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An Efficient Brain Tumor Classification And Segmentation Using Deep Learning Features For ML Algorithms

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ABSTRACT

Brain tumor is a highly aggressive and life-threatening disease; this leads to a very short duration of life to patients when at higher stages. However, early detection of tumors can be cured and extend the life of patients. The early detection of tumor in the brain Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scan images are more challenging as it needs careful study. The proposed work used MRI images for diagnosing brain tumor through binary classification as tumor or non-tumor images through deep learning algorithm, Convolutional Neural Network (CNN) model is used for feature extraction from images. The pre-trained architecture VGG16 is used for feature extraction from the images. These features are used for training and validating Machine learning algorithms and comparing their performance. When the tumor results in the classification of image, the work also implements segmentation of tumor from the brain MRI images to detect the tumor in a given image using image processing techniques. The proposed work performs brain tumor classification, detection as well as segmentation. The application is developed as a web application, which is useful for users to get the results quickly and accurately through the proposed novel technique. Experimental results show that the proposed work has achieved the highest accuracy of 91.6% with a logistic regression model.

Keywords: *Computer Tomography (CT) Scan, Image classification, Deep learning, VGG16, Feature extraction, Convolutional Neural Network (CNN), Image processing, segmentation.*

1. INTRODUCTION

Cancer is a life-threatening disease, according to the World Health Organization (WHO), cancer is the second most common cause of human mortality. Early detection of disease can increase the life for patients; however, early detection is more challenging. Brain tumor is generally classified as benign and malignant types, benign is the detection at early stage, thus spread among the nearest tissue can be avoided through surgery, whereas malignant is next stage. There are different types of diagnostic methods available including MRI and CT scan images. Considering the availability of human specialists at all times, it is difficult to get the results early due to scarcity of experts/specialists. Other types of tumor has the option for taking and diagnosing through biopsy, whereas the brain tumor have no option and only brain surgery is made when tumor is identified. Thus, the MRI or CT scan images are used for diagnosis and this needs to be automated to get an effective tool, which can accurately diagnose tumor.

Artificial intelligence is used in many industries from finance, education, healthcare, manufacturing, retail and more. Exploring artificial intelligence technique in health care industry is huge nowadays, and it highly significant to medical imaging. Medical imaging uses MRI or CT scan images widely by the physician for diagnosis. Machine learning and deep learning are the techniques has been widely used for disease diagnosis. Deep learning algorithms are more preferable as they can extract the features automatically.

As the brain is the central part of the nervous system, the tumor may occur due to abnormal tissue growth and to be carefully examined. Manual examination of MRI images for identifying tumor segmenting is more challenging considering the smaller number of industry experts available. Thus, the automated system is required for brain tumor detection and segmentation. Existing works involved tumor classification as benign and malignant through machine learning and deep learning techniques. The ML and DL techniques are more effective than any other computational models. However, the Machine learning algorithms find difficulty in the extraction of features from images and using it, thus the external techniques for feature extraction are required. Thus, the deep learning algorithm, which has the capability of extracting features automatically from the given brain MRI images are preferred.

