AN OUTLIER BRAIN TUMOR DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: With a rise in the need for automated, trustworthy, quick, and efficient diagnosis that can offer insight into the image better than human eyes, medical imaging is becoming more and more important. The brain tumour is the top cause of cancer in women in the same age range and the second highest cause of cancerrelated deaths in males aged 20 to 39. Painful brain tumours can progress to numerous disorders if they are not treated effectively. An essential component of the tumor's therapy is its diagnosis. The diagnosis of benign and malignant tumours depends heavily on identification. The lack of knowledge on the treatment of a tumour in its early stages is a major factor in the growth in the number of cancer patients globally. This essay explains a machine learning technique that can utilise brain MRI to write the user about the specifics of the tumour. These techniques involve sharpening the image and removing noise, as well as using fundamental morphological processes like erosion and dilation to get the backdrop. Age is retrieved by removing the backdrop and its negative from several sets of photos. We may get information about the tumour that can aid in a better visualisation when diagnosing cases by plotting the contour and c-label of the tumour and its border. This procedure aids in determining the tumor's size, shape, and location. Varying color-labeling for different levels of severity of the tumour aids the medical staff and the patient in understanding elevation. The medical personnel can get information by clicking user-selectable buttons on a GUI that displays the outline of the tumour and its border.

Keywords: classification, convolutional neural network, feature extraction, machine learning, magnetic resonance imaging, segmentation, texture features.

1. INTRODUCTION

There are many different types of cells in the human body. Every cell has a distinct purpose. The body's cells divide and expand in an organised fashion to produce new cells. These new cells contribute to the maintenance of the human body's functionality and health. Some cells expand without control when they lose the ability to control their own development. The tumour is a mass of tissue made up of the extra cells that have grown. Tumors may be benign or cancerous. While benign tumours are not cancerous, malignant ones do. The medical image data obtained from various biomedical equipment that

employ various imaging modalities, such as x-ray, CT scan, and MRI, is a significant factor in the diagnosis. The use of magnetic resonance imaging (MRI) a method that relies on the detection of magnetic flux vectors that are produced when a patient's body's water molecules are appropriately excited by intense magnetic fields and radiofrequency pulses. Since there is no radiation involved, the MRI scan is far more effective for diagnosis than the CT scan. Using MRI, radiologists may assess the brain. The existence of malignancies within the brain can be detected using the MRI technology. Additionally, noise in the MRI that was introduced by the operator may result in incorrect categorization. Because automated systems are less expensive because to the vast volume of MRI that has to be analysed, they are required. Automated tumour identification in MR images is crucial since high accuracy is needed when dealing with human existence. Brain MR images with a modified FCM algorithm may be used to create supervised and unsupervised machine learning algorithms.

used to categorise brain MR images as either normal or pathological. In this research, machine learning methods are used to offer an effective automated brain MRI categorization methodology. The brain MR image categorization process uses the supervised machine learning method.

2.Research Review

[1] By first extracting the tumour section from the brain image, extracting the textural features of the discovered tumour using grey level co-occurrence matrix (GLCM), and then classifying using a neurofuzzy classifier, oshi suggested brain tumour detection and classification methods in MR images. For the purpose of MRI brain tumour identification, Shasidhar suggested a modified fuzzy c-means (FCM) method. A modified FCM algorithm is utilised to detect brain tumours once the texture characteristics from the brain MR image are retrieved.

