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BRAIN TUMOR DETECTION FROM MRI IMAGES USINGDEEP LEARNING TECHNIQUES-VGG 19 and Resnet 50

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Abstract :-

Brain tumor is the growth of abnormal cells in brain some of which may leads to cancer. The usual method to detect brain tumor is Magnetic Resonance Imaging(MRI) scans. From the MRI images information about the abnormal tissue growth in the brain is identified.The detection of brain tumor is done by applying Machine Learning and Deep Learning algorithms. When these algorithms are applied on the MRI images the prediction of brain tumor is done very fast and a higher accuracy helps in providing the treatment to the patients. These prediction also helps the radiologist in making quick decisions.In the proposedwork, a self defined Artificial Neural Network (ANN) and Convolution Neural Network(CNN) is applied in detecting the presence of brain tumor and their performance is analyzed.

I. INTRODUCTION

Medical imaging techniques are used to image the inner portions of a human body for medical diagnosis. And medical image classification is one of the most challenging & affluent topicsin the field of Image Processing. Medical image classification problems, tumor detection or detectionof Cancer is the most prominent one. The statistics about the death rate from brain tumor suggest thatit is one of the most alarming and critical cancer types in the Human body. As per the International Agency of Research on Cancer (IARC), more than 1,000,000 people are diagnosed with brain tumor per year around the world, with ever increasing fatality rate. It is the second most fatal cause of death related to Cancer in children and adults younger than 34 years. In recent times, the physicians are following the advanced methods to identify the tumor which is more painful for the patients.

To analyze the abnormalities in different parts of the body, CT (Computed Tomography) scan and MRI (Medical Reasoning Imaging) are two convenient methods. MRI-basedmedical image analysis for brain tumor studies has been gaining attention in recent times due to an increased need for efficient and objective evaluation of large amounts of medical data. Analysis of this diverse range of image types requires sophisticated computerized quantification and visualization tools. So, automatic brain tumor detection from MRI images will play a crucial role in this case by alleviating the need of manual processing of huge amount of data.

Brain Tumor

According to Ilhan et al, a brain tumor occurs when abnormal cells form within the brain. Many different types of brain tumors exist. Some brain tumors are

noncancerous whereas some brain tumorsare cancerous (malignant) and some are pre-malignant. Cancerous tumors can be divided into primarytumors that start within the brain, and secondary tumors that have spread from somewhere else, known as Brain Metastatis Tumor's.

Classification of Brain Tumor

There are two types of brain tumor. One is Benign Tumor characterized as non-cancerous and the other one isMalignant Tumor- also known as Cancerous Tumor.

Benign Tumor

Benign brain tumors are usually defined as a group of similar cells that do not follow normal cell division and growth, thus developing into a mass of cells that microscopically do not have the characteristic appearance of a cancer. These are the properties of a benign tumor:Most benign tumors are found by CT or MRI brain scans.

- Grows slowly, do not invade surrounding tissues or spread to other organs, and often have a borderor edge that can be seen on CT scans.
- It can be life threatening because they can compress brain tissues and other structures inside theskull, so the term 'benign' can be misleading

Malignant Tumor

Malignant brain tumors contain cancer cells and often do not have clear borders. They are consideredto be life threatening because they grow rapidly and invade surrounding brain tissues. These are the properties of a malignant tumor:

- Fast growing cancer that spreads to other areas of the brain and spine.
- A malignant brain tumor is either graded 3 or 4, whereas grade 1 or 2 tumors are usually classifiedas benign or non-cancerous.

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- Generally these are more serious and often more fatal threat to life

Benign Tumor (left) and Malignant Tumor (Right)

Objective

The main objective of our thesis is to build a model that can predict whether the medical images contain a tumor or not and find its properties. Primarily, dataset collection is the main task to work on a medical image because brain tumor dataset is scarce as well as very much complicated to acquire. Most of the researchers focused on definitive work like filter- ing, segmentation, feature selection or skull removing. Here we tried to establish a model which can accomplish all the fundamental and major necessary tasks to find a tumor and its properties. We proposed an efficient and effective method which helps in the segmentation and detection of the brain tumor without any human assistance, based on both traditional classifiers and Convolutional Neural Network. Finally, we compared all the experimental results to find out which model provides better performance in terms of accuracy, sensitivity and other performance metrics.

