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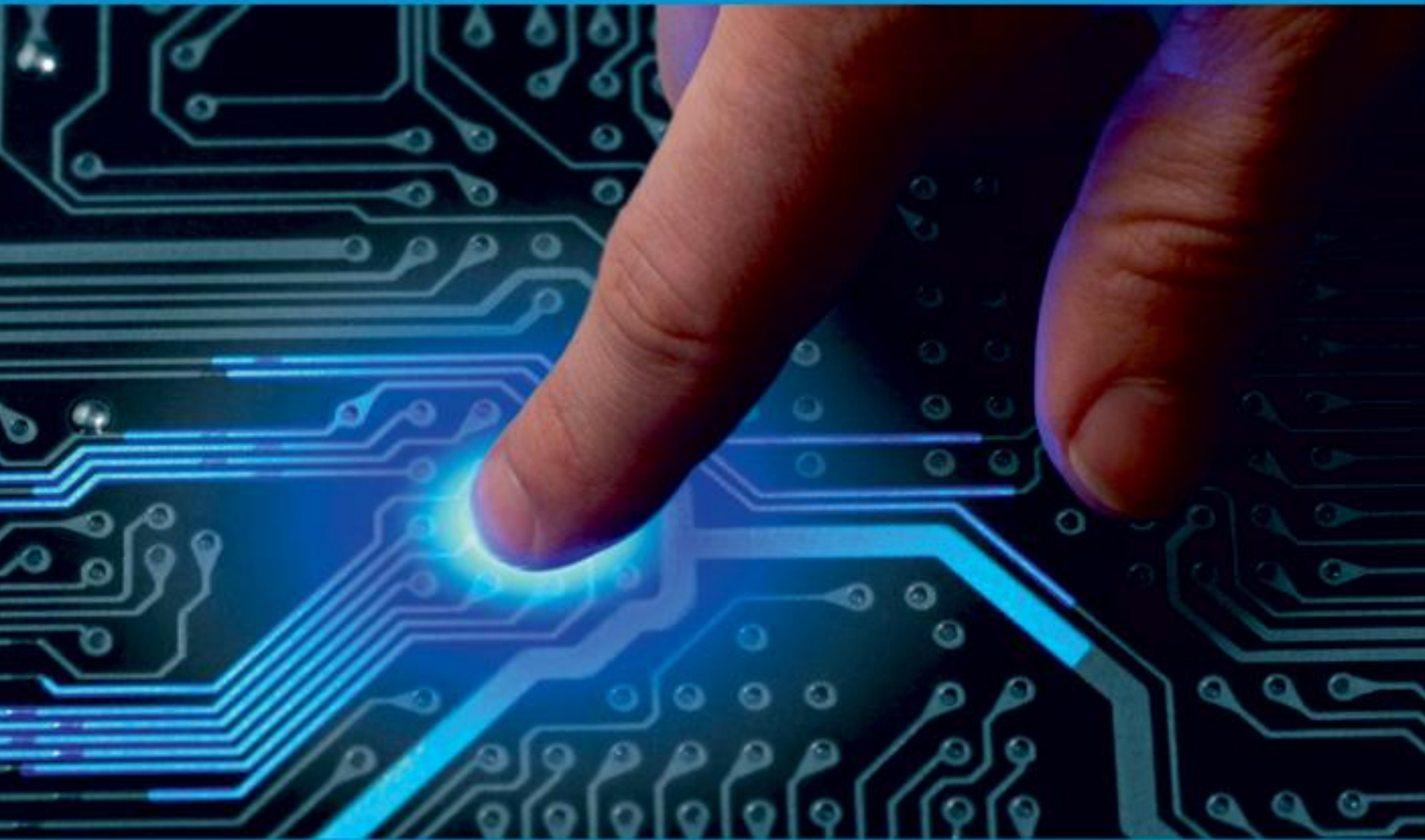

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Brain Tumor Detection Using Deep Learning Based Convolution Neural Network

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ABSTRACT: Brain tumor is considered one of the aggressive diseases, among children and adults. Brain tumors account for 85 to 90 percent of all primary Central Nervous System (CNS) tumors. Every year, around 11,700 people are diagnosed with brain tumors. The last 5-years survival rate for people with a cancerous brain or CNS tumor is approximately 34 percent for men and 36 percent for women. Proper treatment, planning, and accurate diagnosis should be implemented to improve the life expectancy of the patients. The best technique to detect brain tumors is through Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties. Application of automated classification techniques using Deep Learning (DL) and Artificial Intelligence (AI)has consistently shown higher accuracy than manual classification. Hence, we propose a system that detects the brain tumor by using Deep Learning Algorithms using Convolution Neural Networks (CNN) which would be helpful to doctors and every individual suffering with brain tumor all around the world.