[5] The improved FCM algorithm yields average speedups of up to 80 times that of a conventional FCM method. A quick replacement for the conventional FCM method is the modified FCM algorithm. Using feed-forward neural network classifiers and rough set theory, Rajesh and Malar suggested classifying brain MR images. Using rough set theory, the characteristics are retrieved from MR images. [8]

[2] A feed forward neural network classifier that distinguishes between the normal and pathological brain is fed the chosen characteristics as input, and accuracy of roughly 90% is attained. Based on image attributes and automatic abnormality identification, Ramteke and Monali suggested automatically classifying brain MR images into two categories: normal and abnormal. Normal and abnormal photos are utilised to create the statistical texture feature set, which is then employed by the KNN classifier to categorise the images. [6]

[9] The KNN achieves a classification rate of 80%. Othman suggested a probabilistic neural network approach for classifying brain tumours. Principal component analysis (PCA) is used to extract the features, and a probabilistic neural network is used for classification (PNN). A hybrid

strategy was presented by Jafari and Shafaghi for using support vector machines to identify brain tumours in MR images (SVM). The elements of texture and
intensity are applied. [7]

[11] A more reliable accuracy of roughly 83.22% is attained. We discovered that the majority of the existing brain tumour detection system employs texture, symmetry, and intensity as characteristics after conducting a thorough literature review. As texture perception plays a significant role in the human visual system of recognition and interpretation, texture qualities are key brain characteristics. In addition, we suggest using the ml method to get around the shortcomings of conventional classifiers. [8]

[13] In this paper, we examine how well the CNN machine learning algorithm performs. Given its capacity to learn intricate input-to-output mappings, neural networks are valuable. They can complete far more difficult categorization jobs

3.RELATED WORK

By first removing the tumour from the brain picture, extracting the textural properties of the discovered tumour using a grey level co-occurrence matrix (GLCM), and then classifying using a neuro-fuzzy classifier, Joshi suggested brain tumour detection and classification methods in MR images. For the purpose of MRI brain tumour identification, Shasidhar suggested a modified fuzzy c-means (FCM) method. For the purpose of detecting brain tumours, the texture characteristics are extracted. The improved FCM algorithm yields average speedups of up to 80 times that of a conventional FCM method. A quick replacement for the conventional FCM method is the modified FCM algorithm. Using feed-forward neural network classifiers and rough set theory, Rajesh and Malar suggested classifying brain MR images. MR pictures are used to extract the features. basic set theory A feed forward neural network classifier that distinguishes between the normal and pathological brain is fed the chosen characteristics as input, and accuracy of roughly 90% is attained.
Ramteke and Monali suggested automatically classifying MR pictures of the brain into two categories: based on visual attributes and automatically detecting abnormalities. Normal and abnormal photos are utilised to create the statistical texture feature set, which is then employed by the KNN classifier to categorise the images. The KNN achieves a classification rate of 80%. Othman suggested a probabilistic neural network approach for classifying brain tumours. Principal component analysis (PCA) is used to extract the features, and a probabilistic neural network is used for classification (PNN). Using support vector machines, Jafari and Shafaghi suggested a hybrid method for detecting brain tumours in MR images (SVM). The elements of texture and intensity are applied. A more reliable precision of roughly 83.22% is attained. Consequently, we discovered via a thorough literature review that the majority of the current Texture, symmetry, and intensity are used as characteristics in a brain tumour detection method. As texture perception plays a significant role in the human visual system of recognition and interpretation, texture qualities are key brain characteristics. In addition, we suggest using the ml method to get around the shortcomings of conventional classifiers. In this paper, we examine

how well the CNN machine learning algorithm performs. Given its capacity to learn intricate input-to-output mappings, neural networks are valuable. They can do far more challenging categorization jobs.

4.PROPOSED WORK

According to the literature review, automation of brain tumour detection is highly important since high accuracy is required when human lives are concerned. Utilizing feature extraction and classification with a machine learning system, malignancies may be automatically found in MR images. A technique to automatically identify a tumour in MR images is suggested in this research and is depicted in the figure.

