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Brain Tumor Detection Using Deep Learning

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Abstract

On a global basis, brain tumors rank among the leading death factors. Because of its complexity and calm nature, this disease is challenging to diagnose in its early stages. Several types of cells give birth to brain tumors, and these cells can provide information on the type, severity, and rarity of tumors. Tumors can develop in a variety of places, and the location of a tumor may reveal information about the sort of cells that are generating it, assisting with further diagnosis. This paper suggests an innovative method to identify and segment tumor from the MRI images using Deep Learning. We used 3 pre-trained models for training our dataset of brain tumors they are ResNet50, VGG16 model 1 and VGG16 model 2. Afterward, we used Convolutional Neural Network (CNN). In our work, among all implemented models ResNet50 acquired an accuracy of 98.88%, which is really compelling. Its accuracy will help with brain tumor identification and prevention at early stages before the tumor results in any physical side effects.

Keywords: Brain Tumor, MRI, CNN, Deep Learning, ResNet50, VGG16.

Introduction

An abnormal cell growth that has developed in the brain is known as a Brain Tumor. However, while not all brain tumors are malignant (cancerous), some are benign (non-cancerous). The brain controls the bulk of physical functions, including consciousness, movement, sensation, cognition, speech, and memory.The brain's capacity to operate normally and effectively while doing such tasks might be compromised by a tumor. Brain tumors develop when genetic alterations occur in or close to brain cells and by exposure to radiation. Brain metastases or secondary tumors can also develop in the brain in addition to primary cancers. The tumor first appeared elsewhere in the body at this point and then metastasized to the brain. Breast, kidney, lung, leukaemia, lymphoma, and melanoma cancers are the most typical tumors that spread to the brain.In 2020, it is anticipated that 308,102 individuals will receive a primary brain or spinal cord tumor diagnosis worldwide.

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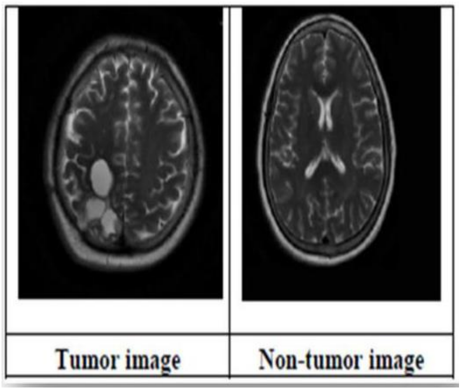

Fig.1. Tumor and Non-Tumor Images

Computer-aided disease diagnosis has recently gained popularity and is assisting doctors in making quick decisions. We have introduced a cutting-edge approach for MRI image-based brain tumor detection in this study.

We developed 3 pre-trained models: Resnet50, VGG16 model 1, VGG16 model 2, and one CNN model. Based on performance we considered Resnet50 model for classification and ResUNet model for Segmentation of tumor. We developed a photo-accepting graphical user interface (GUI) expert system that takes MRI image as input and predicts whether the MRI contains tumor or not. If MRI image contains tumor then, then the mask of the MRI is obtained.

There is no doubt that this project will help with early detection and classification of brain tumours. Further, operations can be carried out on patients of all types at a cheaper cost. The majority of hospitals will see a slowdown in healthcare inflation, less waste, higher productivity, and consequently cheaper production costs.

Literature Survey

Ahmad Saleh, Rozana Sukaik, Samy S. Abu-Naser used CNN, Deep Learning, and AI algorithms to categorize and identify different forms of brain tumors.They gathered dataset from Kaggle.They have trained their dataset using 5 pre-trained models: InceptionV3, ResNet50,Xception, MobileNet and VGG16 resulted in accuracies of 98.00%, 98.50%, 98.75%, 97.25% and 97.50% respectively [1]

Fakhri lahmood HAMEED, Omar DAKKAK developed a system to detect brain tumor utilizing deep learning Convolutional Neural Networks feature extraction technique.Techniques like Grayscale, Resize, and Power Transform are used to process the image samples.They achieved detection accuracy of 92.78% [2].

