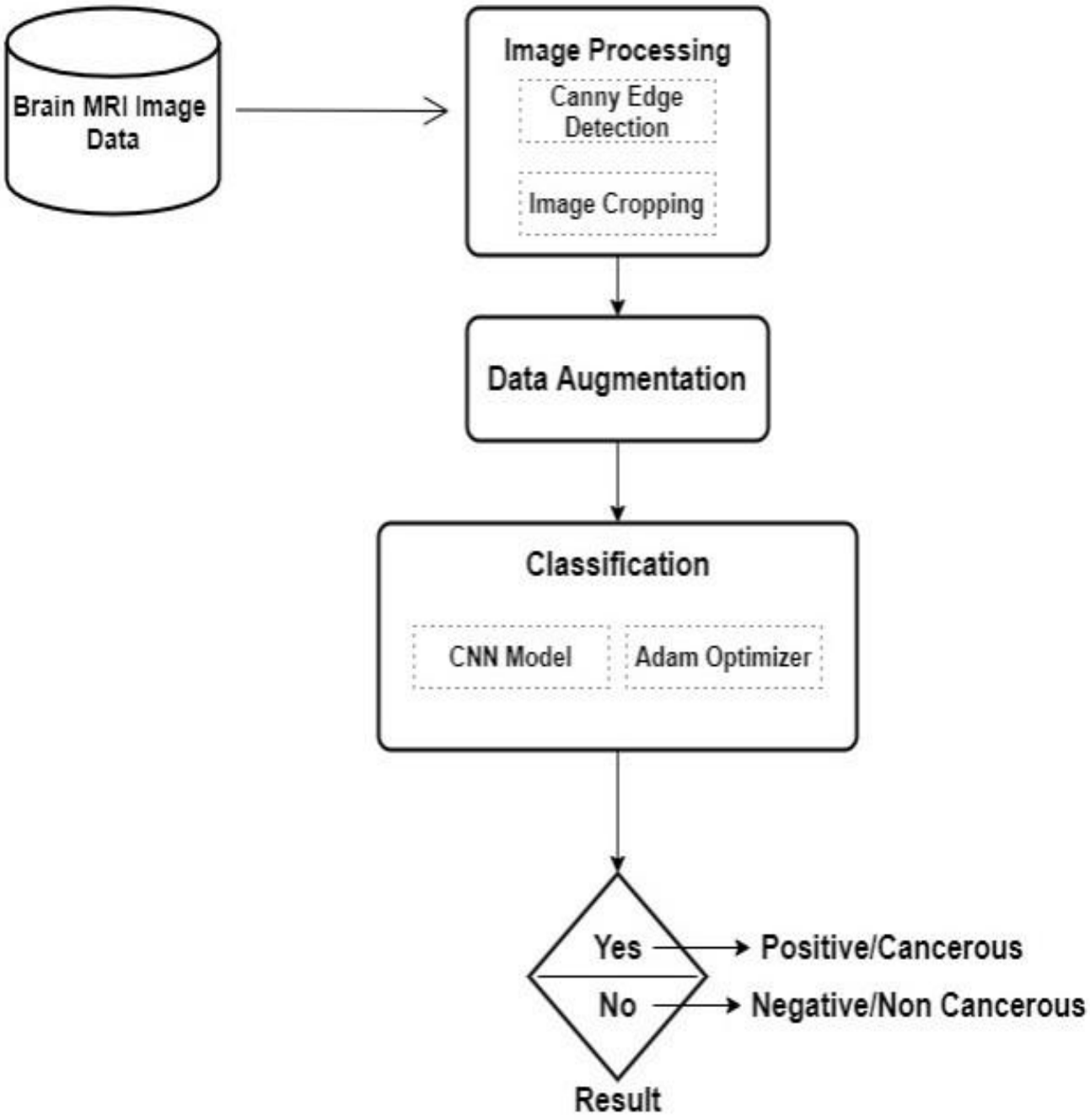


*Figure 2 Design of model*

## Chapter 3 Functionality/Working of Project

Convolution Layers- There are 3 types of layers that make up the CNN, namely the folding layers, the grouping layers, and the fully connected (FC) layers. When these layers are stacked, a CNN structure could form. In addition to these 3 layers, there are additional critical parameter layers which are the dropout layer and the activation characteristic, which are described below.

1. Convolutional Layer-

This layer is the first layer used to extract the various properties from the input images. In this layer the mathematical convolution operation is carried out between the input image and a filter of a certain size MxM. By moving the filter over the input image, the dot product between the filter and the parts of the input image in relation to the filter size (MxM) is formed.

2. Pooling Layer-

In most cases, a folding layer is followed by a grouping layer. The main goal of this layer is to reduce the size of the folded feature map in order to reduce computational costs. It does this by reducing the connections between the layers and working independently in each of them. Feature Map There are different types of grouping operations depending on the method used.

3. Fully Connected Layer-

The input image from the previous levels is flattened and fed to the FC level. The flattened vector then undergoes a few additional FC layers, where the operations of the mathematical functions normally take place. In this phase the classification process begins. 4. Dropout-

When all functions are connected to the FC layer, there can usually be an overfitting in the training data set. Overfitting occurs when a particular model performs so well on training data, which has a negative impact on model performance when used with new data.

To overcome this problem a demolition layer is used where some neurons are removed from the neural network during the training process, resulting in a reduced model size.

5. Activation Functions-

Finally, one of the most important parameters of the CNN model is the activation function, it is used to know and approximate any kind of continuous and complex relationship between variables of the network, in simple terms, it decides what information should be triggered in the model. in the forward direction and which are not at the end of the network. Adds non-linearity to the network.