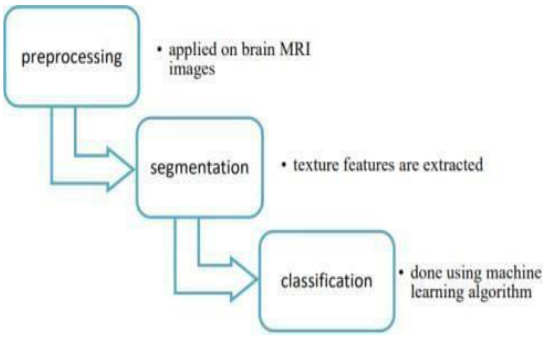

Fig.1.Proposed work

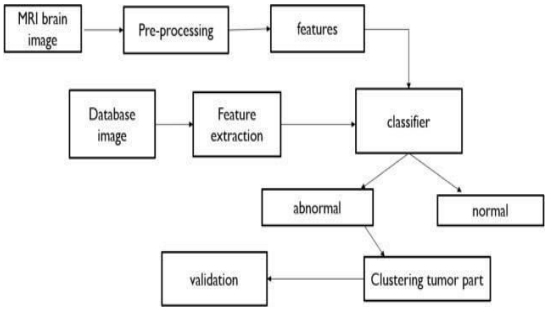

Fig.2.Block diagram

4.1 IMAGE ACQUTTION

Brain MRI pictures for the purpose of detecting brain tumours were utilised as the image data for this issue. It comprises of two kinds of mri scans:

Tumors are encoded as either No (no tumour) or Yes (tumour).

One folder has all of the photographs, with subfolders for yes and no. It will be simpler to deal with photos of the same dimension if I divide the data into train, val, and test folders.

Table1. set of folders of images

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

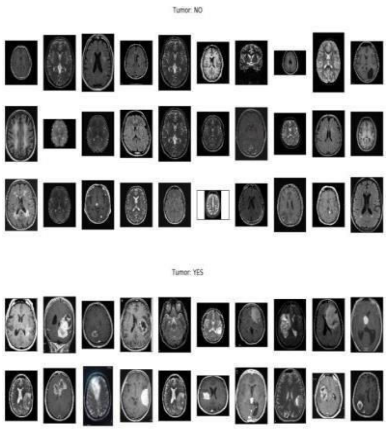

Fig.3.MRI Data Set

- Validation set - is the set used during the model training to adjust the hyperparameters.
- Test set - is the small set that doesn't touch for the whole training process at all.

It's been used for final model performance evaluation these are some sample images of both classesThe images have different width and height and the different sizes of "black corners". Since the image size for the vgg-16 input layer is (224,224) some wide images may look weird after resizing. The first step of "normalization" would be to crop the brain out of the images.

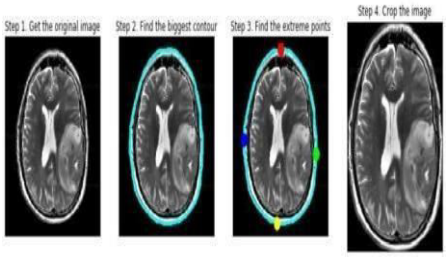

Fig.4.Normalised images

4.2preprocessing

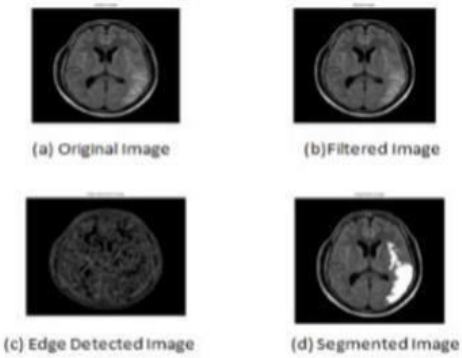

Fig.5.Processed images

Preprocessing is required because it provides an improvement in image data which reinforces a number of the image features which are important for further processing.

The RGB MR picture is transformed to a grayscale image as part of the preprocessing of the MR image, and the median filter is then used to remove noise from brain MR images. For subsequent processing, when great precision is required, the noise must be removed. Then, using clever edge detection, edges are found in a filtered image as demonstrated. The segmentation of the picture requires the edge detected image. The segmentation process seeks to transform an image's representation into one that is simpler to comprehend.