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Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf,MD Abdullah Al Nasim, Faisal Muhammad Shah developed two different models for segmentation and identification of Brain tumor. The very First model segmented the tumor using Fuzzy C-Means clustering and classified using traditional ML algorithms. The other model concentrated on CNN for the tumor identification. They used BRATS dataset. Six traditional classifiers namely KNN, SVM, Logistic Regression, Multilayer Perceptron, Naïve Bayes and Random Forest resulted in accuracies of 89.39%, 92.42%, 87.88%, 89.39%, 78.79%, 89.39% This study got 97.87% as accuracy using five-layer CNN [3].

Nadim Mahmud Dipu, K. M. A. SalamShohan, K. M. A. Salam developed two methods based on deep learning for classifying and detecting brain tumors. YOLO, a cutting-edge object identification framework, and FastAi, a deep learning package, respectively. With the aid of the FastAi V2 library, the MRI scans were classified. The accuracy of the CNN-based classification model was 95.78%, and the YOLOv5-based detection model was 85.95% accurate[4].

S. K. Shil, F. P. Polly,M. A. Hossain, M. S. Ifthekhar, M. N. Uddin and Y. M. Jang presented a scheme for brain MRI's. They performed pre-processing, post processing and classification on images. They used binarization proceeded by K means algorithm for the segmentation. Discrete Wavelet Transform followed by Principal Component Analysis are used to obtain features and reduce the dimensions of features. The condensed features are delivered to SVM for the classification.This method had a 99.33% classification accuracy, a 99.17% sensitivity, and a 100% specificity [5].

Problem Identification

Brain tumors typically results in significant damage to arteries and nerves that can be recognized and detected. These illnesses, which are frequently referred to as the worst diseases, can cause people a great deal of injury and suffering. Brain tumors acts as filters, eliminating waste products from the blood. In certain situations, it decomposes, and become unable to distinguish between nutrients, leading to brain tumor nephropathy.Hence, for the automated brain tumor illness perdition, a robust and stable system is required. [6-14]

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Methodology

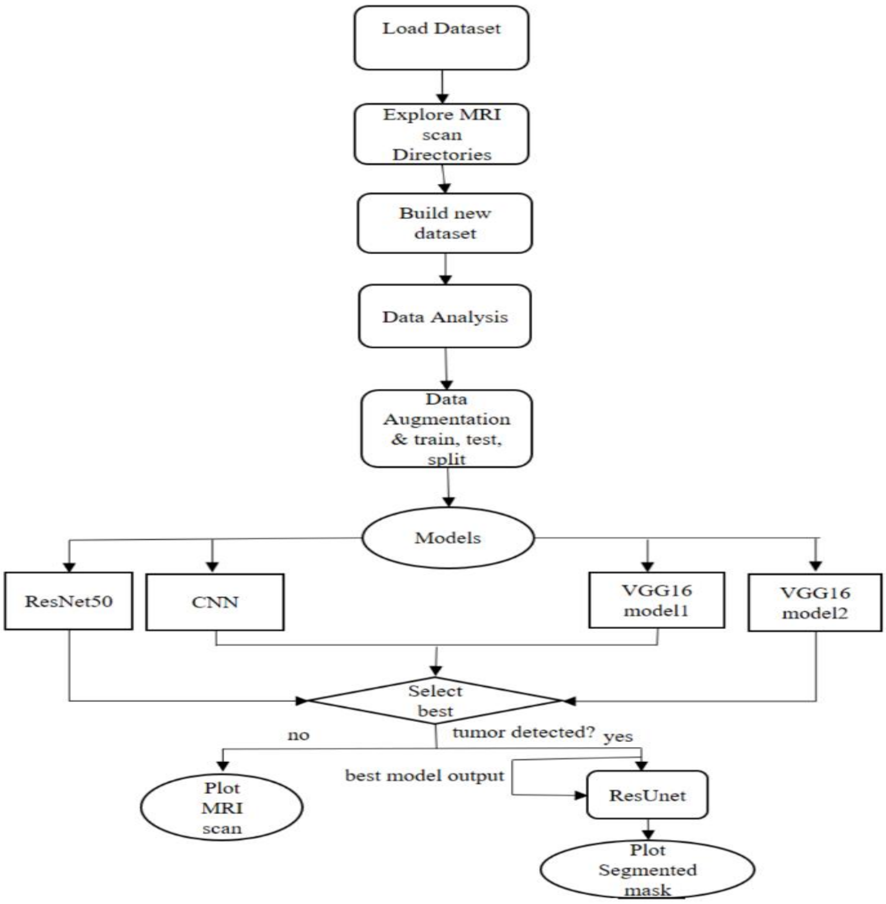
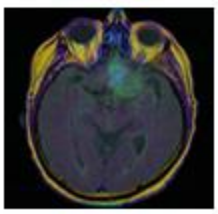


