Generic Model to Analyze and Predict Brain Tumor from MRI and CT Images using Deep Learning

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Abstract
Medical imaging is gaining importance with an increase in the demand for automated, reliable, fast and efficient diagnosis which can provide insight into the image better than human eyes. The brain tumor is the second leading cause for cancer-related deaths in men age 20 to 39 and leading cause cancer among women in the same age group. Brain tumors are painful and should end in various diseases if not cured properly. The diagnosis of the tumor is a very important part of its treatment. Identification plays an important part in the diagnosis of benign and malignant tumors. A prime reason behind a rise in the number of cancer patients worldwide is the ignorance towards the treatment of a tumor in its early stages. This paper discusses such a machine learning algorithm that can write the user about the details of the tumor using brain MRI. These methods include noise removal and sharpening of the image along with basic morphological functions, erosion, and dilation, to obtain the background. Subtractions of background and its negative from different sets of images result in extracted in age. Plotting contour and c-label of the tumor and its boundary provides us with information related to the tumor that can help in a better visualization in diagnosing cases. This process helps in identifying the size, shape, and position of the tumor. It helps the medical staff as well the patient to understand the seriousness of the tumor with the help of different color-labeling for different levels of elevation. A GUI for the contour of the tumor and its boundary can provide information to the medical staff on the click of user choice buttons.

Keywords
Classification, Convolutional Neural Network, Feature Extraction, Machine Learning, Magnetic Resonance Imaging, Segmentation, Texture Features.

I. Introduction
The physical body consists of many sorts of cells. Each cell features a specific function. The cells in the body grow and divide in an orderly manner and form some new cells. These new cells help to keep the human body healthy and properly working. When some cells lose their capability to regulate their growth, they grow with none order. The extra cells formed form a mass of tissue that is named as the tumor. The tumors can be benign or malignant. Malignant tumors lead to cancer while benign tumor is not Cancerous. The important think about the diagnosis includes the medical image data obtained from various biomedical devices that use different imaging techniques like x-ray, CT scan, MRI. Magnetic resonance imaging (MRI) may be a technique that depends on the measurement of magnetic flux vectors that are generated after an appropriate excitation of strong magnetic fields and radiofrequency pulses in the nuclei of hydrogen atoms present in the water molecules of a patient's body. The MRI scan is much better than the CT scan for diagnosis as it doesn't use any radiation. The radiologists can evaluate the brain using MRI. The MRI technique can determine the presence of tumors within the brain. The MRI also contains noise caused thanks to operator intervention which may cause inaccurate classification. The large volume of MRI is to analyze; thus, automated systems are needed because they're less expensive -. Automated detection of tumors in MR images is important as high accuracy is required when handling human life. The supervised and unsupervised machine learning algorithm technique can be employed for the classification of brain MR image either as normal or abnormal. During this paper, an efficient automated classification technique for brain MRI is proposed using machine learning algorithms. The supervised machine learning algorithm is used for classification of brain MR image

II. Related Work
Joshi proposed brain tumor detection and classification systems in MR images by first extracting the tumor portion from brain image, then extracting the texture features of the detected tumor using gray level co-occurrence matrix (GLCM) and then classified using a neuro-fuzzy classifier. shasidhar proposed a modified fuzzy c-means (FCM) algorithm for MRI brain tumor detection. The texture features are extracted from the brain MR image and then a modified FCM algorithm is used for brain tumor detection. The average speed-ups of as much as 80 times a traditional FCM algorithm are obtained using the modified FCM algorithm. The modified FCM algorithm is a fast alternative to the traditional FCM technique. Rajesh and malar proposed brain MR image classification based on rough set theory and feed-forward neural network classifier. The features are extracted from MR images using rough set theory. The selected features are fed as input to feed forward neural network classifier which differentiates between the normal and abnormal brain and the accuracy of about 90% is obtained. Ramteke and monali proposed automatic classification of brain MR images in two classes normal and abnormal based on image features and automatic abnormality detection. The statistical texture feature set is obtained from normal and abnormal images and then the KNN classifier is used for classifying an image. The KNN obtain an 80% classification rate. Othman proposed a probabilistic neural network technique for brain tumor classification. Firstly, the features are extracted using the principal component analysis (PCA) and the classification is performed using probabilistic neural network (PNN). Jafari and shafaghi proposed a hybrid approach for brain tumor detection in MR images based on support vector machines (SVM). The texture and intensity features are used. The accuracy of about 83.22% is achieved and is more robust. Thus, from an extensive literature survey, we found that most of the current brain tumor detection system uses texture, symmetry, and intensity as features. Texture features are important property of the brain as texture perception has a very important aspect in the human visual system of recognition and interpretation. Further, we propose the use of the ml algorithm to overcome the drawbacks of traditional classifiers. We investigate the performance of a machine learning algorithm namely CNN in this work. Neural networks are useful as they can learn complex mappings between input and output. They are capable of solving much more complicated classification tasks.