4.3 Segmentation

Segmenting a brain tumour is the process of separating the tumour from healthy brain tissue; in typical clinical practise, this information is helpful for diagnosis and treatment planning. However, given the uneven

shape and hazy limits of tumours, it is still a difficult process. Thermally, tumour cells resemble a heat source because of their higher temperature than healthy brain cells. The primary goal of this study is to show how segmenting MRI images using thermal information from brain tumours can frequently result in fewer false positive and false negative outcomes. The acquired findings in all cases demonstrated a considerable improvement utilising the suggested technique compared to segmentation using a level set method with an average of 0.8% of the tumour region and 11 2.48% of the surrounding normal tissue. The sole method used to distinguish healthy tissue was thermal imaging. We come to the conclusion that segmentation algorithms in MRI diagnostics may be strengthened and improved by using tumour outlines delineation based on tumour temperature variations.

4.4 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

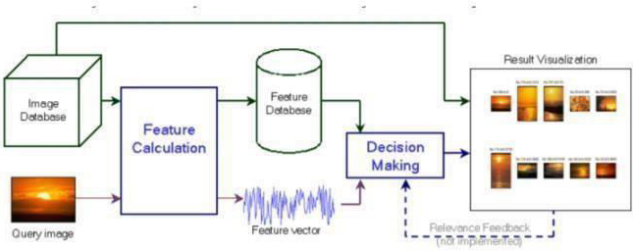

Fig.6.Feature Extraction

(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.

4.5 Classification

The categorization of MR brain pictures as normal or pathological using machine learning methods. Ml algorithms' main goal is to automatically learn and make wise judgments. The following characteristics are used to classify things: (a) feature processing: The extracted feature set can be improved before

classification in order to achieve high classification accuracy.

(b) classifier training: Using the extracted features and pixels that have been classified as normal and abnormal, a classification model that predicts labels based on the features is automatically learned;

(c) pixel classification: based on the characteristics that were collected from the pixels with unassigned labels, the learnt classification model may then be used to forecast the labels for those pixels;

(d) relaxation: Because the learnt classification model might be noisy, a relaxation of the classification results that accounts for dependencies in the labels (i.e., classification) of nearby pixels can be utilised to improve the classification predictions and provide a final segmentation.

Only a little quantity of training data is needed for this CNN approach in order to estimate the classification-related parameters. Training and categorization require less time than they used to. By feeding data at different levels, this may extract valuable properties from training weights and adjust CNN for the particular job.

5.EXPERIMENTAL RESULTS

As a statistic to evaluate the performance of the model, accuracy (ACC), sensitivity (SE), and specificity (SP) might be used.

```
_________________________________________________________________
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%

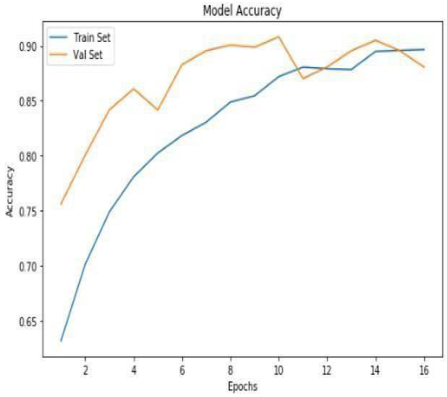

Fig.8.Accuracyfor respective set

6. CONCLUSION

For the purpose of identifying tumours in this suggested study, various medical pictures, such as MRI brain cancer images, are taken. Convolution neural networks are supported in the suggested method for detecting brain tumours and are classified as multi-layer perceptron neural networks. The suggested method combines this neural network technology and entails numerous processes, such as system training, pre-processing, tensor flow implementation, and classification. In the future, we'll examine a large database to provide more accuracy that can be used to any type of MRI brain tumour.

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