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BRAIN TUMOR DETECTION MODEL BASED CNN AND THRESHOLD SEGMENTATION

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***Abstract*: Fast and precise diagnosis is necessary in the medical profession for effective treatment, but current technologies lack this capability. For successful therapy, it is therefore necessary to develop an effective diagnosis application. Global threshold segmentation for pre-processing is used in this study. Image capture and de-noising have been completed in the first stage, while classification and regression have been completed at the second stage using ML approaches. A computer-aided automated identification method are the computational techniques used in this study. 120 brain scans from a real-time MRI brain database—15 normal and 105 abnormal—are used in this investigation.. The accuracy on training and testing pictures was 99.46%, according to performance metrics. Comparing this method to recently published methods, it is determined that LR-ML with Th- segmentation has rapid, precise brain diagnostic system**

***Keywords:* MRI image, CNN, Th-segmentation, MR, Tumor, De-noise.**

I. INTRODUCTION

This study presents a method for segmenting MR (magnetic resonance) brain images into several tissue classes using global threshold-based machine learning algorithms. For each segment, the network collects multi-scale data using a variety of patch sizes and decision trees, ensuring that the approach captures accurate segmentation information. For the method, just one anatomical MR image is needed. This approach not only obtains the De-noise picture but also clean image data[1]. Major causes of brain dysfunction include brain diseases or malignancies. A tumor is a little piece of brain tissue that has grown uncontrollably. The majority of the world's population suffers from brain illnesses, and almost 10 billion individuals have perished from brain tumors [2].Here is an MRI of the brain. To find tumors, an MRI scan is used. Since brain tumors and other problems may now be detected at an early stage thanks to segmentation and classification, this issue has been solved [3]. For this experiment, real-time diagnostic centers have acquired magnetic resonance images of the brain. A software programme for cancer identification is built utilising image processing and computer design [4]. Uncontrolled and rapid cell proliferation is the cause of brain tumour development. If it is not treated in the first stages, it might be deadly[5]. The detection of brain tumours and the making of decisions by clinicians are aided by machine learning approaches. Recent advancements in medical image processing have been greatly influenced by the development of deep learning techniques using the best classifiers [6]. When brain tissues grow atypically, a brain tumor results. Medical image analysis is essential for helping individuals identify a variety of illnesses [7]. Advanced medical imaging techniques are often employed to examine abnormalities in brain tissues, which can help in the early diagnosis of tumors [8].The information is originally taken from a dataset that includes MR images of the brain as shown in Figure 1. The preprocessing layer is where crucial operations like further normalization and patch extraction are carried out to get the picture ready for CNN steps mentioned in Figure 2. The next stage of CNN uses convolution as a mathematical and technical technique to extract features from the input picture in combination [9].

