Deep Learning Approach for Brain Tumor Detection and Segmentation

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Abstract—**Brain tumor is a serious health condition which can be fatal if not treated on time. Hence it becomes necessary to detect the tumor in initial stages for planning treatment at the earliest. In this paper we have proposed a CNN model for detection of brain tumor. Firstly brain MRI images are augmented to generate sufficient data for deep learning. The images are then pre-processed to remove noise and make images suitable for further steps. The proposed system is trained with pre-processed MRI brain images that classifies newly input image as tumorous or normal based on features extracted during training. Back propagation is used while training to minimize the error and generate more accurate results. Autoencoders are used to generated image which removes irrelevant features and further tumor region is segmented using K-Means algorithm which is a unsupervised learning method.**

Keywords—brain tumor, CNN, MRI, noise, tumorous, back propagation, autoencoder, K-Means algorithm, unsupervised learning.

I. INTRODUCTION

Human body contain many types of cells with each cell having its separate function. Cells grow and divide in orderly manner to form new cells which is necessary to keep our body healthy. When cells lose their ability to grow and divide normally, an unordered and uncontrolled growth of cells take place which forms a mass of tissue called tumor. Brain tumor is a mass of tissue containing abnormal cells in the brain. Tumors can be Benign and Malignant, Benign are not cancerous while malignant are cancerous[1].Although some tumors are not cancerous, detecting them in early stages is very important to start proper treatment.

The traditional method to detect brain tumor includes a radiologist analysing the MRI images to find abnormalities and make decisions. It is difficult for a radiologist to analyse these images in limited amount of time as they contain lot of anomalies or noisy data. As the size of the data increases it becomes even more tedious to analyse huge loads of information. Image processing can reduce noise present in these images which a machine can understand for further analysis. MRI images also contain intensity problems which image processing can reduce to certain extent to which machines can easily see that a naked eye cannot. Different deep learning methods can be used in detecting tumors, CNN being one of the methods. CNN has variety of applications in facial recognition, analysing images, classification, understanding climate and many more. CNN is commonly used in the field of image classification. The proposed system combines simple CNN which classifies brain MRI images as tumorous or normal and Autoencoders method which generates a image with less feature dimensions. Further K-Means algorithm is used to perform segmentation on autoencoder generated images overlayed on the original image. With this approach tumor detection and segmentation is achieved without human intervention that saves cost and time.

II. RELATED WORK

Hussna Elnoor Mohammed Abdalla[2] proposed a CAD (Computer Aided Detection System) for classifying input MRI resonance image dataset was collected from Whole Brain Atlas website for this system. Initially after loading the MRI image it is preprocessed and threshold is applied to segment it. Then statistical feature extraction is used for feature extraction and finally proposed ANN model is trained to classify input brain MRI image as tumor or no tumor. Accuracy and sensitivity obtained in this paper is 99% and 97.9% respectively.

Tonmoy Hossain[3] presented two models for brain tumor segmentation and detection. The first model performs segmentation using FCM and classification using traditional classifiers like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and Random Forest for tumor detection. Comparison between the above mentioned classifiers is done with respect to different performance parameters like accuracy, recall, precision etc and it was found that SVM performed better among the different traditional classifiers with

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accuracy of 92.42% for detection. The second model was based on convolution neural network (CNN) and the proposed 5 layer CNN model gave an accuracy of 97.87% for detection.

Miss Krishna Pathak[4] proposed a method for brain tumor detection with the help of convolution neural network(CNN). Scanned brain MRI images were taken as input to this system. Feature extraction and classification is performed by CNN. The classification result either can be normal(no tumor) or tumor image(tumor present). If tumor is present then pre-processing is done on the tumor image and it is segmented by watershed algorithm. Also area of tumor is computed during the process. An accuracy of 98% is achieved by the CNN classifier.

B.Shrinivas[5] presented a paper comparing two unsupervised image segmentation algorithms namely K-means and FCM(Fuzzy C-means). Segmentation performed on scanned MR brain images by both the algorithms and found that FCM produced better results than K-means for the images used.