KEYWORDS: Brain Tumor, Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Network.

I. INTRODUCTION

Brain tumor is the growth of tissue in the brain which contains abnormal cells. As per statistics it is estimated that a total of 11,700 people is dying per year due to the brain tumor. So, the early detection of brain tumors is much more essential to save more lives.

We used the Convolution Neural Network (CNN) algorithm to build a model with 3 layers which takes input of Magnetic Resonance Imaging (MRI) scan images and detects whether the person has a tumor or not.

II. RELATED WORK

Some of the previous methods that are used for brain tumor detection are

1. Review of Brain Tumor Detection using Pattern Recognition Technique

This work was proposed by J. ANITHA, M. BHAGAVATHI AMMAL in the year 2015 and the accuracy of the proposed model is 85.2% [1].

Summary:

Brain tumor detection using pattern recognition techniques has been an active area of research in medical image analysis. These techniques use mathematical algorithms and statistical methods to analyse medical images and identify patterns and features that are indicative of brain tumors. There are some disadvantages to this technique which are low accuracy, Variability in Image Quality, Limited Interpretability, and Limited Generalizability.

In conclusion, pattern recognition techniques have shown promise in the detection of brain tumors. However, there are still several challenges that need to be addressed before they can be widely adopted in clinical practice. Further research is needed to address these limitations and to improve the accuracy and reliability of these techniques.

2. Brain Tumor Detection using K-Means Clustering based on Genetic Algorithm

This method was proposed by A. PATIL, S. BADHE in the year 2016 and the accuracy of the proposed model is 84.3% [2].

Summary:

Brain tumor detection using k-means clustering based on genetic algorithms is a technique that combines two different methods. K-means clustering is a machine learning algorithm that is used to group similar data points based on their

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features. Genetic algorithms are optimization techniques that mimic the process of natural selection to find the optimal solution to a problem.
The use of k-means clustering based on genetic algorithms in brain tumor detection has shown promising results in improving the accuracy of tumor detection. However, this approach may require a large dataset for training the genetic algorithm, which can be time-consuming and computationally expensive. Additionally, the accuracy of this technique may depend on the quality of the MRI images used. Overall, this technique shows potential in improving the accuracy of brain tumor detection and may be a valuable tool for medical professionals.

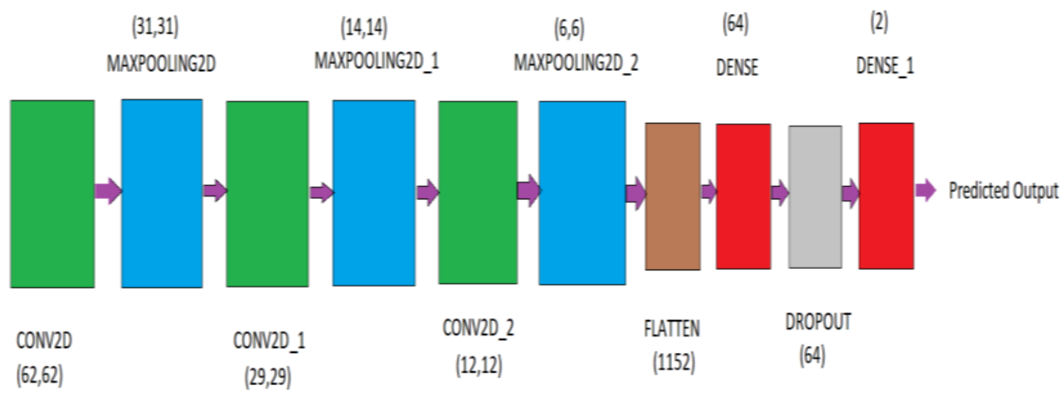
3. A New Threshold Approach for Brain Tumor Segmentation using Neuro-Fuzzy
In 2017, B. KANNAN, S. BAVITHRA, and P. GAYATRI proposed this approach, which has an accuracy of 89.6% [3].
Summary:
A new threshold approach for brain tumor segmentation using neuro-fuzzy combines the use of fuzzy logic and neural networks to improve the accuracy of brain tumor segmentation. Fuzzy logic is a mathematical approach that deals with uncertainty and imprecision in data, while neural networks are machine learning algorithms that can learn from large datasets to make accurate predictions.
The use of neuro-fuzzy in brain tumor segmentation has shown promising results in improving the accuracy of tumor segmentation. This approach is particularly useful in dealing with the uncertainty and imprecision in medical image data, which can affect the accuracy of traditional thresholding approaches. However, the accuracy of this technique may depend on the quality of the MRI images used, and a large dataset may be required for training the neural network. Overall, this technique shows potential in improving the accuracy of brain tumor segmentation and may be a valuable tool for medical professionals.