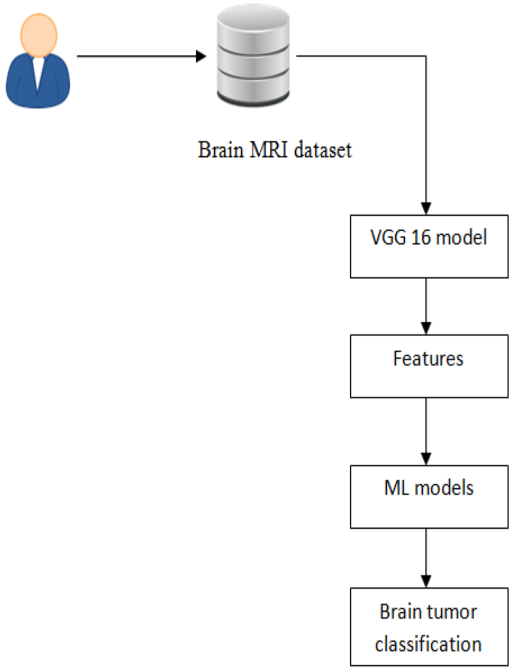

Fig. 1. Overview of Brain tumor Classification

Brain tumor is one of the critical diseases to diagnose, as the biopsy test are not applicable before any surgery, thus the careful study of brain images is highly required for tumor diagnosis. Computation and artificial intelligence models help to overcome this problem for tumor detection as well as classification. Artificial intelligence techniques are used in health care industry for wide variety of applications, diagnosis of disease is one of the major role played by AI techniques. Machine learning algorithms can effectively classify the tumor and non-tumor images, however, the feature extraction process for ML algorithm is more tedious, some external image processing techniques are required in some cases. Thus deep learning algorithms, specifically convolutional Neural Network is preferred for it automatic feature extraction process. In this proposed work, pre-trained model VGG16 model is used for extraction of features from images. VGG16 is the Convolutional Neural Network architecture with 13 layers as Convolutional and 3 fully connected layers, this is preferred for extraction of features from brain MRI images. The extracted features are used for machine learning algorithms for training. The application developed to classify results. The application performs classification of brain MRI images and if tumor is class is identified, it segments the tumor part and gives results.

The major contributions of this paper are

o Brain tumor MRI images feature extraction using CNN pre-trained architecture VGG16.

o CNN extracted features fit into machine learning algorithms for tumor classification as benign and malignant.

o If a tumor is classified, the image is performed tumor segmentation to identify the tumor portion in the given image using image processing techniques.

In the upcoming chapters literature survey on brain tumor classification is discussed briefly. In chapter 3, proposed methodologies such as CNN feature extraction and Machine learning classification are described. In chapter 4, results and evaluations are discussed for brain tumor classification and segmentation. In chapter 5, this work is Conclusion and further enhancements are discussed.

2. LITERATURE SURVEY

Brain tumor classification is most challenging and it has been an interested area of research for many researchers. Machine learning and deep learning techniques were widely used in the existing studies, some of them are discussed briefly in this chapter. Feature extraction for brain tumor classification is the most important area of study, the author in [1] introduced regularization extreme learning machine (RELM) for feature extraction. This technique is used for feature extraction using

GIST feature descriptors, it extracts the spatial structure of the image. Principal component analysis (PCA) based feature extraction performed with GIST to extract brain features. In the training phase, the random weights and bias are taken for the RELM model and trained. This study used brain MRI images for training and evaluation. The classification is done as ternary classification namely Meningioma, Giloma, Pituitary class types. Experimental results showed that the PCA-GIST feature extraction with RELM has achieved good accuracy of around 94%.

Multi-atlas segmentation was proposed in [2], the author addressed the problem of segmentation of brain tumor in atlas images, which is very challenging while considering normal brain images. The technique used is a low-rank method, which considers the spatial constraints to extract the brain regions. These recovered images are registered to the normal images. The iteration is carried out till residual error is reduced. Experimental results showed that the precision for synthetic images is 82.3%, whereas real images is 72.4%. Multi-level feature extraction and concatenation is studied in [3], the authors used brain MRI images with three classes. Pre-trained models Inception V3 and DenseNet are considered for feature extraction. The features extracted from these pre-trained models are concatenated and these features are classified as three classes using softmax classifier. Experimental results showed that the model has achieved the highest accuracy of 99%.

Brain image segmentation is proposed in [4] with brain MRI images, deep neural network-based learning is performed for classification. The dataset is augmented before training to increase the number of images for training. The techniques like horizontal and vertical flip, rotation and transpose were applied. The tumor segmentation is performed with Adversarial network and Unet techniques. Encoding is used for down-sampling brain images and decoder is used for up-sampling them. Hyper parameter used is 200 epochs and 32 batch size of input images. Experimental results showed that the F1 score arrived is 80.9%.

Concatenated and connected random forest for brain image classification and segmentation is used in [5]. Active contour method is used for segmentation. Segmentation maps are generated by concatenated and connected random forest. Features are extracted from sliding patches using random forest for every region with modality space. Data augmentation is also carried out in this work to generate more images for training and validation. Parameter regularization is performed for parameter dropout to regularize and give input for training. Experimental results showed that this work achieved high sensitivity of 85%.

