Detection of Brain Tumor using Machine Learning and Deep Learning Technologies

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Abstract:
The leading cause of death in the world is cancer which stands at the second number after cardiovascular diseases. Every 6th death happening in the world is due to cancer. Two types of cancer are Benign and Malignant Cancer. One of the malignant cancer is a brain tumor. Brain tumor can affect all age groups. There are many types of cancers based on the factors such as shape, texture, size, etc. The survival chances of a patient can be increased if the cancer is detected in an early stage. The detection of cancer is done by MRI scan that is Magnetic Resonance Imaging. It is unpainful and economical also. This method gives a clear picture of the brain in 2D or 3D format. This method is popular and precise to detect cancer. The use of Machine Learning and Deep Learning techniques can improve the accuracy of detecting cancer and hence save many lives of people. Different models like CNN, Alex Net etc. provide different accuracies and precision when used with different machine learning models such as SVM, k-NN etc.
Keywords: Machine Learning, CNN, Deep-Learning, Image processing, ,Brain tumor, MRI imaging, etc.

I. INTRODUCTION:

Cancer is the deadliest disease in the world. The most vulnerable people to cancer are the added ones. It can affect the whole body and hence disturb the working of the cells leading to the death of the person. The Brain is an important part of our body as it commands all the processing taking place in our body. Therefore brain cancer is harmful to our bodies in every possible way. In the early stage of cancer when the cells start growing in an uncontrollable way it is restricted to a particular area in the body. This is the first stage of cancer. And detection at this stage can make it easier for doctors to cure it.
But when cancer enters the second or the third stage then it has the capability to spread to the other parts of the body and hence difficult to treat. The treatment for this is done by using MRI scan. The detection here is manual and therefore has a scope of errors done by humans.

So by the use of deep learning models and machine learning algorithms the detection can be done automatically and increase in precision thus increasing the chances of survival of the patients. Classification and Detection are by using the algorithms like k-NN and by the use of CNN architecture like Alex Net , VGG16 , etc.

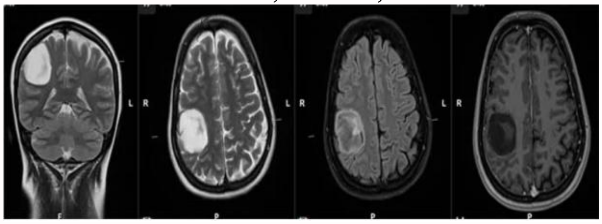

Fig.1: MRI Image of Brain Tumor

II. REVIEW OF LITERATURE:

1. Material and Methods

The brain tumor detection system is based on computer vision image processing and deep learning algorithms. The above system detects the brain tumor based on extracting the features present in the image and then classifying it as tumor detected or not. The first step is pre-processing which includes entering the input images for the detection of brain tumors. Then the data augmentation is used so that the number of the dataset increases which in turn helps us to increase the precision of the system. Normalization is also performed. The noise and error present in the background are discarded. These images are used for training processes in various machine learning and deep learning algorithms.

1.1 Data pre-processing

The images are acquired and then processed further. The pre-processing done here is a critical stage and it should be precise enough so that it can lead to the best performance. Here we perform data augmentation to increase the dataset as the medical images are hard to get as it is considered critical information to disclose. To discard noise we use filters for reduction. After the above procedure, the features are extracted from the images which are further useful for the classification.

1.2 Feature Extraction

Features extracted are of three types that are morphological, color and texture.

1.2.1 Morphological Features

Features based on shape and size of the brain are useful for detecting tumor.

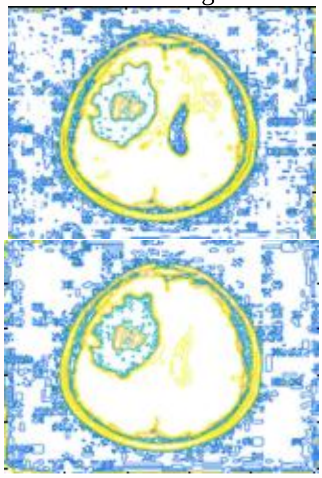

Fig.2: Shape feature of MRI Image

1.2.2 Texture Features

The low-level feature in the image that is principal to express the contents of the image is called texture features.

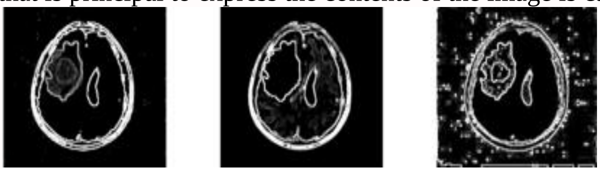

Fig.3: Texture feature of MRI

1.2.3 Color Features

The image is characterized by the intensity of colors present in the image.