Fig.2. Workflow Diagram

A. Dataset

"Brain MRI segmentation" dataset is used from Kaggle which contains brain tumor images and their respective masks. There are 2118 images for training, 907 images for validation and 904 images for testing belonging to 2 classes. In order to increase the amount of data we performed data/image augmentation by using Image Data Generator.



The MRI Image 1

The mask of MRI 1

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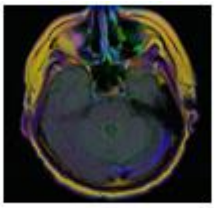

The MRI Image 2 The mask of MRI 2

Fig.3. Dataset Images

B. Training and building models

1. Resnet50:

ResNet-50 is 50 layers deep and it was created by Kaiming with the intention of residual learning, which can easily have interpreted as the derivation of input properties from a particular layer. ResNet may accomplish this by directly linking, input of the kth layer to the (k + x)th layer using shortcut acquaintances for each pair of 33 filters. By re-using actions from the earlier layer until next layer have learned its weights, problematic vanishing gradients are kept missing by intentionally avoiding layers.

2. VGG16:

VGG16 is a deep CNN architecture. The architecture has 16 layers, the first 13 of which are used for convolution and pooling operations, and the remaining three of which are fully connected layers. Typically, an image with dimensions of (224x224x3) is used as the network's input for image classification tasks. Many convolutional layers with kernel sizes of 3x3 and a stride of 1 process this image. Max-pooling layers with a window size of 2x2 and a stride of 2 are fed this result.

The final three layers of the VGG16 design are three fully connected layers. In the first two completely connected layers, Rectified Linear Unit (ReLU) activation function is used, and in the third layer, SoftMax activation function.

3. CNN:

Convolutional neural networks, also known as CNNs or Convent, represent a class of neural networks that excel at handling input having a grid-like layout, such as photos.A digital image is a representation of binary visual data.It has several pixels that are organized in a grid-like pattern and are each given a value to specify how bright and what hue they should be.Convolutional, pooling, and fully connected layers make up the conventional architecture of a CNN. The CNN's fundamental building block is the convolution layer.

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4. ResUNet:

To solve the vanishing gradient issue that deep architecture has, ResUNet design combines UNET backbone architecture with residual blocks. ResUNet consists of three sections –

Encoder: Each block in the contraction path accepts an input, passes it through res-blocks, and then proceeds to 2x2 max pooling. After each block doubles, the feature maps.

Decoder: Each block in the decoder concatenates the matching output features from the res-block with the up-sampled input from the previous layer in the contraction path. the res-block and 2x2 up-sampling convolution layers are then applied after this.

*Bottleneck:*Between the contraction path and the expansion path, the bottleneck block acts as a connector. After receiving the input, the block runs the 2 x 2 up-sampling convolution layers followed by a res-block.