III. METHODOLOGY

A. Database

The dataset used for training and testing was collected from Kaggle. It contains 253 brain MRI images in total. 155 of them are images containing tumor (tumorous images) and 98 images are normal (without tumor). Tumorous images are segregated in folder named “yes” and normal images are kept in “no” folder. The images are in different formats and of variable sizes.

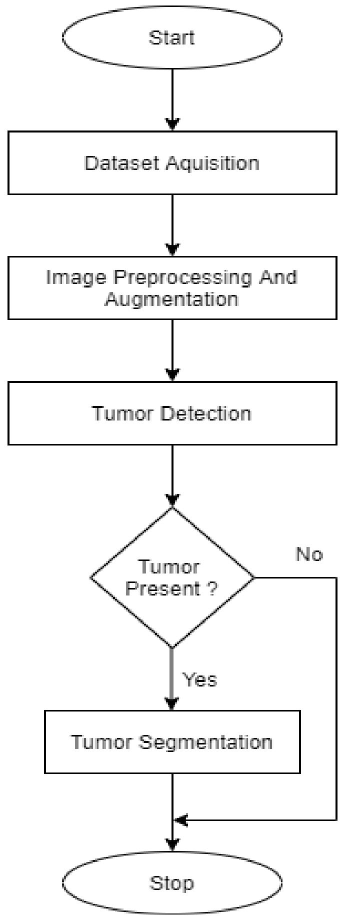


Fig. 1. Flowchart

B. Image Pre Processing

As mentioned the dataset contains images of different formats and sizes which may contain noise. This can lead to errors in classification and segmentation. Pre-processing the image will definitely reduce this problem and data can be transformed in a standard format acceptable for classification and segmentation. Images are converted into greyscale format with a fixed size of 256x256 pixel. Gausian blur is applied on the images to reduce noise. Further the images are passed through high pass filter which will sharpen the image, so that more intricate features can be extracted.

C. Image Augmentation

Deep Learning requires large dataset for producing accurate results. Image augmentation is a process of increasing size of the dataset by producing copies of images through different ways of processing like random rotation, shifts, shear and flips.

D. CNN Model

1) Architecture for tumor detection: The pre-processed image is fed to the CNN model which has a input layer ,convolution layers and a fully connected layer which activates a specific neutron to give specific output or decision. The input image forms the input layer. The image is represented as a 256x256 pixel matrix. Each pixel reveals certain features.

In the first convolution layer 8 filters of 3x3 size kernels each are applied over the input image by sliding through the position one by one and in total 8 feature maps are produced, this process is called feature extraction. These features are then fed to ReLU activation function which performs a threshold operation to each input element where values less than zero are set to zero.

A max pooling layer of 2x2 window size is applied to the output of ReLU layer which results into down-sampling the feature maps into 128x128 pixel size.

The output of previous convolution layer serves as input to second convolution layer. Second convolution layer consists of 12 filters of 3x3 size kernels which are applied to each of the 8 features maps obtained from previous layer.

Similar ReLU and max pooling operations are performed to produce down-sampled data of 64x64 pixel. Same operations are continued for the third convolution layer where 24 filters of 3x3 size kernels are used. Again ReLU operation is applied and fed to the max pooling layer which produces 32x32 pixel data.

The operations performed throughout the three layers extracts prominent and important features necessary for accurate classification.

The output of the third convolutional layer is 24 features maps of 32x32 pixels each. These are then flattened to a single vector of length 32 x 32 x 24 = 24576, which is used as the input to a fully-connected layer with 106 neurons (or elements). This feeds into another fully-connected layer with 2 neurons, one for each of the classes, which is used to determine the class of the image, that is, tumorous or non-tumorous.