Brain tumor using MRI images is classified using convolutional neural network is proposed in [6]. The author used contrast enhanced MRI images for this study and has three classes for classification. The author used data augmentation with rotation about 90 degrees, then flipping the images vertically. Then pre-processed image for normalization and resize of image. There are two blocks of layers used for this study each with one convolution, and dropout. The activation Rectified linear unit (Relu) to produce a softmax output. The architecture contained three convolutional layers, each with 50% of dropout value. Experimental results showed that the highest accuracy is achieved with data augmentation dataset with 97.28%.

This literature study infers that there are many researchers implemented brain tumor classification and segmentation [7][8]. The accuracy of the classification is to be improved and the novelty to be improved. Some of the work used deep learning techniques, however, the accuracy has not improved. The feature extraction technique is less studied. Thus to overcome these problems, the proposed work addressed feature extraction using deep learning algorithm and extracted features are used for ML models [9][10].

3. PROPOSED APPROACH

Detection of brain tumor is more challenging as they have very few symptoms. Some types of tumor can be detected as malignant by biopsy test, whereas for brain tumor biopsy is highly not possible without surgery, which causes unnecessary bleeding. Thus brain tumor classification required highly accurate methods to detect. The proposed system used CNN architecture VGG16 for feature extraction. Various machine learning techniques used on these extracted features and its accuracy are compared. By image processing techniques, we also addressed the tumor segmentation in the given MRI images[11][12]. The below Figure 2, represents system architecture of the proposed system. The dataset loaded as shown in the figure is given to the VGG16 model for the feature extraction process. The extracted features fit into machine learning algorithms for classification [13][14]. The results of ML models are evaluated and compared with accuracy of algorithms. When a user gives a brain MRI image, the results are classified and the tumor is segmented [15].

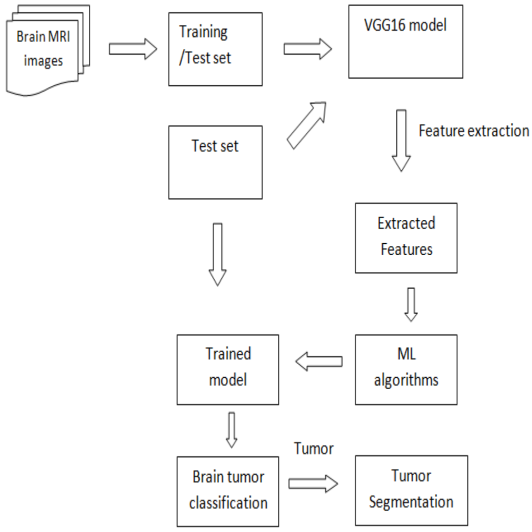

Fig. 2. Architecture of Brain MRI Classification

A. Dataset Details

Brain MRI images as binary dataset with tumor and non-tumor images are considered for this study. Dataset has tumor class 155 images and non-tumor class 98 images are available. Validation dataset is considered around 20% of the whole dataset.

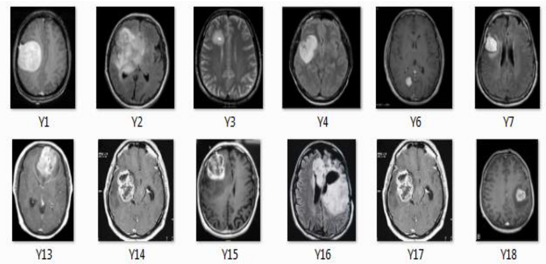

Fig. 3. Brain MRI images for training

B. Data Pre-Processing

Brain MRI images are followed by image pre-processing before extracting the features. The data pre-processing includes resizing the image for the required shape. The image required shape is taken 32x32. The next step is converting the resized images to array data. Then the converted array is normalized by dividing the data by 255. Finally the normalized data is reshaped to required data.

The pre-processed image and label of the folder after label encoding is taken for input for algorithm. The MRI image feature X and label Y is passed to the algorithm.