C. Evaluation metrics

A few parameters are calculated and looked at in order to evaluate performance and gauge system stability. They are listed as:

$$Accuracy = tp+tn/tp+tn+fp+fn$$

$$Recall = tp/tp+fn$$

$$Precision\ metric = tp/tp+fp$$

Implementation

A. Loading Dataset

Loading “Brain MRI Segmentation” dataset downloaded from Kaggle using pandas includes 3930 brain MRI scans in“.tif” format, together with details on the individuals and the locations of their brain tumors.

B. Data Preparation

Before we used our dataset for training we have done data/image augmentation. More data can help our model to give better performance. Image Augmentation is a technique used to add a little-changed copies of either available data or using existing data to create new data to enhance the amount of the data. Our data-set has 3930 images; thus we need to expand it. ImageDataGenerator produces variations internally, which consumes very little time and memory.

C. Building models

1. *Resnet50*

To the pre-trained model we have added additional layers such as AveragePooling2D with pool-size (4,4), followed by a flatten layer, then a layer called dense of 256 units having a

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ReLu activation funtion, again a layer called dense having 128 units with ReLu as the activation function, then a layer of dropout having frequency rate of 0.3, and the final fully connected layer of 2 units with SoftMax as a activation function. The model was compiled using categorical_crossentropy as loss function and optimizer as adam.

After training on 100 epochs, the Renet50 model gave an accuracy of 98.88%.

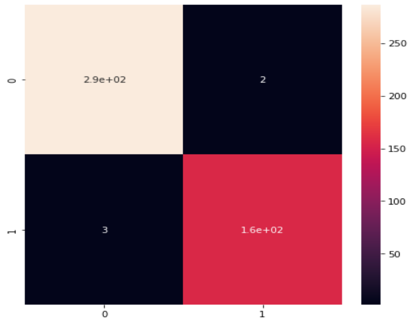

Fig.4. Confusion matrix for ResNet50 model

2. VGG16 model1

In this model we have added one flatten layer, followed by one dense layer with the 128 units having a ReLu as the activation and lastdense layer with 2 units having the SoftMax as activation function to the existing pretrained model. The model was compiled using categorical_crossentropy as loss function and optimizer as adam. After training on 20 epochs it gave an accuracy of 82.14%.

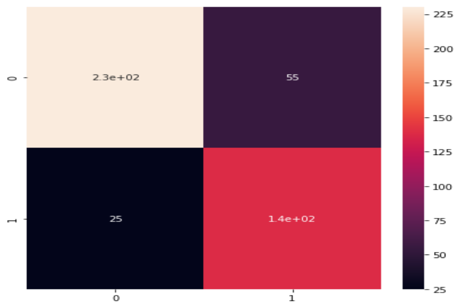

Fig.5. Confusion matrix for VGG16 model 1

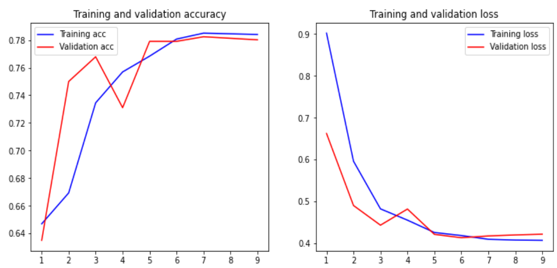

Fig.6. Accuracy and Loss graphs of training and validation

3. VGG16 model2

In this model we have added one average pooling2D layer having pool-size of (4,4), one flatten layer, 3 dense layers with ReLu as activation function ,2 dropout layers with frequency rate as 0.3 and 0.1 and finally one fully connected layer with the 2 units having SoftMax as the activation function to existing pretrained model. The model was compiled using theloss function, and optimizer as adam.

After training on 20 epochs the model gave an accuracy of 83.03%.