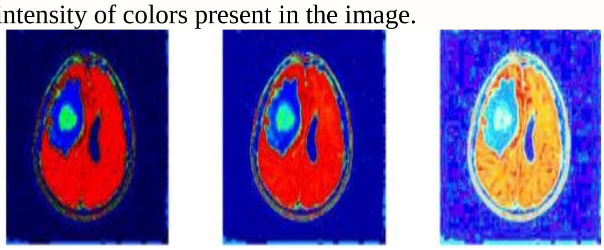

Fig.4: Color feature of MRI Image

2.Model Development

2.1 Artificial Neural Network (ANN)

A neural network comprises of linked neurons to each other. The function of these neurons is to provide a result of a problem. Input, hidden layer and output layer are the three layers that when connected make an ANN. The input layer consists of neurons which are variable in number and it dependent on the characteristics of the input dataset.

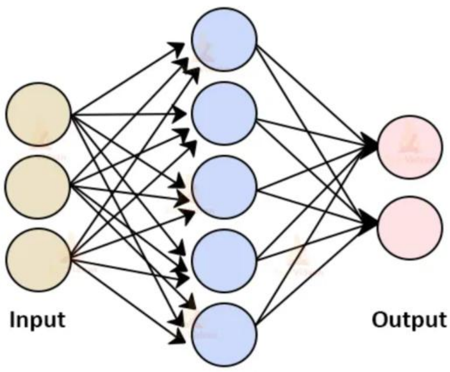

Fig.5: Artificial Neural Network (ANN)

The trial and error method is used for determining the number of hidden layers. Different types of activation layers like linear, sigmoid, Tanh, RELU, ELU, etc are used in ANN according to the requirements.

While processing to reduce the cost function backward and forward propagation is used so that our model's accuracy is increased and it is trained in an efficient way. The accuracy of the model depends on the number of iterations that takes place during the training of the model. The number of images present in the dataset also plays an important role in the accuracy of the model.[16]

2.2 Convolution Neural Network

The designed network is efficient in detecting the tumor. The layers present in the network, the number of epochs and the dataset's size decide the training time of the model.

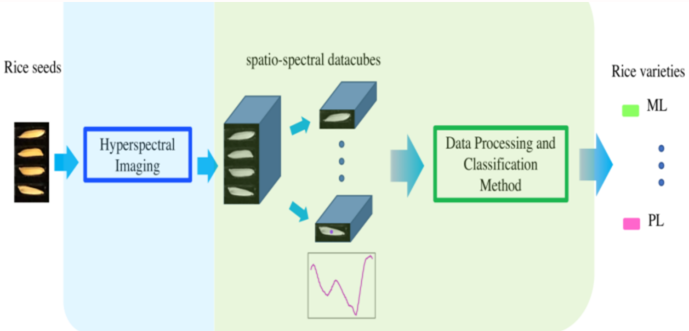

Fig.6: Convolution Neural Network

A hierarchical approach is used for feature detection. A single layer of CNN consists of four layers inside it. The three layers are as follows-

1. Convolution Layer-

   It is a main building block of the CNN. The presence of feature detector is seen in this layer it is also called as a kernel. The size of the kernel varies according to the input size it can be 2x2 , 3x3 or nxn. The feature detector moves across the input image in search of the feature and this process is known as convolution.

2. Pooling Layer-

   It performs dimension reduction which helps to reduce the number of parameters in the input. Here this layer just adds the filter to the whole input but only the dissimilarity being that this filter doesn't have its own weights that is they are weightless. Here we see that there are two types of pooling that are Max pooling and Average Pooling.

3. Fully connected layer-

   Here each neuron in the output layer is connected to each layer in the previous layer in CNN. This layer is an important one as it helps in classifying the input into its categories. Classification is done on the basis of the features that are extracted in the previous layers. This layer often uses the softmax activation function which is more efficient.[19]

2.3 Deep Residual Network50 (ResNets50)

It is a Convolution neural network that is 50 layers deep. The fifty layer consists of forty-eight convolution network, one MaxPooling Network and one AveragePooling Layer. It is a type of artificial neural network as it is formed by stacking the residual blocks by the network. This architecture follows key design rules. The first one is that the filter number in each and every network is dependent on the size of the output feature map. And the second rule is that the size of the feature map is inversely proportional to the number of filters in each network that is if the feature map size is reduced by half then the filters in each layer are doubled so by doing this we keep the time complexity of all the layers maintained. The main feature of this is that it uses a bottleneck of 1x1 in turn helping us to reduce the number of parameters and multiplication of the matrices. This in turn increases the training speed and uses a stack of three layers.