We carried out two types of classifications to detect the tumor. Tumor classification us-ing TraditionalMachine Learning classifiers and Convolutional Neural Network were carried out and comparison ofperformance measures was done between these two models.

A five-layer convolutional neural network is applied to the dataset which gives an improved result with respect to other research studies. The model is less complex as we detected the tumor using only five-layer CNN. In terms of training time and accuracy, the proposed CNN model gives a betterresult than most state-of-the-art works. The model is less complex as we detected the tumor using only five-layer CNN.

II LITERATURE REVIEW

In recent years, numerous and diverse types of work have been carried out in the field of medical image processing. Researchers from the various ground such as- computer vision, image processing, machine learning came into a place in the field of Medical Image Processing. We have studied some of the existing papers to find the most useful and advanced methods that were used in the existing articles in recent times. We worked on a total of 52 research articles. In this chapter, we will discuss thoroughly about these papers and their working procedures which are related to our work.

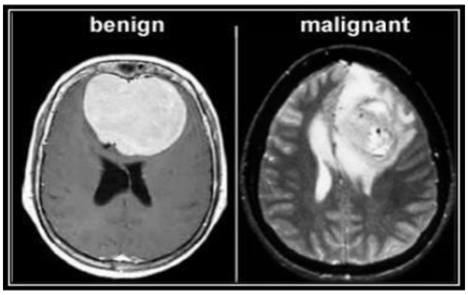
Reviews of the Related Papers:

Shehzad et al. proposed an algorithm to detect brain tumor from the MR images and calculate the area of the tumor. The designed algorithm claims to detect and extract the tumor of any shape, intensity, size, and location.

Working Approach:

MRI images are converted to gray-scale images. Gaussian low pass filter is used to blur the image and then the blurred image is addedto the original image. Median filter is used to remove noise. The morphological gradient is computed by dilation and erosion. Morphological gradient image and filtered image are added for image enhancement. The threshold value is calculated with the help of standard deviation and mean of the filter ed image. Image is binarized by comparing the threshold value with every pixel value of theimage. Erosion is done again for thinning the image and dilation is done again to get removed (caused by erosion) part of the tumor back. Tumor is extracted by comparing the original image with the dilated image. Erosion is done to shrink any noise remaining in the resultant tumor extractedimage. The area of the tumor is calculated.

Sankari et al. along with the other researchers came up with a model for cancer diagnosis for a brain tumor which is the toughest task. Most researches has been done in this field using



PCA, Route set theory and Wavelet method. The authors here used Convolutional neural networks to solve the problem.

Working Approach:

The bilateral filter is used to remove the noise from the MRI. Histogram Equalization is used for enhancing and feature extraction of the image. And finally CNN is used to classify the images.Boras et al. used computer-based procedures to detect tumor blocks and classify the type of tumor by using Artificial Neural network. They used MRI images for their training and testing stage

Working Approach:

High pass filter is used for noise removal and pre-processing. For segmentation, region growing method is used. After segmentation, every set of connected pixels having the same gray-levelvalues are assigned the same unique region label. Artificial Neural Network is applied for classification. K-means clustering technique could be a better option for pre-processing of the images.Erosion is done again for thinning the image and dilation is done again to get removed (caused by erosion) part of the tumor back. The tumor is extracted comparing the original image with the dilated image. Erosion is done to shrink any noise remained in the resultant tumor extracted image.Furthermore, we extended our study into some more recent articles and a thorough description is given by-

Devkota et al. established the whole segmentation process based on Mathematical Morphological Operations and spatial FCM algorithm which improves the computation time, but the proposed solution has not been tested up to the evaluation stage. It detects cancer with 92% accuracy and classifier has an accuracy of 86.6%. Yantao et al. resembled Histogram based segmentation technique. The brain tumor segmentation task as a three- class (tumor including necrosis and tumor, edema and normal tissue) classification problem regarding two modalities.FLAIR and T1. The abnormal regions were detected by using a region-based active contour model on FLAIR modality. The edema and tumor tissues were distinguished in the abnormal regions based on the contrast enhancement T1 modality by the k-means method and accomplished a Dice coefficientand sensitivity of 73.6% and 90.3%respectively.