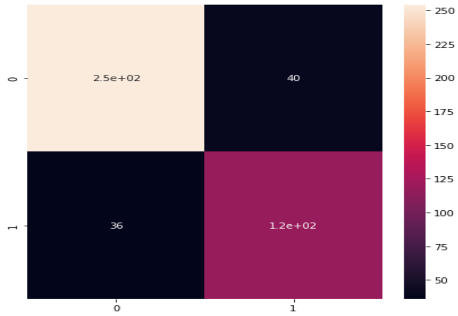

Fig.7. Confusion matrix for VGG16 model 2

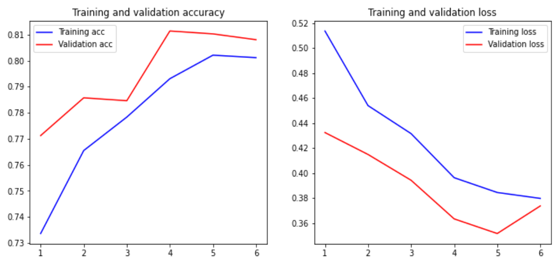

Fig.8. Accuracy and Loss graphs of training and validation

4. CNN model

We built CNN model by adding layers like Conv2D layer with kernel size (3,3) with ReLu as the activation function, followed by MaxPooling2D with pool-size (2,2) then a dropout layer with frequency rate 0.2. Again repeated these three layers for two times, and finally added one flatten layer, two dense layers with units 128 and 2, having ReLu and SoftMax as activation functions.

By training the model for 20 epochs, it gave an accuracy of 88.61%.

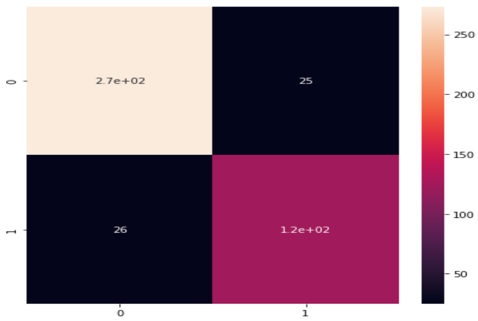

Fig.9. Confusion matrix for CNN model

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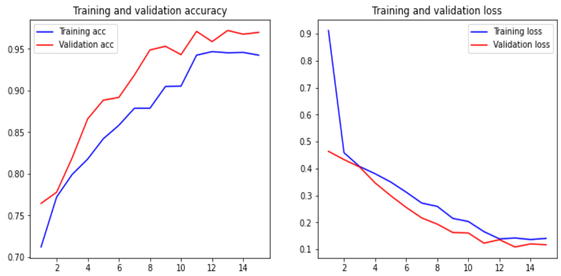

Fig.10. Accuracy and Loss graphs of training and validation

D. Pixel Segmentation

The images are segmented using CNN, With the least amount of pre-processing necessary, it immediately extracts characteristics from pixel pictures. The network used is called ResUnet. The encoder and decoder blocks in the ResUnet Network effectively separated and rebuilt the picture before it was transmitted via a few final convolutional layers. CNN is an important deep learning technique that is used in image recognition applications.

It uses the two fundamental techniques of convolution and pooling. Layers for convolution and pooling are constructed to obtain high classification accuracy. Moreover, only a small number of feature maps are found in each convolutional layer, and weights associated with convolutional nodes (in the same map) are shared. Such configurations enable understanding of diverse network properties while preserving the number of traceable parameters. Compared to conventional approaches, CNN performs less specialized jobs and aids in comprehensively extracting characteristic. The accuracy of ResUnet segmentation model is 85.85%.

