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Detection And Classification Of Tumour Using Image Processing And Machine Learning

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Abstract- Tumours, or aberrant unregulated cell development in any body component, can put enormous pressure on the numerous nerves and blood vessels, causing irreversible damage to the body. The key to avoiding such compilations is early tumour diagnosis. Advanced machine learning and image processing techniques can be used to detect tumours. Image pre-processing, segmentation, and feature extraction are all stages of tumour identification. Pre-processing include applying multiple filters to the image and removing noise. Methods such as thresholding and region growth are used in segmentation. For the retrieved tumour, features such as contrast, skewness, and entropy are calculated. To identify the tumour as benign or malignant, various classifiers such as convolution neural networks and nave bayes are used.

Keywords- Medical Images, MRI, Segmentation, Tumor, Classifications.

I. INTRODUCTION

The many cells that make up the organs are the body's building components. Tumors are diseases that develop from these cells. Image processing is currently one of the most rapidly growing study topics in medical image processing. Noise and image clarity are restrictions in MRI imaging. Unwanted information in photographs is referred to as noise. Noise can sometimes affect the edges and small details, limiting the contrast resolution. Noise makes it difficult to establish the exact boundaries and classification of the tumour, making it an emerging topic of image processing research. We compare an effective and skilled approach for segmentation, detection, and classification of brain tumours in this work.

The radiology-based medical imaging technology magnetic resonance imaging (MRI) is used to construct representations of the structure and physiological processes of the body in health and disease. Strong magnetic fields are used in MRI scanners.

II. EXISTING METHODOLOGY

The results of a survey on segmentation and classification have been tabulated in Table 1 below. The process for segmenting the brain tumour and subsequently extracting the features employed in the past by many studies has limitations that result in low accuracy in the results. K-means segmentation and watershed segmentation are the most commonly utilised segmentation algorithms, both of which result in over segmentation of the tumour. When compared to newer classification methods based on neural networks, the regularly used classifier SVM has been proven to produce worse results.
First and foremost, they want to provide a complete overview of brain tumours and brain tumour imaging. Then they look at the state of the art in cancer-related brain images, with a focus on gliomas in terms of division, detection, and modelling. The goal of segmentation is to delineate the cancer and its sub-compartments, as well as adjacent tissues, while the major purpose in segmentation is to identify the cancer and its sub-compartments.

Author	Year	Segmentation	Accuracy
Zuliani Zulkoffli	2019	k-means and morphological operations	91.65%
G.Hemanth	2019	Pixel based segmentation	91%
Reema Mathew	2017	Morphological operations	86%
Ravindra Sonavane	2017	Image normalization and morphological operations	Mammography Database: 68.85%,Clinical database (MRI) 79.35%

III . PROPOSED METHODOLOGY

The proposed system in this paper is a modified version of traditional PNN. The changes are based on the automatic use of defined areas of interest (ROIs) inside the tumour area in MRI images. A set of retrieved features is extracted and normalised from each ROI, including tumour intensity and form properties. The PDF of each tumour in the MRI image is then estimated by assigning a weight to each ROI. These weights are used to modify the traditional PNN through a modelling approach. This method is based on LVQ (learning vector quantization), a supervised competitive learning strategy that reduces the size of the hidden layer by obtaining decision limits in input space based on training sets. It establishes prototypes for class borders, a nearest-neighbour rule, and a winner —all in one paradigm. The LVQ has three layers: an input layer, a competitive laver, and an output laver. In the competitive layer, the input data is categorised, and then the weight of winner neuron is adjusted.
he proposed approach for brain tumour classification has four basic components. The first phase is ROI segmentation, which identifies the tumor's boundary (ROI) in an MR image; the second step is feature extraction, which extracts the ROI's significant features; and the third step is feature selection: The classification process is the final phase, which entails learning a classification model based on the features.