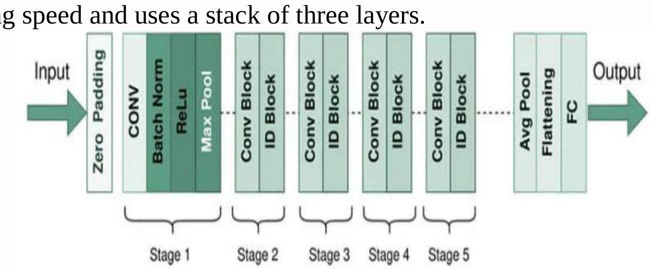

Fig.7: Architecture ResNets50

The results of uses this architecture is that the top-1 error rate is 20.47% and top-5 error rate is 5.25%.[8][15][19]

2.4 Visual Geometry Group (VGG-16)

This architecture was given by Karen Simonyan and Andrew Zisserman. This architecture has 16 layers deep. The most prominent feature of this network is that it has convolution layer of 3x3 filter with stride 1 and uses same padding and maxpooling layer of 2x2 of stride 2. 138 million parameters consists in this network.

The input to this network is of the size 224x224x3. Fist two layer consists of the 64 channels of 3x3 filter size with same padding. Then the max pooling layers comes in with stride of 2.The next two layers have convolution layers of 128 filter size and filter size of 3x3. Maxpooling layer of (2,2) stride same as the previous pooling layer. The next two layers of 256 filters and filter size (3x3). The two sets of three convolution layers with maxpooling layer having 512 filters and filter size of 3x3.

Fig.8: Architecture VGG-16

The model has accuracy of 92.7% in top-5.[13]

2.5 Inception-V3

This models consists of 42 layers. It is built by symmetric and a symmetric blocks which includes convolution layers, pooling layers, both max and average , concatenations , dropouts and fully connected layers. Here the loss is calculated by using softmax. The input for this layer is 299x2999x3 and the output given is 8x8x2048.

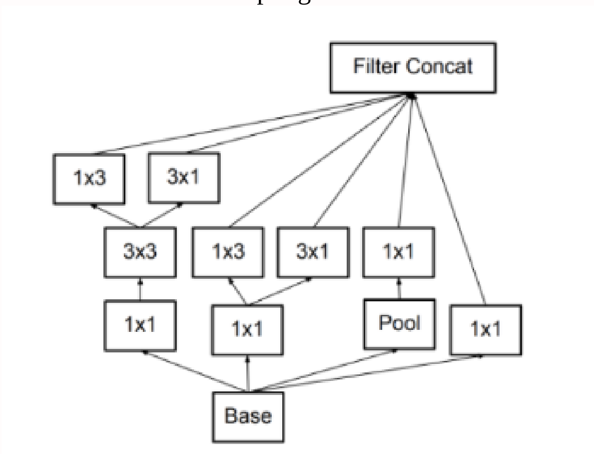

Fig.9: Architecture Inception-V3

It attains 78.3% accuracy on ImageNet dataset. The top-5 error is 4.2%.[2]

2.6 MobileNet V2

It is a CNN that works efficiently on mobile devices. It is a network that is 53 layers deep and one average pooling layer.

In this network, there are two types of blocks the one block being the residual block with stride 1 and the other with stride 2 which is helpful for downsizing. There are three different layers for both the blocks. The first layer is 1x1 convolution with activation function ReLU6. Depth-wise convolution is the second layer and the third layer is the 1x1 convolution layer but the dissimilarity being that this is non-linear.[2]

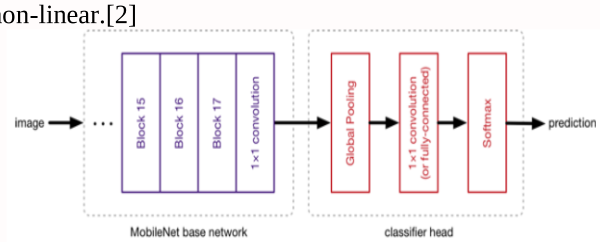

Fig.10: Architecture MobileNet V2

2.7 AlexNet

This network is designed by Alex Krizhevsky. This network is the first one which helped to boost the performance of the GPU. This network consists of 13 layers. Here network consists of 5 convolution layer which consists of filters and ReLU activation function, three maxpooling layers, two normalization network, two fully connected layer and one softmax layer. The input size is 224x224x3. And it has 60 million parameters. The result is 37.5% in top-1 error and 17% top-5 error.[15]

2.8 GoogleNet

This is a 22-layer deep convolution Neural network. The input for this model is of size 224x224. There are seven inceptions layers in this model. The max pooling layer is present in between seven inceptions layer.