III PROPOSED METHODOLOGY

Proposing a system performing detection and classification by using Deep Learning Algorithms using Convolution Neural Network (CNN), Artificial Neural Network (ANN), and Transfer Learning (TL). Application of automated classification techniques using Machine Learning(ML) and Artificial Intelligence(AI)has consistently shown higher accuracy.

Deep Learning

Deep Learning is a subset of machine learning algorithms that is very good at recognizing patterns but typically requires a large number of data. Deep learning excels in recognizing objects inimages as it is implemented using three or more layers of artificial neural networkswhere each layeris responsible for extracting one or more features of the image.

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Neural Network:

The basic building unit of neural networks are artificial neurons, which imitate human brain neurons. These artificial neurons are powerful computational units that have weighted inputsignals and produce an output signal using an activation function. These neurons are spread across the several layers in a neural network.

An artificial neuron (also called a unit or a node) mimics the biological neuron in structure and function The artificial neuron takes several input values with weights assigned to them Inside the node, the weighted inputs are summed up, and an activation functionis applied to get the results

A neuron has three parameters, namely:

Weight: When a signal (value) arrives, a neuron gets multiplied by a weight value.If a neuron has three inputs, it has three weight values which can be adjusted during training time.

Bias: It is an extra input to neurons and it is always 1, and has its own connection weight. This makes sure that even when all the inputs are none (all 0's) there is going to be an activation in the neuron.

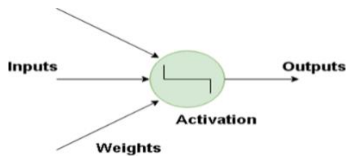

Fig 3.1 Basic structure of a neuron.

A Neural Network(NN) is made of several neurons stacked into layers. For ann-dimensional input,the first layer (also called the input layer) will have n nodes and the t-dimensional final/output layerwill have t neural units. All intermediate layers are called hidden layers, and the number of layers ina network determines the depth of the model. The Figure below shows a 3–4–4–1 NN.

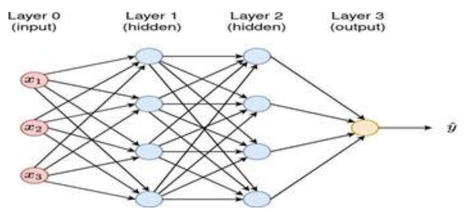

Figure 3.2: A Neural network

Using Neural Networks for Images

Neural network can be used to recognize or detect object category but it will require more works to uniquely identify an object. A classical neural network requires to input a set of features extracted from each of the image. Deep neural network (DNN) works with image pixels

Types of Neural Networks

There are several kinds of artificial neural networks. These type of networks are imple- mented basedon the mathematical operations and a set of parameters required to determinethe output. Some of thepopular neural networks are

Feedforward Neural Network: This neural network is one of the simplest forms of ANN, where the data or the input travels in one direction. The data passes throughthe input nodes and exit on

the output nodes. This neural network may or may not have the hidden layers. In simple words, it has a front propagated wave and no back propagation by using a classifying activation function usually.

Radial Basis Function Neural Network: Radial basis functions consider the distance of a point withrespect to the center. RBF functions have two layers, first where the features are combined

with the Radial Basis Function in the inner layer and then the output of these features are taken into consideration while computing the same outputin the next time-step which is basically a memory.

Convolutional Neural Network: Convolutional neural networks are similar to feed forward neural networks, where the neurons have learn-able weights and biases.

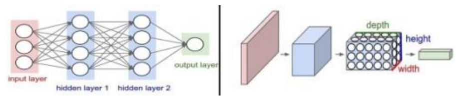

Fig: 3.3 A simple neural network and A Convolutional Neural Network

Convolutional Neural Network

The basic idea of Convolutional Neural Network was introduced by Kunihiko Fukushima in 1980s .Convolutional Neural Networks (ConvNets or CNNs) are a category of Neural Networks that have proven very effective in areas such as image recognition and classifica- tion. Computer vision techniques are dominated by convolutional neural networks because of their accuracy in image classification. CNN is a class of deep, feed-forward artificial neu- ral networks

Every layer of a CNN transforms the 3D input volume to a 3D output volume of neuron activation's.In this example, the red input layer holds the image, so its width and height would be the dimensions of the image, and the depth would be three (Red, Green, Blue channels).