Xavier Initialization is used to initialize weights in the network. The error between actual result and predicted result is calculated called as cross-entropy. The Adam optimizer used propagates this error back through the Network using the chain-rule of differentiation and updates the filter-weights so as to improve the classification error. This process is refereed as *Back-propagation* and performed iteratively number of times until the classification error is significantly low.

During training, overfitting can occur when model learns the details and noise in the data used for the training and influences performance of model on new unseen data. To prevent overfitting a dropout function is used in fully-connected layers. Dropout is a regularization technique which randomly drops some units i.e. set to 0 at certain rate. In proposed model 60% of units are dropped to reduce overfitting.

2) Architecture for Auto-Encoder Image Generation: Unsupervised learning is used for tumor segmentation as the dataset used for the proposed model does not contain ground truth segmentation results required to train the model. Variety of techniques are available for segmentation using unsupervised learning, we are using Autoencoder for our proposed model. Autoencoder is a unsupervised learning algorithm which learns to effectively compress data using encoder and then reconstruct the data using decoder in a way such that there is no loss of important data during decoding process. The decoded data regenerated from the encoded data has close resemblance with the input image. Size of the output image is same as that of the input image. The decoded image looks just like the input image but carries only the important features in the image and hides the irrelevant noisy data. Thus by the process of encoding and decoding unwanted noise can be reduced which improves the accuracy in locating region of interest.

The Encoder Consists of 3 convolution layers. First Convolution layer takes the tumorous image as input and applies 16 filters of 3x3 kernel size with stride of 1 to generate 16 feature maps of 256x256 size which are fed to ReLU activation function followed by max-pooling layer which reduces the feature map size to 128x128 pixels. Second Convolution applies 8 filters of 3x3 kernel size to generate 8 feature maps of 128x128 pixels size with ReLU activation function and fed to max-pooling layer which reduces the feature map size to 64x64 pixels. Third Convolution applies 8 filters of 3x3 kernel size to generate 8 feature maps of 64x64 pixels which ReLU activation function and fed to max-pooling layer which reduces the feature map size to 32x32 pixels.

The Decoder consists of 3 de-convolution layers each of which uses 3x3 kernel and stride of 2 to reconstruct the image with less and important features. First decoder layer up-samples the image to 64x64 pixels with 8 feature maps. Second decoder generates 8 features maps of 128x128 pixels which are fed to third decoder layer.

Third layer again up-samples the image to the original size of 256x256 pixels with 16 feature maps generated.

The result of third decoder layer is passed to the final convolution layer which is the output layer of the autoencoder. This layer constructs the image from the feature maps generated by third decoder layer.

The output of the final convolution layer is a image which is compressed i.e. irrelevant features are dropped and image is represented with less feature dimensions. This output image is overlayed on the original image to perform segmentation..

3) Post-Processing (Tumor Segmentation): The overlayed image obtained from the autoencoders is used for segmentation. This image contains only the important features and makes it easier to segment the tumor region. The image is then normalized so that all the pixel values fall between 0 and 1. K-means unsupervised algorithm is used to perform final segmentation. During this process K-means algorithm partitions the image into two clusters iteratively. K-means algorithm is repeated for 40 iterations to generated a binary image with segmented tumor region.