Algorithm for CNN based Classification

1. Apply convolution filter out in first layer

2. The sensitivity of clear out is reduced with the aid of smoothing the convolution filter (i.E) subsampling

3. The sign transfers from one layer to every other layer is managed by activation layer

4. Fasten the schooling period by means of the usage of rectified linear unit (RELU)

5. The neurons in proceeding layer is hooked up to each neuron in next layer

6. During training Loss layer is brought on the end to deliver a feedback to neural network

## Chapter 4 Results and Discussion

Our dataset contains tumor and non-tumor magnetic resonance images and they were collected from various online resources containing real patient cases, tumor images were obtained from Radiopaedia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015 test dataset 14. In this thesis an efficient automatic detection of brain tumors using the Convolution Neural Network is carried out. The simulation is carried out using the Python language. The accuracy is calculated and compared with all other Vanguard methods. Training Precision, Validation Precision and Loss of Validation are calculated to determine the efficiency of the proposed brain tumor classification scheme. In , the existing technology, the classification based on the Support Vector Machine (SVM), was used to detect brain tumors Requires the feature extraction output . Based on the feature value, the classification output is generated and the precision is calculated. The computation time is high and the precision is low in -based tumor and non-tumor detection SVMs. In the proposed model system does not require separate feature extraction steps. The value of the feature is taken from the CNN itself. In Fig. 4. shows the classified result of the brain image of tumor and non-tumor. The result of the precision classification of brain tumor is shown in Figure 3. The classification results in tumor brain or non-tumor brain

based on probability value. The normal brain image of has the lowest probability score.

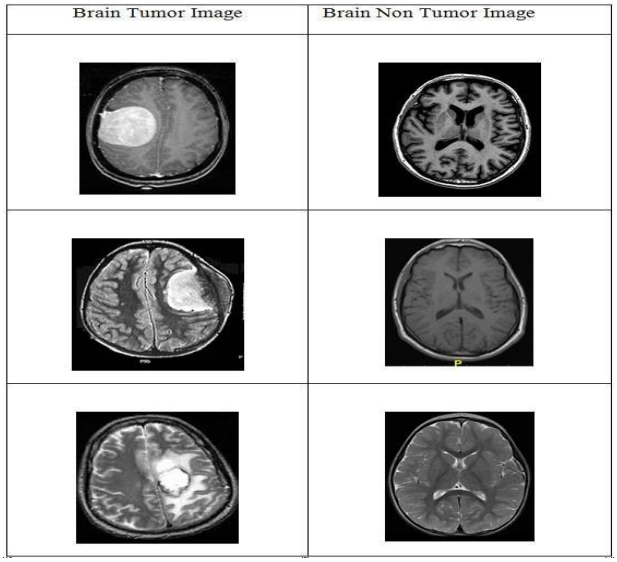


*Figure 3 CNN based classified results*

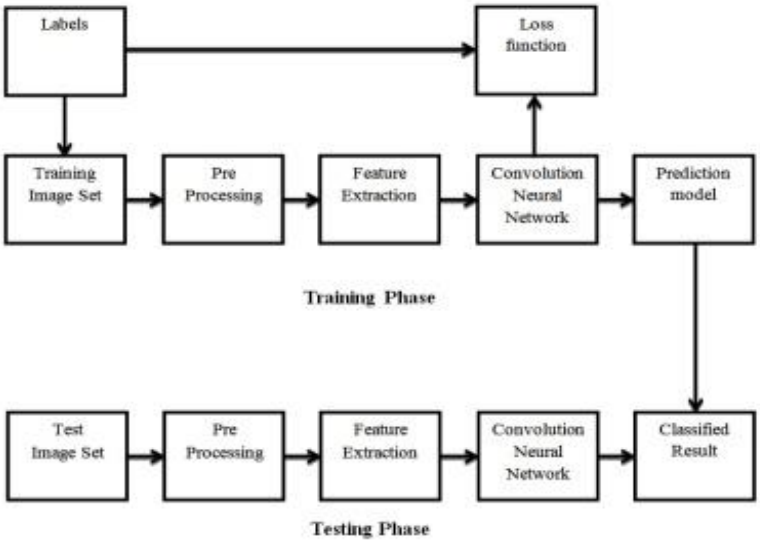


*Figure 4 Block diagram of proposed brain tumor*

## Chapter 5 Conclusion and Future Scope

In this paper, a new approach was presented to classify brain tumors. First, using the image edge detection technique, we find the region of interest in MRI images and cropped them then, we used the data augmentation technique for increasing the size of our training data. Second, we provide an efficient methodology for brain tumor classification by proposing a simple CNN network. For sophisticated and accurate results neural network requires a large amount of data to train on, but our experimental result shows that even on such a small dataset . Our proposed system can play a prognostic significance in the detection of tumors in brain tumor patients. To further boost the model efficiency, comprehensive hyper-parameter tuning and a better preprocessing technique can be conceived. Our proposed system is for binary classification problems, however, in future work, the proposed method can be extended for categorical classification problems such as identification of brain tumor types such as Glioma, Meningioma, and Pituitary or may be used to detect other brain abnormalities. Also, our proposed system can play an effective role in the early diagnosis of dangerous disease in other clinical domains related to medical imaging,

particularly lung cancer and breast cancer whose mortality rate is very high globally. We can prolong this approach in other scientific areas as well where there is a problem in the availability of large data or we can use the different transfer learning methods with the same proposed technique.

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