C. Convolutional Neural Network

Convolutional Neurla Networks are preferred for image dataset, as this can extract the features automatically from the given dataset. The proposed work is used VGG 16, it is the CNN architecture pre-trained model, and more efficient in image feature extraction. The brain MRI dataset is taken and image resized to 32x32. The resized iamge is converted to numpy array value is given as input for VGG16 architecture. Pre-trained Convolutional Neural Network (CNN) architecture VGG16 is used for the implementation. The model summary is shown in the below figure. The first and second layers are convolutional layer with input 32x32 image size and 64 filters. The third layer is Maxpooling layer with 64 filters. The next two layers are Convolutional layers with 128 neurons. The followed layer is Maxpooling layer with 128 neurons. The next three layers are Convolutional layer with 256 neurons followed by a Maxpooling layer. The last layer is Flatten layer to get the output features.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
block1_conv1 (Conv2D)        (None, 32, 32, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 32, 32, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 16, 16, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 16, 16, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 16, 16, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 8, 8, 128)         0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 8, 8, 256)         295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 8, 8, 256)         590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 4, 4, 256)         0
_________________________________________________________________
flatten (Flatten)            (None, 4096)              0
=================================================================
Total params: 1,735,488
Trainable params: 1,735,488
Non-trainable params: 0
```

Fig. 4. CNN Architecture for Brain Feature extraction

The above figure 4 shows the CNN architecture used for feature extraction of brain MRI images.

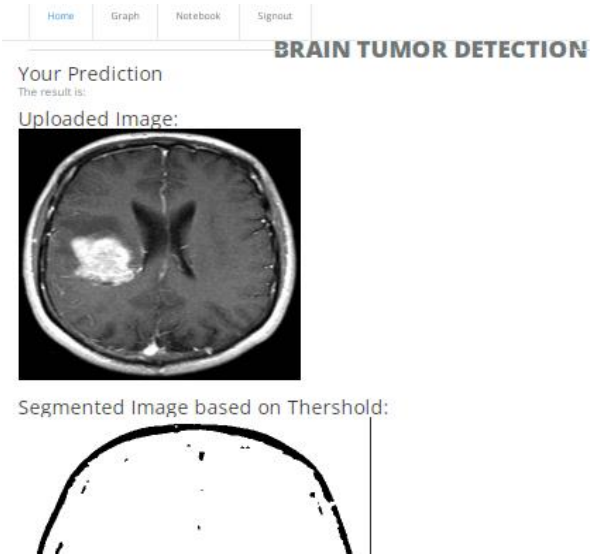

Fig. 5. Application for Brain Tumor Classification

The above figure shows the application web framework design as user interface.

4. RESULTS AND DISCUSSIONS

Brain tumor classification and segmentation of tumor is performed in this implementation with Python. The application is designed as a web application in Flask. The classification is performed with 9 different machine learning and ensemble models. The features extracted using VGG16 architecture are used for ML algorithms. VGG16 extracts the important features from given brain MRI images as a two-dimensional array is fit into machine learning and ensemble model for classification.

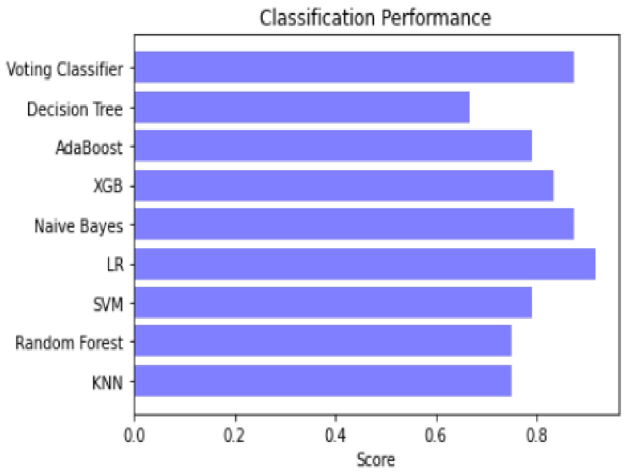

Fig. 6. Comparison of Different ML models for Brain MRI classification

The above figure shows the evaluation metric 'accuracy' computed for different machine learning and ensemble models for brain MRI classification. From the results it is arrived that Logistic regression and voting classifier has achieved the highest accuracy.

The below table shows the accuracy, precision metric, recall and F1 scores computed for Machine learning and ensemble models for brain tumor classification. The table shows that the highest accuracy achieved by logistic regression (LR) is 91%. The highest precision is 94% achieved by LR.