III. METHODOLOGY

The main purpose of our work is to improve accuracy so we used the Convolution Neural Network (CNN) algorithm for building a model.

CONVOLUTION NEURAL NETWORK (CNN)
Convolutional Neural Network is a type of neural network commonly used in computer vision applications such as image and video recognition, object detection, and classification.CNNs are inspired by the biological process of visual perception in animals, where the visual cortex performs a series of hierarchical computations to extract features[4] from images. Similarly, a CNN consists of multiple layers, each layer learning increasingly complex features of the input image [5]. The layers in a CNN typically include convolutional layers, pooling layers, and fully connected layers.
In a convolutional layer, the network learns filters or kernels that slide across the input image and extract features such as edges, corners, and textures. Pooling layers down sample the output of convolutional layers by taking the maximum or average of a group of nearby values, reducing the dimensionality of the feature maps [6]. Finally, fully connected layers take the flattened output of the previous layers and produce a class prediction.
CNNs have achieved state-of-the-art performance in many computer vision tasks, including image classification, object detection, and segmentation.

CNN ARCHITECTURE



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The CNN model consists of 5 layers. They are
1. Convolution layer
2. Max pooling layer
3. Flatten layer
4. Fully Connected layer
5. Dense layer

CONVOLUTION LAYER: Convolutional layers are the primary building blocks of a CNN. They apply a set of learnable filters (also known as kernels or weights) to the input image of size 62x62 in order to extract features that are useful for the task at hand. Each filter slides over the input image, performing a dot product between its weights and the corresponding pixels in the image. The output of this operation is a feature map, which highlights the areas of the image that are most relevant to the given filter. After convolution, we need to use an activation function (RELU) to add non-linearity to the network.

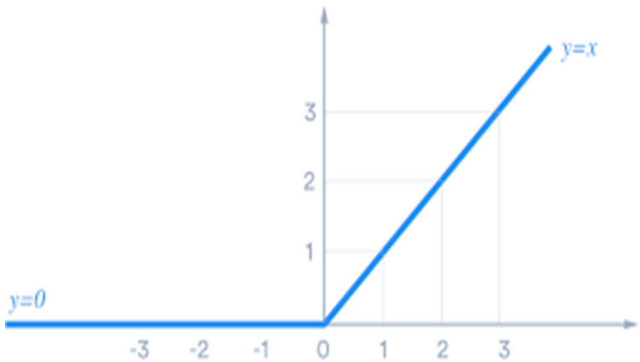
POOLING LAYER: The next step after the convolution is to down sampling the maximum facility. The objective is to reduce the mobility of the feature map to prevent overfitting and improve the computation speed. Max pooling is a traditional technique, which splits feature maps into subfields and only holds maximum values.

FLATTEN LAYER: Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. We flatten the output of the convolutional layers to create a single long feature vector.

FULLY CONNECTED LAYER: All neurons from the past layers are associated with the other Neurons from next layers. After that CNN will classify the label according to the features from convolutional layers and pooling layers.

DENSE LAYER:A simple layer of neurons which receives all the inputs from the previous layers. It is used to classify images based on output. In this dense layer, activation function is used to learn complex patterns in the data.
In this CNN model we used two activation functions in convolution layer and dense layer they are

RECTIFIED LINEAR UNIT (RELU) : The rectified linear activation function is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance.