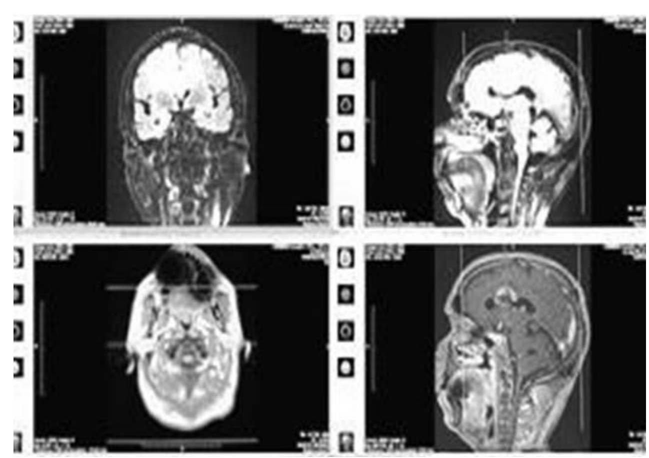

Figure 1: MRI Brain Images

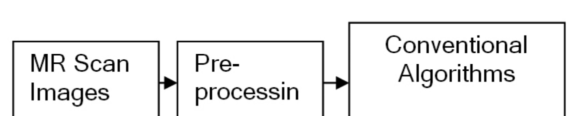

Figure 2: MR Scan Conventional Model

II. LITERATURESURVEY

K. Selvanayaki et al. published a description of the MRI brain tumour diagnosis method with automatic CAD recognition in 2010[10]. In this project, computer-aided design 2008 was created using segmentation on MR brain images [11]. Three-winged emergent cad system has been studied and addressed by H. Fujita et al. The Japanese health care monitoring system uses this computerised method for brain diagnoses. Yet more precision needs to be achieved. H. Arimura et al.'s 2012 explanation of the application of machine learning to MRI image processing is available here [12]. There are issues with this method, including ones with accuracy and imaging time. (2011) Zhang, Y., et al. to acquire the necessary diagnostic information concerning tumors (such as the type, size, location, shape, etc.), There are numerous medical imaging techniques in use. [13]. A system's sensitivity, specificity, and accuracy are all analysed to determine how well it functions. Using SVM and FCM algorithms, the researchers in [14] created a hybrid technique for classifying brain MRI data. The authors of [15–18] contrasted naive Bayes, J48 decision trees, and neural networks; this strategy has the disadvantage of being a conventional approach. On the other hand, [19, 20] proposed that machine learning might be used to categories brain cancers. The accuracy of the model, as measured by KNN and SVM, was 0.95 percent. Due to the outcomes of the automated intelligent system, this model's accuracy is higher, but its sensitivity is lower. The authors [21, 22] suggested a method for more accurately identifying and classifying mental tumors by combining support vector machines (SVM) and artificial neural networks (ANN); nevertheless, despite the high accuracy, the precision was not entirely adequate [23, 24].

2.1 Problem Identification

1. Denoising an MRI of the brain
2. Decisions made using processed data are risk-free
3. The existing technique has lower efficiency and PSNR

2.2 Parameters estimated:

1. Mean square error
2. Peak signal to noise ratio
3. Correlation Coefficient
4. Structural similarity index measure
5. Contrast to noise ration

For a quick and precise method, a hybrid export MRI brain system has been used in this study. The method, however, has limitations in terms of categorization and noise. So, a new application has to be designed. (2006). Support vector machine has been used to construct a wavelet transform-based MRI brain picture system. This neural network's action control is based on an application for biomedical signal processing.

III. METHODOLOGY

Threshold-based segmentation has been carried out in the third phase. The segmentation threshold value for these MRI brain pictures was set by averaging the grey and white pixels as in Figure 3.

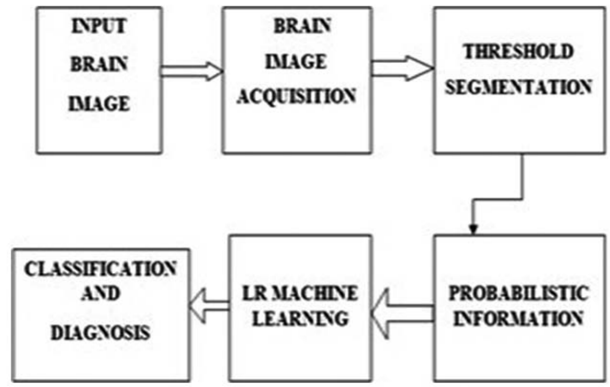

Figure 3: Proposed Methodology

MRI brain pictures from a dataset are needed for this input brain image block. This dataset consists of 100 MRI brain scan pictures, both normal and pathological, combined. The second part of the process was the capture of images using histogram equalisation and adaptive median filter denoising techniques. This adaptive median filter has been constructed for denoising using Yi,j as the weighted MR image, Wmax as the weight maximum, Si,jmin,w, Si,jmed,w, and Si,jmax,w (Algorithm 1).

Algorithm 1

Step 1: Enter an image
Step 2: Grayscale conversion
Step 3: Bring in local data
Step 4: Calculate the threshold.
Step 5: Compare the outcome. Threshold has been designated as background if it is less than the current pixel value, otherwise it is an object.
Step 6: Stop the process

Six phases make up this suggested block diagram for quick and precise diagnosis, which is seen in figure 3. The mathematical equations in [5] make up the method mentioned above. Accurate brain tumor identification has been achieved using these computational techniques, and in the same step, classification-related statistical data has been produced.