TABLE I. Comparison of Evaluation metrics for Brain tumor classification

Algorithm	Accuracy	Precision	Recall	F1 score
KNN	0.75	0.81	0.81	0.81
Random Forest	0.75	0.78	0.88	0.82
SVM	0.79	0.82	0.88	0.85
Logistic regression	0.91	0.94	0.94	0.94
Naïve Bayes	0.87	0.88	0.94	0.91
XGBoost	0.83	0.83	0.94	0.88
AdaBoost	0.79	0.79	0.94	0.86
Decision Tree	0.66	0.75	0.75	0.75
Voting Classifier	0.87	0.88	0.94	0.91

Web application is designed in Flask framework in Python, the user is authenticated and access the application. The user can upload the brain MRI image. The trained model is used for classifying the given image as tumor or non-tumor image. The tumor detected image is further image processing techniques are applied to detect the tumor location. The image is converted to a Gray scale image. The Gray scale image is applied morphology, the operation such as dilation, erosion, open, close are performed. The close operation removes the noise in the image and canny edge detection is applied to detect the edges of the tumor. The method auto canny () is applied to detect the lower and upper thresholds for edge detection. The external contours are detected from the binary image and contours are drawn in red lines.

The given is first pre-processed before detecting the tumor. The given brain MRI is converted into BGR to Gray scale conversion. The binary images are applied threshold value 155,255. The binary image is applied morphology and the masked region is shown in the below image. The below figure shows the morphology applied masked image of brain MRI.

Fig. 7. Tumor segmentation

The below figure shows the contours drawn on brain tumor and showing the segmentation image. The red coloured mark on the image shows the contour drawn using image processing through canny edge detection, this canny is computed through median value of image feature, it is computed by averaged of min and max value of image features.

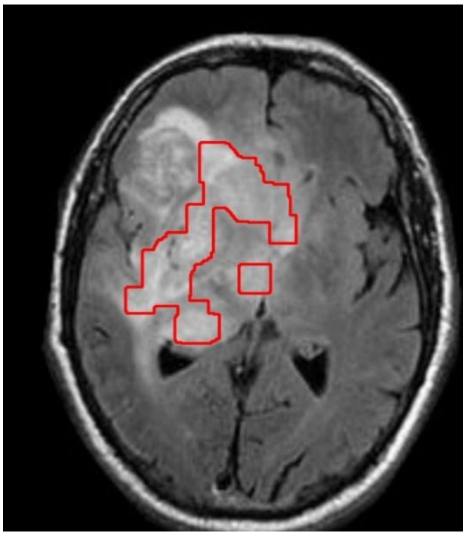

Fig. 8. Brain tumor segmentation showing contours

5. CONCLUSIONS

Brain tumor diagnosis is one the challenging problem, as it controls the central nervous of human, the tumor test is not much applicable as it most sensitive part of nervous system. Brain imaging is the only way to detect tumor, if detected accurately and early, the life of the patient can be prolonged. The proposed work introduced a hybrid model, which involves the extraction of features from brain MRI images through deep learning model CNN's architecture VGG 16 is used. These features are trained and evaluated with machine learning algorithms and various ensemble models such as Random Forest, XGBoost and voting classifier. The web application is developed to classifies and show the result instantly to users, this application reduces the wait time for experts' availability. The accuracy of classification is high using the CNN extracted features for ML algorithms. The application classifies and shows the result as tumor and non-tumor. If a tumor is detected the segmentation of the tumor is also shown in the results. The experimental results showed that the accuracy of brain tumor classification using Logistic regression algorithm is around 91% and precision is around 94%.

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