Operation:

Convolutional Neural Networks perform a mathematical operation, known as convolution operation. Convolution is a mathematical operation ontwo functions (f and g) and it produces a third function.

$(f * g)(t) = (r)(t-r)dr$

There are three elements that enter into the convolution operationInput image: It is the image that is given as an input.

Feature detector: The feature detector is often referred to as a "kernel" or a " filter". Sometimes a5*5 or a 7*7 matrix is used as a feature detector feature map: The feature map is also known as an activation map. It is called feature map because it is also a mapping of where a certain kind of feature is found in the image.

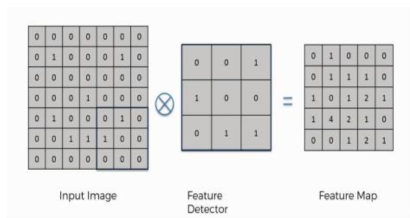

Fig: 3.4Convolution Operation

Convolution Arithmetic:

Back-propagation for Convolutional Layer: In back-propagation, the cost function is first found out, thenthis cost function measures the displacement with the output. After that, applying gradient descent on this function will update the filter value of the previous layer. This process continuesuntil it reaches to the input layer.Layer's Used to a Build CNN Model: A simple CNN is a sequence of layers, and every layer of a Activation Function: Activation functions are used to introduce non-linearity to neural networks. It squashes the values in a

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smaller range. For example, a sigmoid activation function squashes values between a ranges 0 to 1.

Fig: 3.5 Before(left) and after(right) applying activation function

FlowChart:

Flow Chart

CONVOLUTIONAL NEURAL NETWORK:

Convolutional Neural network is broadly used in the field of Medical image processing.Over the years lots of researchers tried to build a model which can detect the tumor more efficiently.It is a class of deep neural networks which is applied to interpreting visual imagery. A fully-connectedneural network can detect the tumor, but because of parameter sharing and sparsity of connection, weadopted the Convolutional Neural Network (CNN) for our model. A Five-Layer Convolutional Neural Network is introduced and implemented for tumor detection

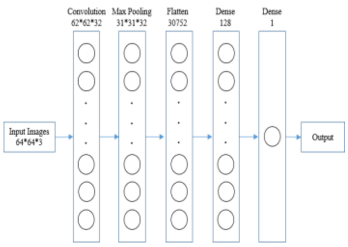
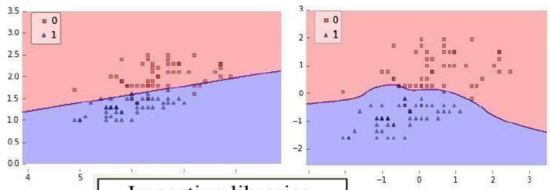


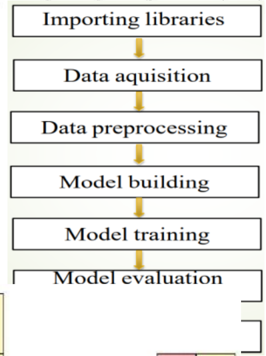
Figure 3.7: Proposed Methodology for Brain tumor detection using 5-Layer ConvolutionalNeural Network

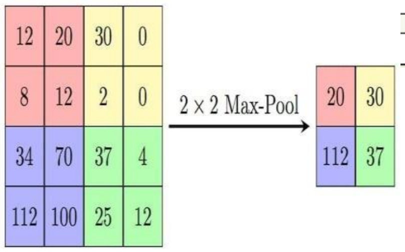
Convolutional Layer

A Convolutional layer is the core building block of a CNN model. Using convolutional layeras the opening layer, an input shape of the MRI images is generated which is 64*64*3, converting all the images into a same dimension. After accumulating all the images in the same aspect, we created a convolutional kernel that is convoluted with the input layer administering with 32 convolutional filters of size 3*3 each with the support of 3 channels tensors. Rectified Linear Unit (ReLU) is used as an activation function.