In this study, a multilayered support vector machine (ML-SVM) technique is merged with a convolution neural network (CNN). As illustrated in Figure 1, the major five functional units of this system are image acquisition, preprocessing, patch extraction, feature extraction, CNN classification, and ML-SVM classifier. Here, the steps, each block, and the subsequent results are discussed. Images are imported

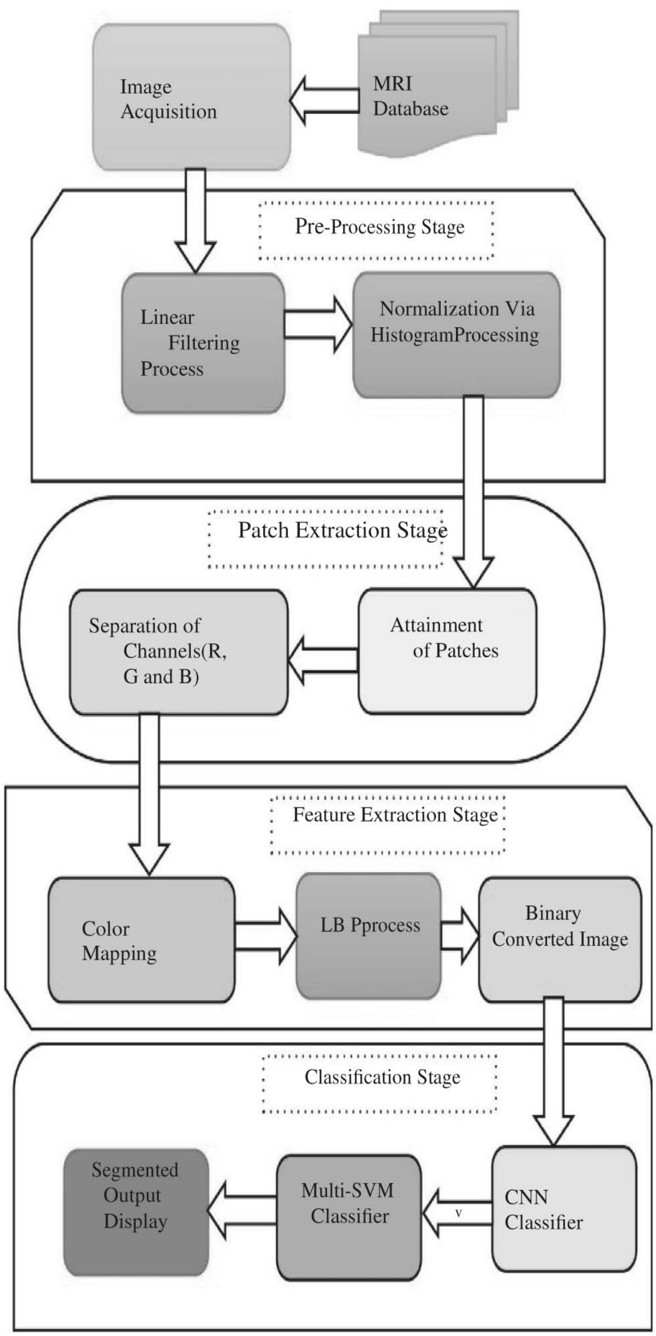

Figure 4: Step by Step Process of MRI Brain Tumor Detection

throughout this procedure from a dataset. This imported MRI scan picture is intended to be from the brain's glioma area, and it was processed to look for tumours.The Kaggle medical image database, which is the most widely used and accepted database in the field of research, is where the brain scan photos were found. As shown in the suggested block diagram, image filtering techniques are used to treat the obtained pictures before image intensity normalization. The input pictures produced by medical imaging modalities contain artifacts as a result of the modalities' inherent characteristics. These photos must first be treated to eliminate any extraneous disruptions and to normalize them. Here, a neighborhood operation using weight adjustment processes is used to do linear filtering on the picture. This filtered picture has been adjusted for constant intensity.

By using histogram processing to alter the contrast of the pixel values, image normalization is accomplished.
The color map technique is used to transform the RGB picture to a binary image for feature extraction, and local binary pattern (LBP) is then used to complete this process. CNN has fewer parameters and connections than traditional feed-forward neural networks, which simplifies training. This comprises the training and testing of the necessary dataset as the main step in order to get improved results. Iterative in nature, it is only terminated when the best outcomes are obtained. It was found that this model is capable of both autonomous classification tasks and character extraction from unprocessed images. The first step, as depicted in the block diagram suggested, is to train CNN and multilayered SVM models. The models are put through their paces in the second step to provide the final segmentation results (Algorithm 2).

Algorithm 2

Step 1: First, import the MRI data from the medical database.
Step 2: Gaussian-based linear filter
Step 3: Histogram processing for normalisation
Step 4: Start the patch extraction process after obtaining the patches and separating the RGB channels.
Step 5: start the feature extraction process by establishing a threshold value and color mapping.

i LBP technique to produce a binary image
ii The image is transformed into a grayscale version.
iii Choose the P nearby pixels for each pixel in the image. The coordinates of grey pixels are given.
iv Set the threshold for its P neighbours to be the central pixel (gc).
v Set to 1 if the value of the adjacent pixel is greater than or equal to the value of the central pixel, and 0 otherwise.