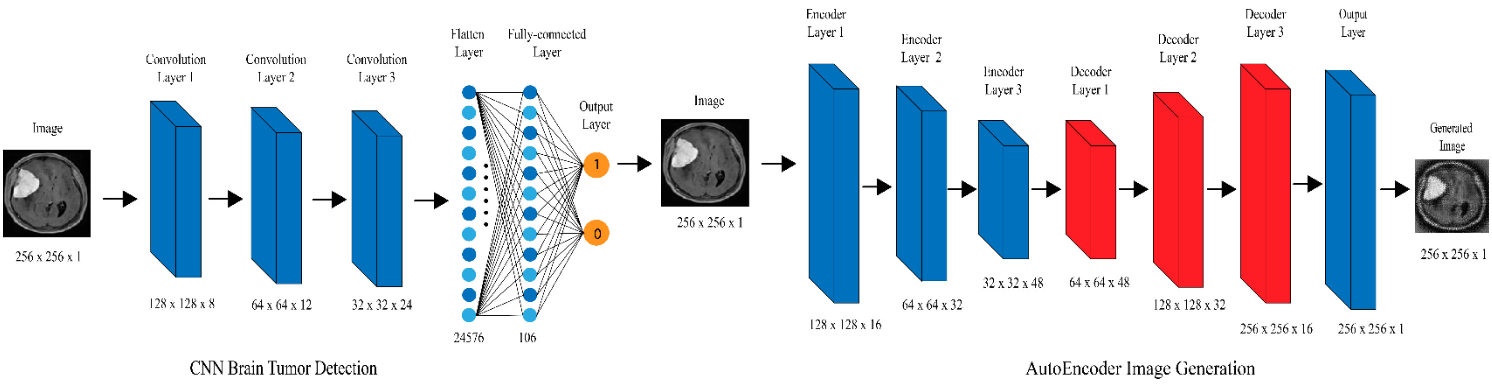


Fig. 2. Proposed architecture

IV. RESULTS

A. Classification Results

The Fig. 3 represents brain MRI images that are correctly classified by the proposed model. If image actually contains tumor (True: 1), the model also predicts it contain tumor (Pred: 1) and if the image does not contain tumor (True: 0), the model predicts no tumor or normal image (Pred: 0).

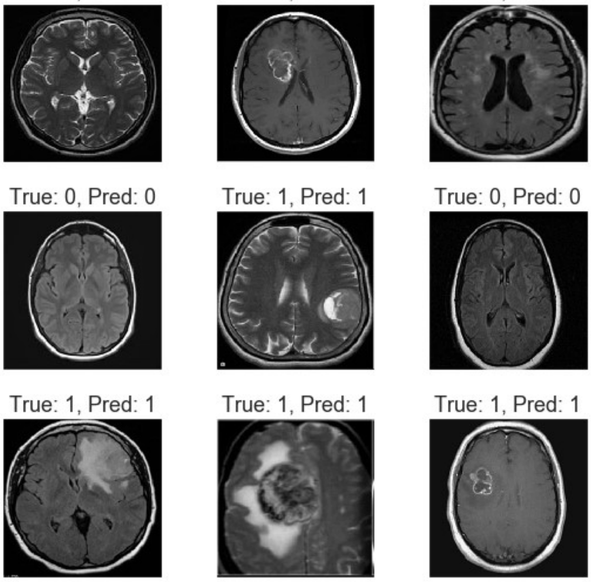


Fig. 3. Classificationr results

The Fig. 4 represents brain MRI images that is Misclassified by the proposed model. If image actually contains tumor (True: 1), the model predicts it does not contain tumor (Pred: 0) and if the image do not contain tumor (True: 0), the model predicts it does contain tumor (Pred: 1).

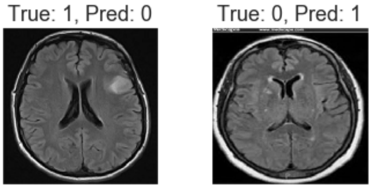


Fig. 4. Missclassified image

The Fig. 5 represents confusion matrix that describes the performance of our brain tumor detection model. Following performance measures can be derived from the same.

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP} \quad = 95.55\% \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad = 96\% \tag{2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad = 96\% \tag{3}$$

$$\text{F1 Score} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad = 96\% \tag{4}$$