The input volume has size 64*64*3 which means 64 pixels width, 64 pixels height, depth of3 and the filter size is 3*3. Then each neuron in the Convolutional Layer will have weightsto a 3*3*3 region in the input volume, for a total of 3*3*3 = 27







weights and one will be added for bias parameter. There are three hyper parameters which we will evaluate and those are- depth, stride and zero-padding. For our model, the input volume size is 64*64*3, filter size is 3*3 so the spatial extent or filter size is 3.

Max Pooling Layer: The main focus of pooling layer is to progressively reduce the spatial size of the represen- tation in order to reduce the number of parameters and computational task in the network. It can control over-fitting because it can scale down the parameters. Using the max pooling layer, it can operate independently on every depth slice of the input and resizes it spatially.

Fig 3.8 Max Pooling Layer

Flatten layer:

After the pooling layer, a pooled feature map is obtained. Flatten layer is one of the essential layers after the pooling because we have to transform the whole matrix representing the input images into asingle column vector and its imperative for processing. It is then fed to the Neural Network for the processing. The dimension of this layer is 31*31*32 = 30752.

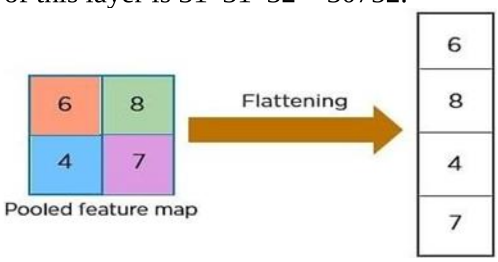


Fig 3.9 Flatten layer

There are 128 nodes in the hidden layer. Because the number of dimension or nodes pro- portional with the computing resources we need to fit our

```
In [21]: # Build VGG16 structure
cnn_base = VGG19(weights='imagenet',
                 include_top=False,
                 input_shape=(228, 228, 3))
print('VGG19 Loaded')
print(cnn_base.summary())
```

model we kept it as moderate as possible and for this perspective 128 nodes gives the most substantial result. ReLU is used as the activation function because of showing better convergence performance.

```
In [25]: # Specify dataset size
batch_size = 16
nb_train_samples = 2084
nb_validation_samples = 167
nb_test_samples = len(os.listdir('data/test/tree')) + len(os.listdir('data/test/not_tree'))
```

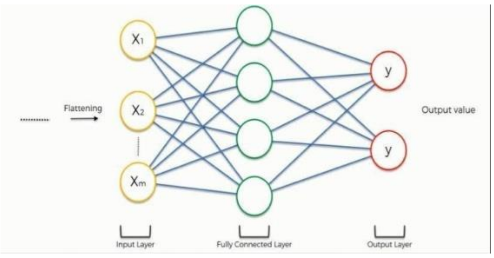


Fig 4.0 Fully Connected layer

In a nutshell, we have a five-layer CNN model by which we can detect a tumor from an MRI image. The entire working flow of the five-layer CNN

```
In [26]: # Build extraction function to get features and labels
def extract_features(directory, sample_amount):
    features = np.zeros(shape=(sample_amount, 7, 7, 512))
    labels = np.zeros(shape=(sample_amount))
    datagen = ImageDataGenerator(rescale=1./255)
    generator = datagen.flow_from_directory(
        directory, target_size=(228, 228),
        batch_size = batch_size,
        class_mode='binary')

    i = 0
    for inputs_batch, labels_batch in generator:
        features_batch = cnn_base.predict(inputs_batch)
        features[i * batch_size : (i + 1) * batch_size] = features_batch
        labels[i * batch_size : (i + 1) * batch_size] = labels_batch
        i = i + 1
        if i * batch_size >= sample_amount:
            break
    return features, labels
```

model is illustrated in figure-3. First, wehave to load the input dataset and all the images should be identical in size in the input image. After the input layer, we introduced a Convolution layer with 32 convolutional fil- ters along ReLU as an activation function..