Step 6: Start the classification process by classifying the test cases and transforming the training data into kernel space using the Multi-SVM procedure.

i. Classification by CNN
ii. Data loading for the test train
iii. 100 iterations of the procedure will result in an error value of 1.2% less.
iv. For CNN, create layers and sub sampling layers with different kernel sizes. Sort the data and forecast the outcome.

IV. EXPERIMENTAL RESULTS

It demonstrates steps such as image acquisition, in which input images are taken from a dataset, preprocessing, in which the images are filtered to remove any undesirable artefacts, patch extraction, in which patches are achieved in relation to the RGB channels, feature extraction, in which colour mapping .The MRI scan of the brain's glioma region is imported as the input image, as seen in Figure 3, and it is processed to look for tumours. To create the filtered output image, the imported image is further fed into the filtering procedure, as depicted in Figure 4.In this case, filtering is carried out in two steps: first, linear filtering, which employs the Gaussian filter kernel because it has all the qualities of other filters due to the structural organisation of its density function, and second, nonlinear filtering.As a result of the filtering, it generates a 2D Gaussian smoothing kernel, a rotationally symmetric Gaussian low pass filter with a positive standard deviation value, and less artefacts. The final step is to normalise the resulting image using histogram processing. In this instance, a technique called mapping is used to translate the intensity levels in the resulting grayscale image to new values.

The outcome is a normalised image that saturates the lowest and highest one percent of all imaginable pixel values, as seen in Figure 5. Normalization has the effect of increasing the contrast values in the resulting image.

After the normalised image is put into the patch extraction step, the patch extracted image shown in Figure 6 is created. In order to maintain equilibrium, the size of each patch must be taken into account when obtaining the patches.

The basic conversion procedure is then performed on this channel split picture using the grey thresholding approach. The resulting image must next be subjected to the LBP technique. LBP is a particular kind of visual descriptor that is employed in this situation to classify. Figure 10 illustrates the output image at this point, which is a binary transformed image.

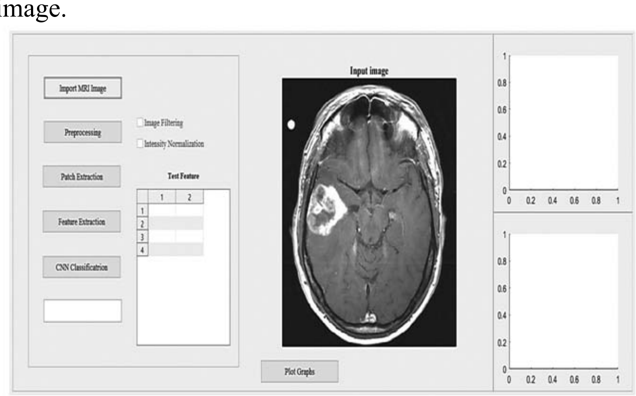

Figure 5: Interface of brain tumor segmentation displaying the stages involved.

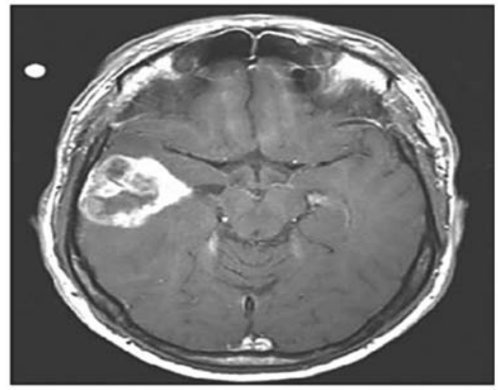

Figure 6: Imported MRI image from the dataset

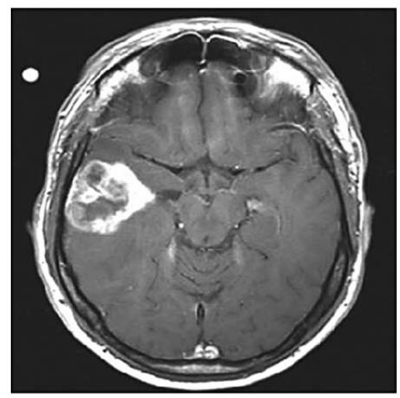

Figure 7: Filtered Input MRI image

When the model accurately predicts the positive class, the outcome in these equations is referred to as a "true positive" (TP). While TN stands for true negative to denote a result that the model expected to be negative, FP stands for false positive to denote a result that the model anticipated to be positive. When the model predicts the negative class inaccurately, it is referred to as a "false negative".