III. Proposed Work

As per the literature survey, it was found that automation of brain tumor detection is very essential as high accuracy is needed when human life is involved. Automated detection of tumors in MR images involves feature extraction and

- No - no tumor, encoded as 0
- Yes - tumor encoded as 1

A. Preprocessing

All images are in one folder with yes and no subfolders. I Preprocessing is required because it provides an improvement will split the data into train, val and test folders which makes it in image data which reinforces a number of the image features easier to work with the same dimension of images. which are important for further processing.

Table 1. set of folders of images

No. of images	Folder directory
253	Train
25	Test
50	Validation

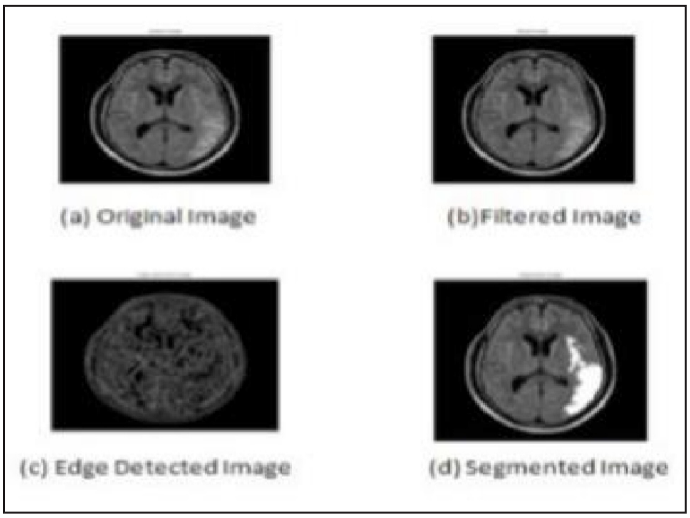


Fig. 5. Processed images

The pre-processing steps that are applied to the MR image are as follows: the RGB MR image is converted to grayscale image and then the median filter is applied for noise removal from brain MR images. The noise is to remove for further processing as high accuracy is needed. Then edges are detected from a filtered image using canny edge detection as shown. The edge detected image is needed for the segmentation of the image. The segmentation aims to change the representation of an image into something easier to analyze.

C. Segmentation

Brain tumor segmentation is the process of separating the tumor from normal brain tissues; in clinical routine, it provides useful information for diagnosis and treatment planning. However, it's still a challenging task thanks to the irregular form and confusing boundaries of tumors. Tumor cells thermally represent a heat source; their temperature is high compared to normal brain cells. The most aim of this paper is to demonstrate that thermal information of brain tumors is often wont to reduce false positive and false negative results of segmentation performed in MRI images. The obtained results in all patients showed a significant improvement using the proposed method compared to segmentation by a level set method with an average of 0.8% of the tumor area and 11 2.48% of healthy tissue was differentiated using thermal images only. We conclude that tumor contours delineation based on tumor temperature changes can be exploited to reinforce and enhance segmentation algorithms in MRI diagnostics.

D. Feature Extraction

(a) Image-based features: the extraction of features based on the image data, potentially including intensity features, texture features, histogram-based features, and shape-based features;

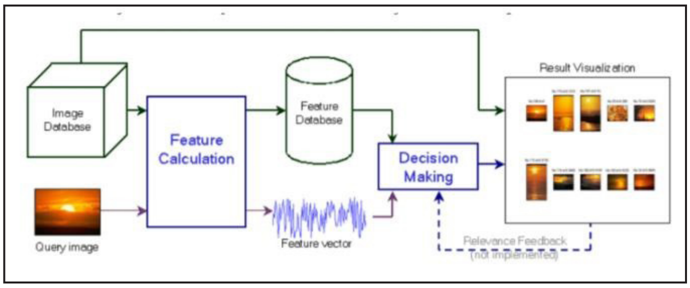


Fig. 6: Feature Extraction

(b). coordinate-based features: the extraction of features based on the registration to a standard coordinate system, potentially including coordinates features, spatial prior probabilities for structures or tissue types in the coordinate system, and local measures of anatomic variability within the coordinate system;
(c) registration-based features: the extraction of features based on known properties of the one or more aligned templates, potentially including features based on labeled regions in the template, image-based features at corresponding locations in the template, features derived from the warping field, and features derived from the use of the template's known line of symmetry.