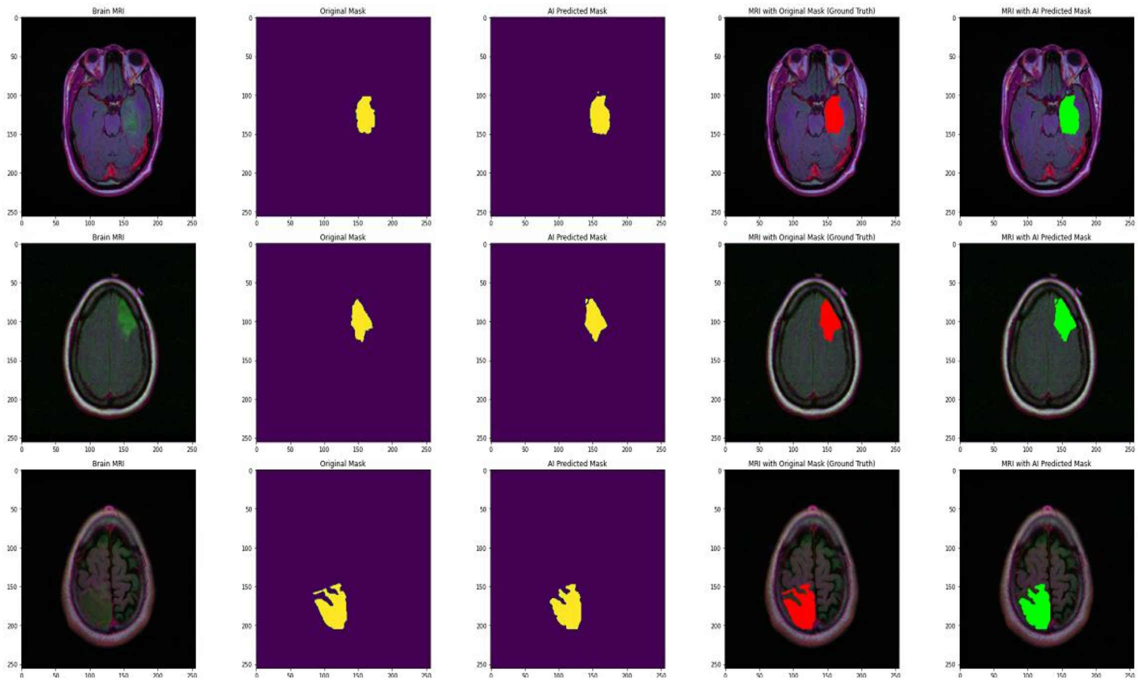

Fig.11. MRIs with original mask, predicted mask by ResUNet model

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Results and Conclusion

Model Name	Accuracy	Recall	Precision
CNN	88.61	88.61	88.61
VGG16 Model 1	82.14	82.14	83.14
VGG16 Model 2	83.03	83.03	83.03
ResNet50	98.88	98.88	98.88

Table.1. Results

Among all implemented models ResNet50 gave highest accuracy of 98.88%. Hence we developed a Graphical User Interface using Flask server by considering ResNet50 model for classification and ResUNet model for Segmentation of tumor.

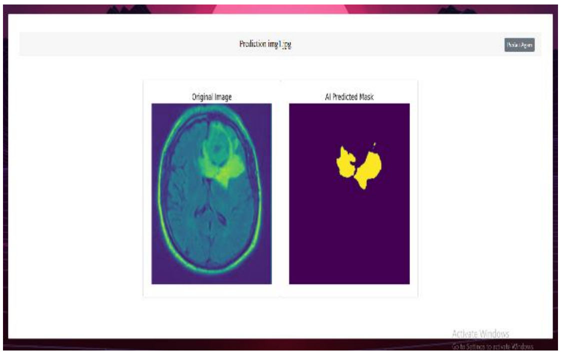

Fig.12. the predicted output for uploaded MRI image.

In this study, we suggested a novel ResNet50-based system that can distinguish between different Brain MRI images and label them as tumorous or not.Several images are subjected to the suggested method, and the most desirable and efficient results are obtained.

Future Scope

The future work can concentrate on reducing processing time and more trustworthy features can be discovered for classifying types of tumors like benign and malignant.

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