VGG 19

TheVGG is abbreviation for Visual Geometry

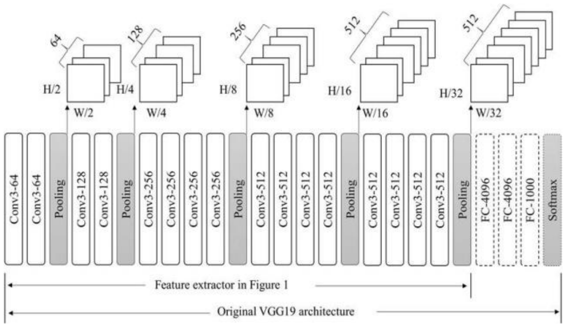
```
In [27]: # Apply extraction function to 3 datasets
train_features, train_labels = extract_features(train_folder, nb_train_samples)
validation_features, validation_labels = extract_features(val_folder, nb_validation_samples)
test_features, test_labels = extract_features(test_folder, nb_test_samples)
```

Group Net was used in CNN that has approximately143 million parameters, these parameters are learnt using ImageNet dataset comprising of 1. 2 millionimages which contains thousands of classes for training. It is very good architecture used for benchmarking. The VGG-19 Neural Network consists of 19 layers of deep neural network and has more weight. The size of "VGG-19" network in terms of fully connected nodes is 574 MB. As the number of layer increases, accuracy of DNN is improved. The VGG

Vgg-19 model comprised of 19 deeptrainable layers performing convolution, which is fully connected Below is an 8 step configuration of my best performing VGG19 model. VGG19 is an advanced CNN with pre-trained layers and a great understanding of what defines an image in terms of shape, color, and structure.

Load your model.

Load your data set size. In this case, the photos designated for training, testing and validation have already been randomly shuffled into different folders and manually separated between those with (target = 1) and without trees (target = 0).




```
In [29]: # Save features and labels
os.mkdir('data/bottlenecked')
np.save('data/bottlenecked/train_features.npy', train_features)
np.save('data/bottlenecked/train_labels.npy', train_labels)
np.save('data/bottlenecked/validation_features.npy', validation_features)
np.save('data/bottlenecked/validation_labels.npy', validation_labels)
np.save('data/bottlenecked/test_features.npy', test_features)
np.save('data/bottlenecked/test_labels.npy', test_labels)
```

Fig 5.7 VGG 19 Architecture

Set up a function to extract and freeze the VGG-19's initial layers which process the features and labels of images under the hood. This will allow the model to apply transfer learning wherein it can recall its pre-training from millions of photos on the web.

Apply the function to your training, validation & test datasets so it extracts the features and labelsfrom all of them

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```
In [30]: # Build classifier on top of  VGG19
model = Sequential()

# Add dense layers on top of VGG19
# 1
model.add(Dense(256, activation='relu', input_dim=reshape_y))
# 2
model.add(Dense(1, activation='sigmoid'))

# Compile
model.compile(optimizer=optimizers.RMSprop(lr=1e-4),
              loss='binary_crossentropy',
              metrics=['acc'])

history = model.fit(train_features, train_labels,
                    epochs=20,
                    batch_size=16,
                    validation_data=(validation_features, validation_labels))

# Save VGG19 results
model.save('models/model_VGG_01.h5')
```

Make sure data is in the right shape to reflect the dimensions of your datasets.

Save extracted features and labels into a 'bottlenecked' folder for your final classifying layer to referto and conclude which binary category an image belongs toBuild the image classifier final layer on top of the VGG-10 "brain" and put it to work.

To visualize how well your model learned using your accuracy and loss metrics, print your traininghistory. As you can see, with each epoch (or iteration), our accuracy increase and loss decreased.