The suggested algorithm begins by reading the input age, converting it to a greyscale image, and then extracting the Region of Interest using image segmentation algorithms (ROD) The training database is made up of a set of reference MRIs. During the training phase, feature vectors are extracted for each image in the training set; during the testing phase, the feature vector of the test image is generated.

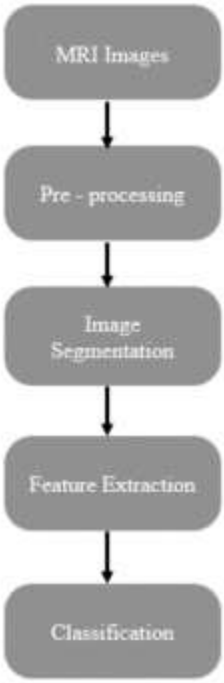

Fig: Steps for Image processing

A. PREPROCESSING OF MRI IMAGES

Noise is removed during preprocessing, and any minor details are addressed. The accuracy of the segmentation algorithm output is reduced when clinical MRI cans are riddled with nonne. To eliminate the various types of none, multiple filters are utilised. This module is required to provide noise-free segmentation since median fitters are used to reduce salt and pepper noe while anisotropic fibres are utilised to preserve them. The overall image quality is improved as a result of this enhancement. The control a n dalled and a preprocessed image are shown in the graphic below.

B. SEGEMENTATION METHODS

1. Boundary Approach (Thresholding)

Thresholding is one of the most basic methods of segmentation that is used to isolate the tumour All the pixels are allocated to a category based on the range that they lie in That is for a certain threshold value t, the pixel located at position (I, j) with a grayscale value fij as shown in equation

Pixel (I, j) =0 if fij less than or equal to t

Pixel (I, j) =1 if fij greater than t

2. Edge based segmentation

The discovered edges are supposed to be the representational boundaries of objects in the edge-based segmentation approach. It's exceedingly improbable that this strategy will result in a closed distinct edge. Edge linking is also required to unite incomplete edges in order to obtain a complete cloned distinct edge of an item.

3. REGION BASED APPROACH OR CLUSTERING

The pixel connectivity is used in region based segmentation or clustering based segmentation. In a two-dimensional image, a pixel might have four, six, or eight connections. It means that all of the pixels in a certain region are congruent with one another or have a similar value. The focus is on finding poses that meet the connection requirement rather than the object's edges. Clusters are made up of pixels that are similar.

Clusters are made up of congruent pixels the various clustering algorithms used are

1.K-means algorithm
2.Genetic algorithm
3.Jaya algorithm
4.Particle swarm optimization

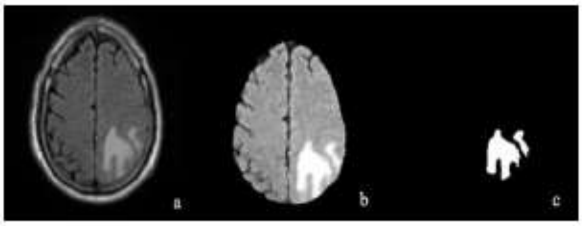

Figure 1: Segmented image

C. <u>Feature Extraction</u>

Because of the brain's intricacy, isolating the tumour is tough. For feature extraction of the segmented tumour from MRI scans, several aspects are taken into account: The expressions of the Gray-Level Co-Occurrence Matrix (GLCM) descriptors Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity, Energy, Entropy, Homogeneity, and Maximum Probability 1201 are the essential parameters for the area of interest. The tumour is subsequently classified as benign or malignant based on the results of feature extraction.

D. <u>Classification</u>

The findings of feature extraction are used to classify the data. Various patterns are mapped based on the collected features, and the retrieved tumour is then classified. Artificial Neural Networks, Tree J84, Naive Bayes, and the Lazy IBK, convolutional neural network are some of the algorithms used for classification.