SOFTMAX : SoftMax is a mathematical function that converts a vector of numbers into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector.

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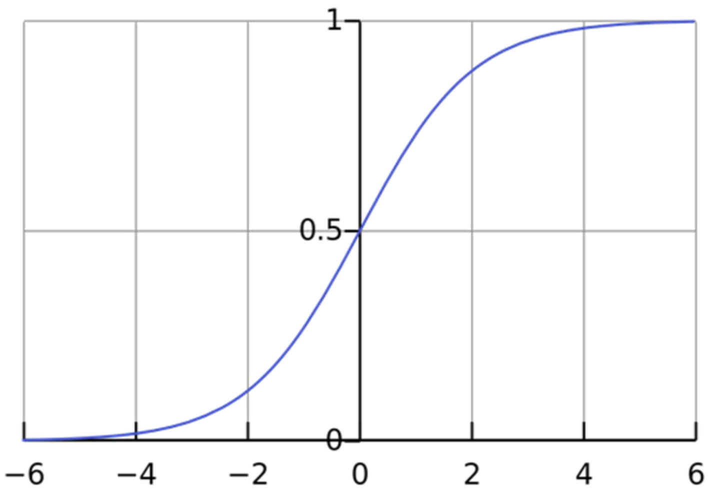

IMPLEMENTATION STEPS

Step-1: Installing the required software and libraries.

In this work we used Visual Studio Code (VS Code) software with version 1.71

Step-2: Downloading the datasets

(I) BR35H

(ii) Brain MRI images for Brain Tumor detection

By using these two datasets we will train and test the models.

Step-3: By Creating our model using the CNN algorithm we will train and test the model.

Step-4: Now using this 3 layer CNN model we can predict whether the person has a brain tumor or not.

DATASET

We used a hybrid data set which is a combination of two data sets namely

- BR35H
- Brain MRI images for Tumor detection

- In BR35H, we have two folders namely “yes” and “no”. These two folders each contain 1500 images
- In Brain MRI images for Tumor detection, we have two folders namely “yes” and “no”, where the “yes” folder has 155 images and the “no” folder has 98 images.

Folder	Number Of Images	
	Brain Tumor	Normal
Testing	294	357
Training	932	1670

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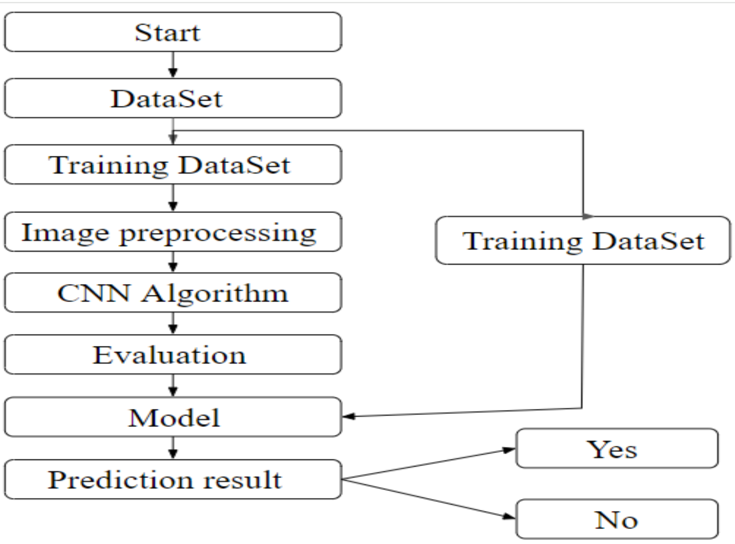
FLOW CHART



The flow chart shows the flow of our work. At first, the dataset is divided into two sets which are the training dataset and the testing dataset. From the dataset the training dataset uses 70% of the data and the testing dataset uses the remaining 30% of the data for their respective process. The training dataset is used for training the model and the testing dataset is used for the testing of the model. Now, the training dataset undergoes some pre-processing techniques to reduce noise and enhance the edges and after pre-processing, they will get assigned to the proposed algorithm which is Convolution Neural Network (CNN). This model can predict the tumor by taking the testing data as input.