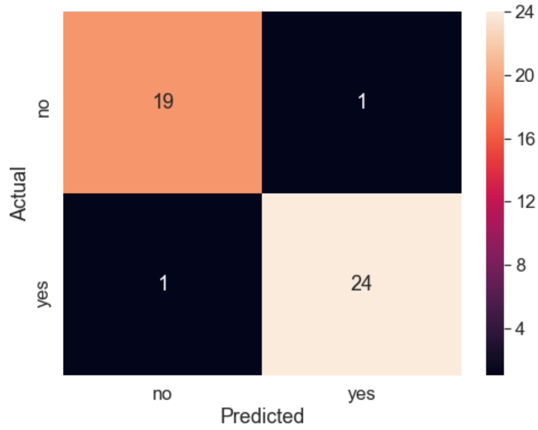


Fig .5. Confusion matrix

B. Segmentation Results

Images containing tumor are segmented to locate the region of tumor. The Table I represents Tumorous brain MRI images that are properly segmented with the tumor region clearly visible without any noise. The first column contains brain MRI images detected for tumor (tumorous images). These images are passed through autoencoders and a image is generated, second column in the table represents the same i.e generated image of each tumorous image. These images are put over the respective original images to generate new images. This process is called as image overlay. Image overlays are represented in the third column. Finally K-means is applied over the Image overlays images and tumor region is located. These segmented images are represented in the last column of the table.

TABLE I. SEGMENTATION RESULT

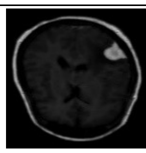
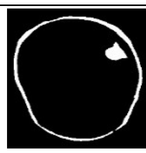
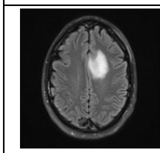
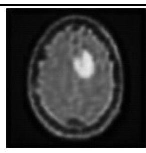
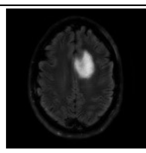
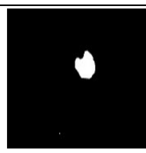
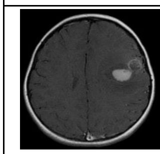
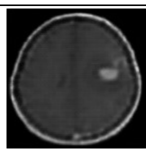
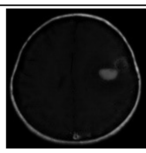
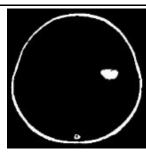
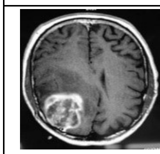
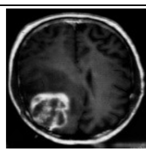
Original Image	**Generated Image**	**Image Overlay**	**Segmentation**
			
			
			
			

Table II represents Tumorous brain MRI images that are not properly segmented where the tumor region is visible but along with some noise which makes the quality of segmentation poor.

TABLE II. SEGMENTATION WITH NOISE

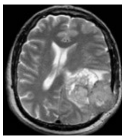
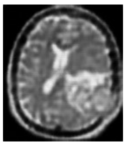
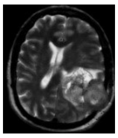
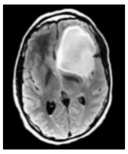
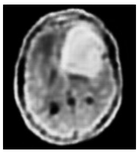
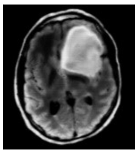
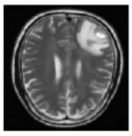
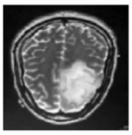
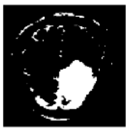
Original Image	Generated Image	Image Overlay	Segmentation
			
			

TABLE III. COMPARISON OF SEGMENTATION WITH K-MEANS AND PROPOSED MODEL(AUTOENCODERS + K-MEANS)

Original Image	K-means	Proposed model
		
		

V. CONCLUSION

The time-consuming process of brain tumor detection is thus simplified by automation. An accuracy of 95.55% on testing data is achieved by the proposed model for detecting brain tumour. After detecting the tumor with convolutional neural networks segmentation techniques like autoencoders and K-means are applied over the tumorous image to locate the region of tumor in the image. As shown in Table III , when segmented the tumor image directly with K-means it sometimes produces a noisy poor segmented image. Hence for segmentation we combined Autoencoders with K-means which produced more precise and clear segmented images with less noise. Thus an efficient model for detection and segmentation of brain tumor is build which saves human efforts and time.

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