IV. EXPERIMENTAL RESULTS

A set of MRI-scan grayscale image database was used in this experiment each image size is 220-220

pixels. A group of 64 MRI images were used that were categorized into 6 respectively.
<u>Comparison table between existing and our proposed method</u>:

	Results presented in existing methodology	**Results obtained in our proposed method**
No of training images	20	64
No of testing images	15	18
Spread value	1	1
Network performance for correct images	73%	99.9%

A group of 18 randomly selected patients' MRI pictures were chosen as a test set out of 64 participants, MRI while the remainder of the dataset was used for training. The training data was fed into the neural network inputs, and the weight of the hidden nodes was determined on the output. Many trials on the same Many Neural Network seketina 1 octs randomly every time selec for testina and the remaining subjects for retraining to identify rema accacy of neural network prediction shows the performance tests the results reported in 1301 are covered. According to the malts and provided in this table, the proposed system outperforms the presented system in 301. and successfully equal handle the process of MRI image classification with 100 accuracy when the spread value is equal to I b is alo neted that the proposed LVO-basel PNN wystam decreased the c e to approximately 79 compared with PNN.

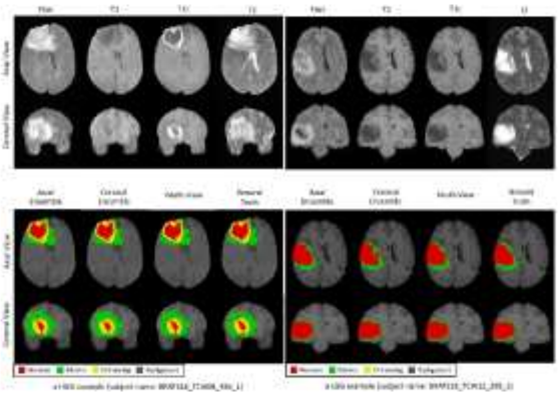

Figure 2

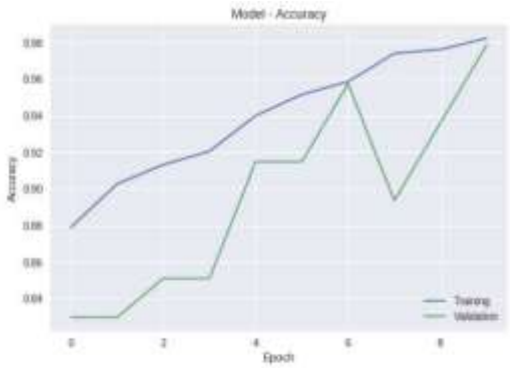

Figure 3: Accuracy curve

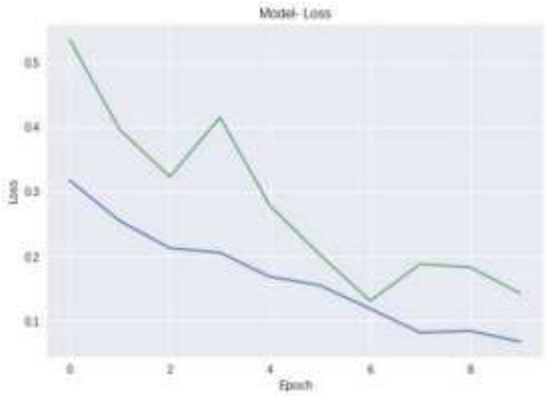

Figure 4: Loss curve

V.CONCLUSION

The primary goal of this research is to develop a reliable automatic brain tumour classification system with high precision, speed, and simplicity. Using FCM-based division, texture and outline feature extraction, and SVM and DNN-based arrangement, traditional cerebrum tumour classification is realised. The level of difficulty is reduced. However, the calculation time is longer, and the precision is lower. A CNN-based classification is implemented in the proposed scheme before to improve the accuracy and reduce the calculation time.

Figures 3 and 4 show the model accuracy and loss, respectively. In comparison to SVM and FCM-based classification, training accuracy is 96.5 percent and testing accuracy is 90 percent. Validation precision is likewise good, and validation loss is quite low. In future, we can increase accuracy by using transfer learning on large datasets. We can also improve the model's performance by using a better pre-processing strategy.

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