D. Classification

Machine learning algorithms are used for the classification of MR brain images either as normal or abnormal. The major aim of ml algorithms is to automatically learn and make intelligent decisions the classification is done based on the below features:

- feature processing: before classification, the extracted feature set can be refined to make it more appropriate for achieving high classification accuracies:
- classifier training: pixels that are labeled as normal and abnormal are used with the extracted features to automatically learn a classification model that predicts labels based on the features;
- pixel classification: the learned classification model can then be used to predict the labels for pixels with unassigned labels, based on their extracted features;
- relaxation: since the learned classification model may be noisy, a relaxation of the classification results which takes into account dependencies in the labels (i.e. Classification) of neighboring pixels can be used to refine the classification predictions and yield a final segmentation.

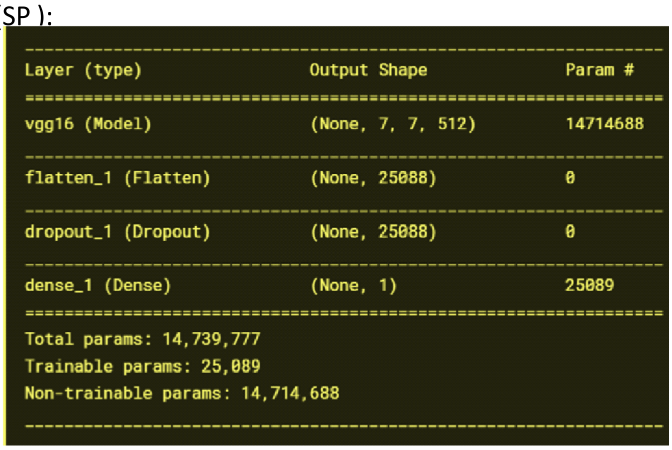
This CNN method requires only a small amount of training data to estimate the parameters which are needed for classification. The time taken for training and classification is less. This can extract useful attributes from trained weights by feeding data by levels and tune CNN for the specific task

ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

IV. Experimental Results

Accuracy as a metric to justify the model performance which can be defined by accuracy (ACC), sensitivity (SE), specificity

(SP):



```
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dropout_1 (Dropout)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 25089
=================================================================
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
_________________________________________________________________
```

Fig.7.Experimental Results

$$ACC = \frac{TP+TN}{TP+TN+FP+FN}$$

$$SE = \frac{TP}{TP+FN}$$

$$SP = \frac{TN}{TN+FP}$$

Final results look as follows:

Training	Tumor	Non Tumor
Tumor	148	7
Non Tumor	92	6

Total ACC =94%:

Val set	Tumor	Non Tumor
Tumor	29	2
Non tumor	17	2

Val set ACC =92%; SE =93%;SP =89%

Test set	Tumor	Non Tumor
Tumor	16	1
Non Tumor	7	1

Test set ACC =91%:SE =94%:SP =87%

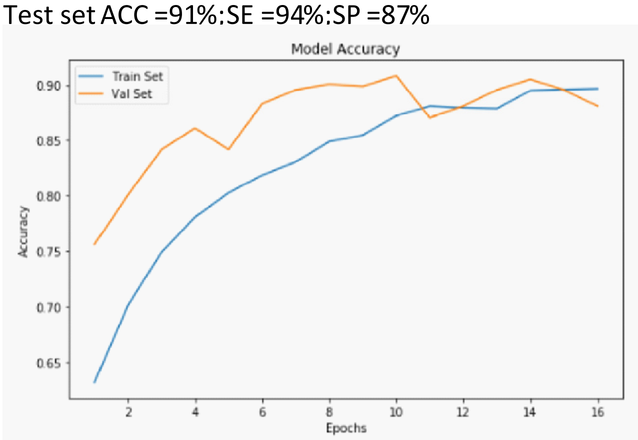


Fig.8.Accuracy for respective set

V. Conclusion

In this proposed work different medical images like MRI brain cancer images are taken for detecting tumor. The proposed approach for brain tumor detection supported convolution neural network categorizes into multi-layer perceptron neural network. The proposed approach utilizes a mixture of this neural network technique and consists of several steps including training the system, pre- processing, implementation of the tensor flow, classification. In the future, we'll take an outsized database and check out to offer more accuracy which can work on any sort of MRI brain tumor.

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