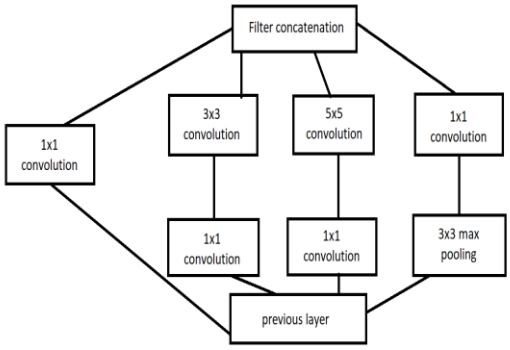

Fig.11: Architecture GoogleNet

There is a presence of a dropout layer which is used to reduce the overfitting of the model. The last layer is the softmax layer. The top-5 error of this model is 6.67%.[8]

III. CLASSIFICATION MODELS

3.1 Support Vector Machine (SVM)

Most classification problems are solved using SVM. It can also be used in regression problems. Here we take each data point and plot it in n-dimension plane. Unique coordinate corresponds to a unique data point. SVM classifies the data into linear, planar, and hyper plane in 2-D, 3-D and multi-dimensional plane respectively.

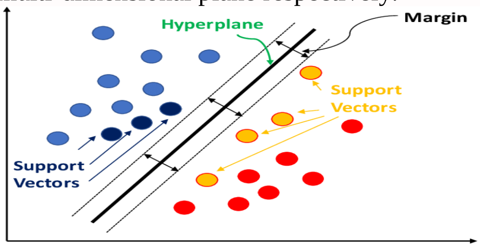

Fig 12: Support Vector Machine (SVM)

The accurate hyper-plane is the one having the most margin between the classes. The hyperplane helps us to classify the data points into different classes.[18]

3.2 K- nearest neighbor (k-NN)

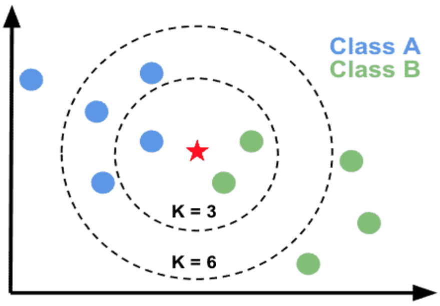

Fig 13 : K- nearest neighbor (k-NN)

This is a type of non-parametric learning algorithm. Euclidean distance is used to classify the dataset. Here k stands for number of neighbors. This algorithm is best used where the data set class is not known.

Here each point is plotted in a dimensional space and each point depicts a different variable. The test data are learned one by one. Hence some points would be close to each other and these all make one class. Hence accordingly the data is classified into different classes. This algorithm is more accurate than the others and is more flexible to the input dataset. The property of a decision tree is that it can deal with complex problems and give the result in logical classification rules. This is one of the advantages.

3.3 Logistic Regression

This is one of the most used and important machine learning algorithms. It is most helpful to speculate probabilities in classification problems. Here the output is in the form of probabilistic decisions. It distinctly tells us about the independent and dependent variables.

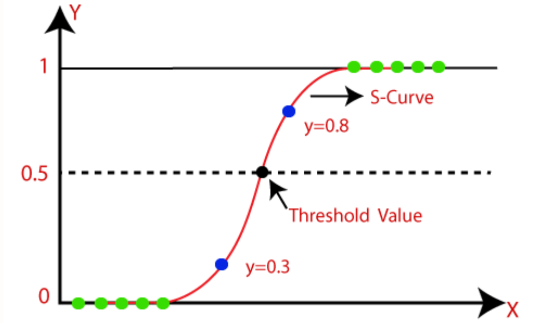

Fig 14: Logistic Regression

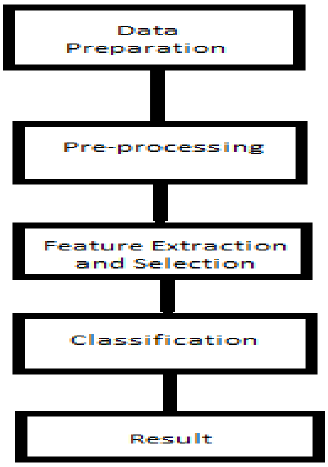

Fig 15: Methodology diagram

IV.PERFORMANCE MEASURES

These are the parameters that help us to tell about the success of the model. It tells us about the performance and the accuracy of the model. One of the way to calculate the accuracy of our model is by using a complexity matrix.
The matrix tells us the details about real classes and the predicted classes after the classification performed after the model.