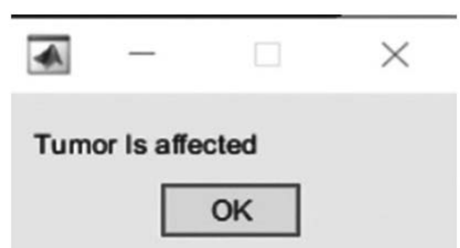

Figure 8: Final Output from Console

$$\text{Dice similarity coefficient } (DSC) = \frac{(2TP)}{(FP + 2TP + FN)} X100, \quad (1)$$

$$\text{Jaccard similarity index } (JSI) = \frac{(TP)}{(TP + FN + FP)} X100. \quad |(2)$$

With a DSC value of 96.21% and a JSI value of 94.32%, the table and graphical representation clearly show that the suggested technique is superior to earlier ones for the identification and classification of brain tumours. The proposed multilayered SVM with CNN yields values for the Dice Similarity Coefficient (DSC) that are obviously superior to those of earlier techniques.

The metrics sensitivity, accuracy, specificity, and precision are provided in Table 1 in a similar manner.

Table 1: Parametric evaluation and comparison

Classification Methods	Accuracy (%)	Sensitivity (%)	Specivity (%)	Precison (%)
CNN	96.45	92	95	94.82
CNN+SVM	95.63	93	95	92.32
Proposed Multi-SVM+CNN	99.23	95.73	97.12	97.34

Figure 9 also offers a pictorial depiction for comparing variables including sensitivity, accuracy, specificity, and precision.

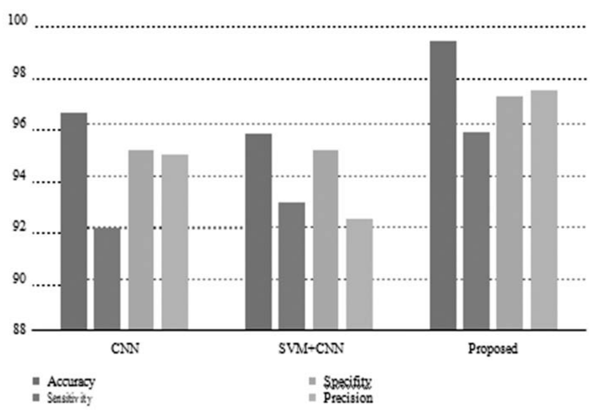

Figure 9: Graphical plot of sensitivity, accuracy, specificity, and precision

In this case, the rate of accurate tumor region of interest classification as in equation (3). Equation (4) offers the equation for the accuracy (ACC) parameter, which is utilized to get the corresponding value of the tumor identification rate by estimating the precise percentage value of how sensitive the procedure is.

$$\text{Accuracy } (ACC) = \frac{(\text{TP} + \text{TN})}{(TP + TN) + (FP + FN)} X100, \quad (3)$$

$$\text{Sensitivity (SE)} = \frac{(\text{TP})}{(\text{TP} + \text{FN})} X100. \quad (4)$$

$$\textbf{Specificity (SP)} = \frac{(\textbf{TN})}{(\textbf{TN} + \textbf{FP})} \boldsymbol{X100}, \quad (5)$$

$$\textbf{Precision (PR)} = \frac{(\textbf{TP})}{(\textbf{TP} + \textbf{FP})} \boldsymbol{X100}. \quad (6)$$

The table and graphical depiction make it clear that the suggested method, when compared to earlier techniques for brain tumor identification and classification, has a significant advantage in terms of accuracy by 99.23%, sensitivity by 95.73%, specificity by 97.12% (eq 5), and precision by 97.34% (eq 6).

V. CONCLUSION

Many techniques for diagnosing and classifying brain tumours have been published and studied in the literature in an effort to expand the range of treatment options and patient endurance. In this study, preprocessing, training, testing, and classification were used to advance the segmentation and identification of brain tumours. The intensity levels of the images used as the dataset's input are first filtered and normalised. The characteristics were first obtained, trained, and evaluated in a CNN environment, and then provided to a multiple layer SVM classifier in order to display the tumour status in the MR images. CNN's main advantage over its forerunners is that it recognises significant elements automatically and without human assistance. The suggested method proved to be the best with a 99.23% accuracy rate.

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