```
In [31]: # Print training history
pd.DataFrame(history.history).plot(figsize=(5, 5))
plt.title('Pre-Trained Training Performance')
plt.xlabel('Epoch')
plt.ylabel('Metric')
plt.show()
```

ResNet-50 Model:

ResNet stands for Residual Network and is a specific type of convolutional neural network (CNN) introduced in the 2015 paper "Deep Residual Learning for Image Recognition" by He Kaiming, Zhang Xiangyu, Ren Shaoqing, and Sun Jian. CNNs are commonly used to power computer vision applications

ResNet-50 Architecture

The original ResNet architecture was ResNet-34, which comprised 34 weighted layers. It provided anovel way to add more convolutional layers to a CNN, without running into the vanishing gradient problem, using the concept of shortcut connections. A shortcut connection "skips over" some layers,converting a regular network to a residual network.The regular network was based

VGG neural networks (VGG-16 and VGG-19)—each convolutional network had a 3×3 filter. However, a ResNethas fewer filters and is less complex than a VGGNet
Special characteristics of ResNet-50
ResNet-50 has an architecture based on the model depicted above, but with one important difference.

The 50-layer ResNet uses a bottleneck design for the building block. A bottleneck residual block uses 1×1 convolutions, known as a "bottleneck", which

```
In [27]: # Apply extraction function to 3 datasets
train_features, train_labels = extract_features(train_folder, nb_train_samples)
validation_features, validation_labels = extract_features(val_folder, nb_validation_samples)
test_features, test_labels = extract_features(test_folder, nb_test_samples)
```

reduces the number of parameters and matrix multiplications.
The 50-layer ResNet architecture includes the following elements, as shown in the table below

```
In [28]: # Shape data
reshape_y = 7 * 7 * 512
train_features = np.reshape(train_features, (nb_train_samples, reshape_y))
validation_features = np.reshape(validation_features, (nb_validation_samples, reshape_y))
test_features = np.reshape(test_features, (nb_test_samples, reshape_y))
```

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig 5.8 50-layer ResNet Architecture

```
In [31]: # Print training history
pd.DataFrame(history.history).plot(figsize=(5, 5))
plt.title('Pre-Trained Training Performance')
plt.xlabel('Epoch')
plt.ylabel('Metric')
plt.show()
```

A 7×7 kernel convolution alongside 64 other kernels with a 2-sized stride.

A max pooling layer with a 2-sized stride.

9 more layers—3×3,64 kernel convolution, another with 1×1,64 kernels, and a third with1×1,256 kernels. These 3 layers are repeated 3 times.
12 more layers with 1×1,128 kernels, 3×3,128 kernels, and 1×1,512 kernels, iterated 4 times.

18 more layers with 1×1,256 cores, and 2 cores 3×3,256 and 1×1,1024, iterated 6 times.

9 more layers with 1×1,512 cores, 3×3,512 cores, and 1×1,2048 cores iterated 3 times.

IV. RESULTS AND DISCUSSION

1. sample image

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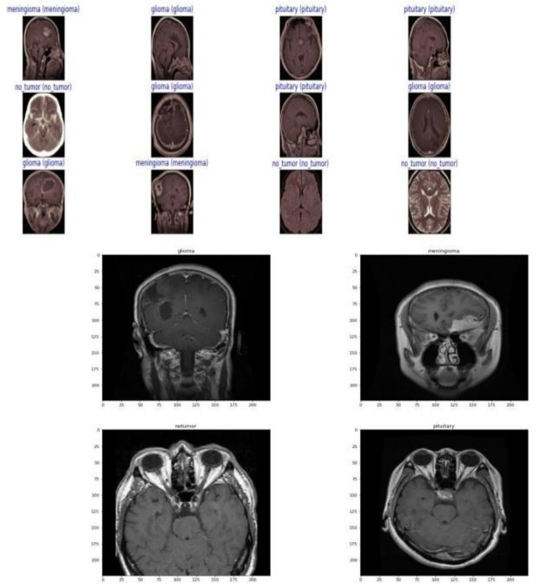


Fig4.1: sample image

2. croppedimage

Fig4.2: croppedimage

3. Split Data

Fig: 4.3 Split Data

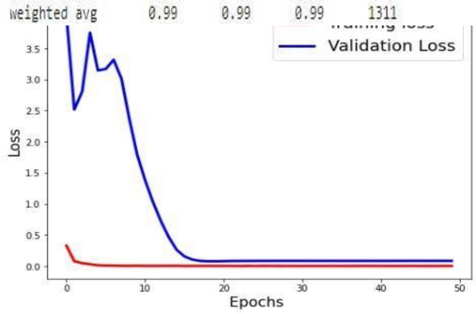
4. AugementedImage

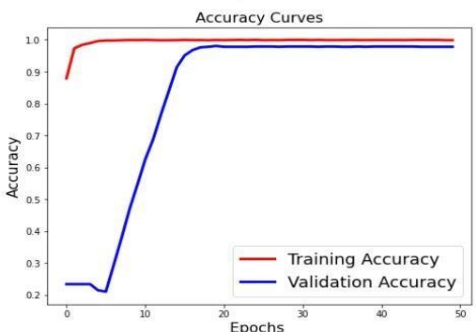
Fig: 4.4 AugementedImage

5. DataLengths

Fig 4.5 DataLengths

	precision	recall	f1-score	support
glioma	0.99	0.97	0.98	300
meningioma	0.97	0.99	0.98	306
no_tumor	1.00	1.00	1.00	405
pituitary	1.00	1.00	1.00	300
accuracy			0.99	1311
macro avg	0.99	0.99	0.99	1311
weighted avg	0.99	0.99	0.99	1311





6. Trainingresults

Fig 4.6 Training Results

7. GraphicalResult

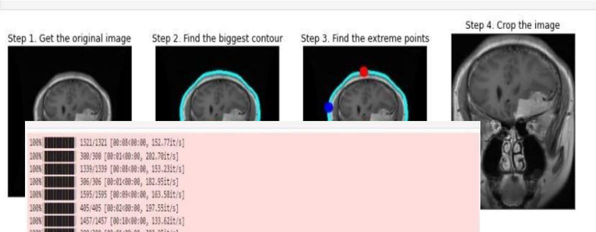
Fig 4.7 Graphical Result

8. PredictedResults

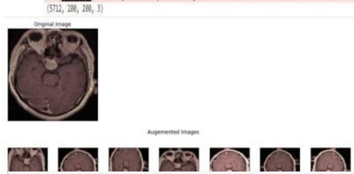
Fig 4.9 Predicted Results

V. Conclusion and Future scope:

Performance analysis of brain tumor detection from MR imaging using basic image processing techniques based on various hard and soft computing has been performed in our work. we applied CNN for brain tumor detection to include deeplearning method in our work. We compared the result of the traditional one. Furthermore, our work presents a generic methodof tumor detection and extraction of its various features.