IV. EXPERIMENTAL RESULT

SIMULATION RESULT

Model: "sequential"

Layer (TYPE)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
activation (Activation)	(None, 62, 62, 32)	0
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	9248
activation_1 (Activation)	(None, 29, 29, 32)	0
max_pooling2d_1 (MaxPooling 2D)	(None, 14, 14, 32)	0
conv2d_2 (Conv2D)	(None, 12, 12, 32)	9248
activation_2 (Activation)	(None, 12, 12, 32)	0
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 32)	0
flatten (Flatten)	(None, 1152)	0
dense (Dense)	(None, 64)	73792
activation_3 (Activation)	(None, 64)	0
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 2)	130
activation_4 (Activation)	(None, 2)	0

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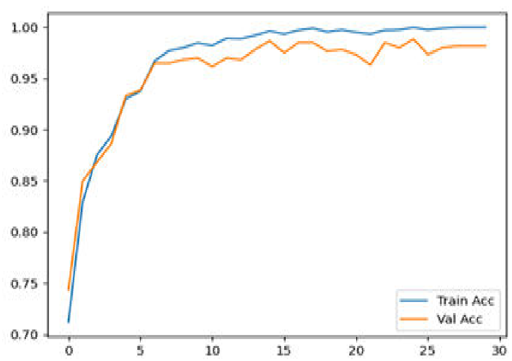
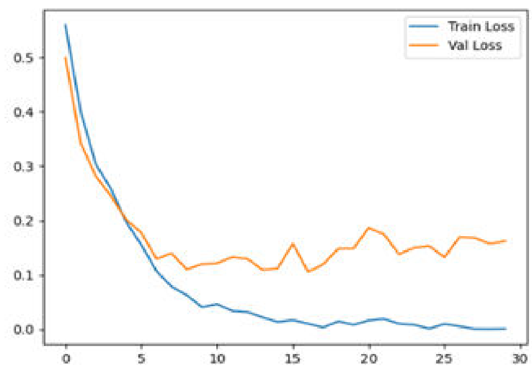
TOTAL PARAMS: 93,314
TRAINABLE PARAMS: 93,314
NON-TRAINABLE PARAMS: 0

EXPERIMENTAL RESULT



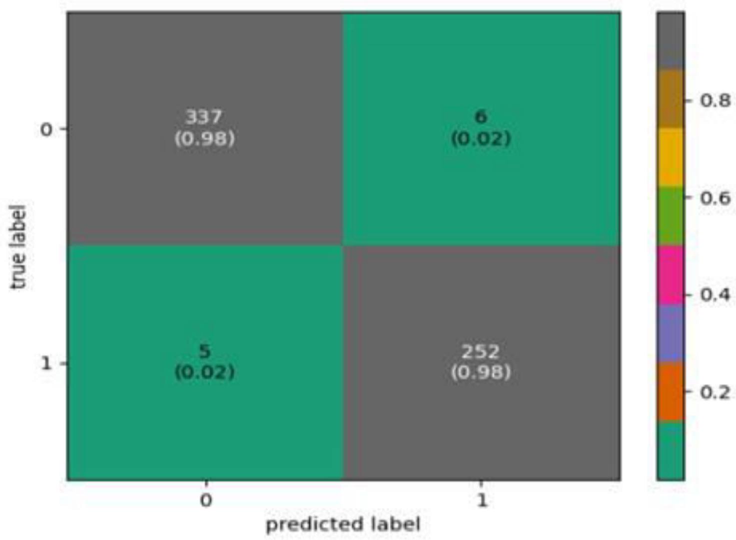
TRAINING VS VALIDATION ACCURACY



TRAINING VS VALIDATION LOSS

EVALUATION OF MODEL BY USING CONFUSION MATRIX

CONFUSION MATRIX: A confusion matrix is a table that is used to define the performance of a classification algorithm. A confusion matrix visualizes and summarizes the performance of a classification algorithm.
True Positive (TP) — A test result that correctly indicates the presence of a condition or characteristic
True Negative (TN) — A test result that correctly indicates the absence of a condition or characteristic
False Positive (FP) — A test result which wrongly indicates that a particular condition or attribute is present
False Negative (FN) — A test result which wrongly indicates that a particular condition or attribute is absent



The parameters that are measured from the confusion matrix are

Accuracy:
Accuracy is the measure of the classifier producing the correct prediction.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

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Precision:
Precision is the ratio of the number of tumor images that are correctly classified (TP) and the number of images classified or misclassified as tumor (TP + FP).