Table 1: Classification of Real and Predicted class

	Predicted Class		
Real Class		Class 1	Class 2
	Class 1	tp	fp
	Class 2	fn	tn

The matrix has the following parameters

- tp- True Positive The model predicts it true and it to matches the real class.
- fp- False Positive The model predicts it true but it doesn't match to the real class.
- fn- False Negative The model predicts it false and actually it doesn't match to the class.
- tn- True Negative The model predicts it is false but it is actually true.

Table 2: Performance Measures

No.	Measure	Definition
1.	Accuracy	Regularity of the model to predict accurate output. It is ratio between number of correct predictions to all predictions.
2.	Precision	The prediction by the model is accurate and matches the real classes.
3.	Recall	Out of total positive class how many were correctly classified by our model.
4.	Specificity	Ability of the model to predict that the observation doesn't belong to a specific class

V.SURVEY AND ANALYSIS OF RECENT TECHNIQUES

The recent deep learning techniques on modality of MRI images for image segmentation, classification and detection of brain tumor is shown in Table 3. The fresh approaches used for the detection of MR brain images with pre trained module improves accuracy, specificity precision and is quick in diagnosis as modules doesn't has to be trained from the beginning. Fast and error free diagnosis of brain tumor is done using chosen methods for brain tumor detection using MRI images .

Table 3: Analysis of deep learning and Machine learning

Reference	Model Used	Number of classes	Performance	Training /Testing data
[1]	CNN with SVM	4	Accuracy – 90%	Total - 789
[2]	VGG16 MobileNet Inception V3	2	VGG16 – 79% Inception V3- 84% MobileNet – 86%	Total – 253
[3]	CNN rectangular, Triangular architecture	2	Rectangular – 97.9% Triangular – 97.5%	Total – 30000 Test- 7600
[4]	LSFHS Method	2	Increases accuracy by	-
[5]	CNN	2	-	-
[6]	CNN	3	Accuracy- 96%	-
[7]	CNN	4	Accuracy – 99.33%	Total- 70220
[8]	AlexNet , GoogleNet, ResNet	2	79%-AlexNet 85%-ResNet 83% - GoogleNet	-
[9]	CNN	3	Accuracy- 97.3%	3064-total
[10]	C-CNN	2	Sensitivity – 97.12%	BRATS 2018
[11]	CNN, Le-Net, VGG16	2	Le-Net – 88% VGG16 – 90%	Training- 253 Testing- 50
[12]	CNN	2	Accutracy- 98.32%	Training-762 Testing-419
[13]	VGG16 CNN	3	Accuracy- 77.60%	Training – 1924 Testing- 482
[14]	CNN architecture	2	Accuracy – 96.56%	
[15]	AlexNet, ResNet50 Inception V3 GoogleNet Densenet	2	91.04% - Densenet 89.55% - AlexNet 92.54% - ResNet50	Total- 253
[16]	ANN CNN	2	94%-CNN 71.5%-ANN	Training – 1672 Testing- 207
[17]	Deep Autoencoder	2	Accuracy – 98.5%	BRATS 2015
[18]	CNN and SVM	2	Accuracy- 98%	
[19]	CNN, ResNet50	3	Accuracy – 97%	Training - 3064

I. RESULT AND DISCUSSIONS

The survey here studies about many techniques used for segmentation /classification effective for detecting brain tumor. It also tries helps researchers for deciding the main characteristics of different deep learning techniques for brain tumour detection using MRI . The survey tells us about the most appropriate approaches and precision of different deep learning and machine learning modules for MR image-based brain tumor diagnosis. It is done with intention to help researchers in determining on new approaches, the present approaches with relation to different AI techniques used in brain tumour detection could be summarised.

II. CONCLUSION:

In this paper we aim to analyze different CNN and ANN modules to detect the tumor through MRI scans. Above implementation algorithms provide different approaches for successful classification of brain tumor.
In every approach, MRI images are processed by converting them into binary or greyscale images for feature extraction. The features are extracted on the basis of size, color and texture etc. which can help us to detect the tumor from the images.
A variety of CNN and ANN models are used for training and testing. The CNN based models used for training are VGG16, MobileNet, Inception V3 ,etc. Along with these pretrained models, for classification SVM, k-NN,etc algorithms are used to increase the accuracy of the model. To test the precision of the model test parameter like confusion matrix will help to check the accuracy and precision of the model.

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