```
100%|██████████| 1321/1321 [00:08<00:00, 152.77it/s]
100%|██████████| 300/300 [00:01<00:00, 202.70it/s]
100%|██████████| 1339/1339 [00:08<00:00, 153.23it/s]
100%|██████████| 306/306 [00:01<00:00, 182.95it/s]
100%|██████████| 1595/1595 [00:09<00:00, 163.58it/s]
100%|██████████| 405/405 [00:02<00:00, 197.55it/s]
100%|██████████| 1457/1457 [00:10<00:00, 133.62it/s]
100%|██████████| 300/300 [00:01<00:00, 202.25it/s]
(5712, 200, 200, 3)
```




```
train_len = len(x_train)
val_len = len(x_val)
print("----------Training Data Length--------------")
print(train_len)

print("----------Validation Data Length--------------")
print(val_len)
```

```
----------Training Data Length--------------
4569
----------Validation Data Length--------------
1143
```

In the context of the full dataset, it is necessary to parallelize and utilize high-performance computing platform for maximum efficiency. We tried our best to detect the tumors accurately. So, we will try to work on those images and on the complete dataset. Hence, we apply other deep learning methods and classifiers, those are VGG-19 and ResNet 50.

VI. Future Scope

There are more opportunities for improvement or research on our work in the future.

- Firstly, the number of images can be increased. The bigger the number of the imagesis, the better the model is trained.

i. Secondly, we want to work

on 3D images in future.

ii. Thirdly, more traditional classifiers can be applied to get more increased accuracy.
iii. Fourthly, we will try to classify the tumor if its benign or malignant after the detectionof the tumor.
iv. Last but not the least, more variations of deep learning methods can be tested in future.

VII . References

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