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

Recall:
The recall is the ratio of the number of tumor images that are correctly classified and the number of images that are to be predicted. Sensitivity, Hit Rate, and True Positive Rate are the other names for Recall

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1 Score:
It is the harmonic mean of Precision and Recall and is a measure of test accuracy. F-score reaches its best value at 1 (100% precision and recall) and worst value at 0.

$$\text{F1 score} = \frac{2*Recall*Precision}{Recall*Precision}$$

CLASSIFICATION REPORT

	Precision	Recall	F1 Score	Support
Yes	0.99	0.98	0.98	343
No	0.98	0.98	0.98	257

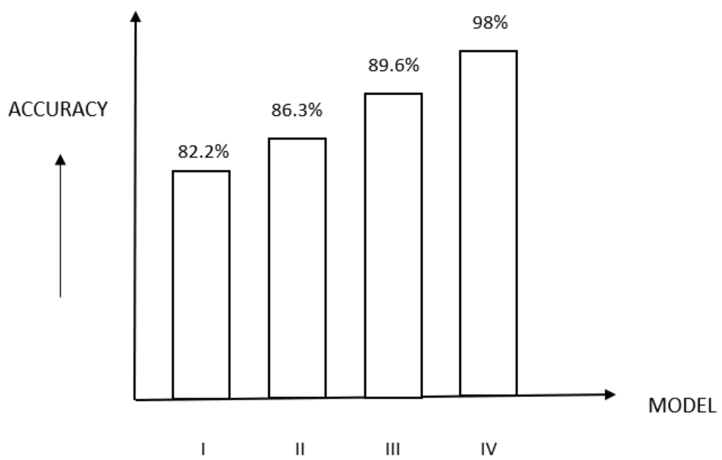
The overall model Accuracy is 98%

COMPARISON OF ACCURACY WITH RELATED WORK ACCURACY

Parameter	Related work			Proposed work
	Using Pattern Recognition	Using K-means Clustering	Using Neuro-fuzzy	Using CNN
Accuracy	85.2%	84.3%	89.6%	98%

From the comparison we can say that our model can detect the tumor more accurately.

COMPARISON OF ACCURACY USING GRAPHICAL REPRESENTATION



I ---- using Pattern Recognition Technique
II ---- using K-Means Clustering based on Genetic Algorithm
III ---- using Neuro Fuzzy

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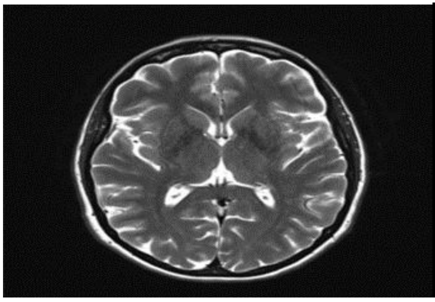
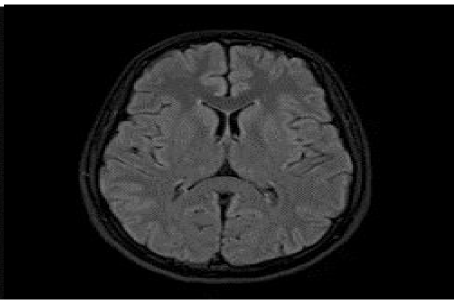
IV ---- using Convolution Neural Network (CNN)

PREDICTED RESULT





TUMOROUS IMAGE NON-TUMOROUS IMAGE

V. CONCLUSION

In conclusion, deep learning based Convolutional Neural Networks (CNNs) have shown promising results in detecting brain tumors. This CNN model takes in MRI images of the brain and processes them through multiple convolutional layers to extract features, which are then classified as either tumor or non-tumor. Our model's overall accuracy is 98%. The output of this CNN model is a binary classification, with 1 indicating the presence of a tumor and 0 indicating its absence. This output can help healthcare professionals make informed decisions about treatment options and provide better care to patients.

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