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Brain tumor detection model based on CNN and threshold segmentation

Jaishree Jain*, Shashank Sahu and Ashish Dixit

Department of Computer Science & Engineering, Ajay Kumar Garg Engineering College, Ghaziabad, India

E-mail/Orcid Id:

JJ, jainjaishree@akgec.ac.in, https://orcid.org/0000-0003-0173-7664; *SS*, sahushashank75@gmail.com, https://orcid.org/0000-0001-6720-4284; *AD*, ashishdixit1984@gmail.com, https://orcid.org/0000-0002-3842-6934

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Abstract: Brain tumours pose a substantial global health issue, emphasising the criticality of timely and precise identification to ensure optimal treatment outcomes. This research introduces an innovative methodology for the identification of brain tumours by employing a fusion of Convolutional Neural Networks (CNNs) with threshold segmentation techniques. The objective of the suggested model is to improve the precision and effectiveness of brain tumour identification in medical imaging, namely Magnetic Resonance Imaging (MRI) scans 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 were completed in the first stage, while classification and regression were completed in the second stage using ML approaches. A computer-aided automated identification method is the computational technique used in this study. This investigation uses one hundred twenty (120) brain scans from a real-time MRI brain database, of them 15 normal and 105 abnormal. According to performance metrics, the accuracy of training and testing pictures was 99.46%. Comparing this method to recently published methods, it is determined that LR-ML with the threshold segmentation has a rapid, precise brain diagnostic system.

Introduction

This study proposes global threshold-based machine learning algorithms for brain images. 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 obtains the De-noise picture and clean image data. Major causes of brain dysfunction include brain diseases or malignancies. A tumor is a very little piece of brain tissue that has grown uncontrollably. Most of the world's population suffers from brain illnesses, and almost 10 billion individuals have perished from brain tumors (Cha, 2006). Here is an MRI of the brain. To find tumors, an MRI scan is used. This issue has been solved since brain tumors and other problems may now be detected at an early stage thanks to segmentation and classification (Louis et al., 2007). For this experiment, real-time diagnostic centers have acquired brain magnetic resonance images. A software programme for cancer identification is built utilizing image processing and computer design (Zacharaki et al., 2009). Uncontrolled and rapid cell proliferation is the cause of brain tumor development. It might be deadly if not treated in the first stages (Litjens et al., 2017). Recent advancements in medical image processing have been greatly influenced by the development of deep learning techniques using the best classifiers (Schwartzbaum et al., 2006). Usually, a brain tumour develops from the growth of brain tissues. Medical image analysis is essential for helping individuals identify a variety of illnesses (Tiwari et al., 2020; Patil and Kirange, 2023). Advanced medical imaging techniques are often used to examine the abnormality to detect the tumour early

*Corresponding Author: jainjaishree@akgec.ac.in

(Singh and Ahuja, 2019). The information is originally taken from a dataset that includes MR images of the brain, as shown in Figure 1. The pre-processing layer is where crucial operations like further normalization and patch extraction are carried out to prepare the picture for the 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 (Isin et al., 2016; Saleck, 2017).

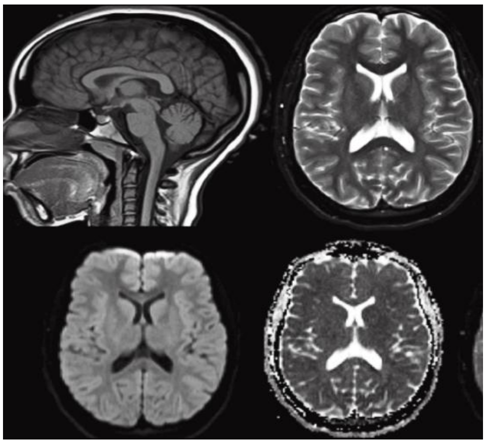

Figure 1. MRI Brain Images

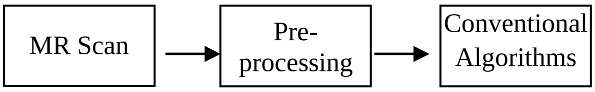

Figure 2. MR Scan Conventional Model

Literature survey

K. Selvanayaki et al. (2010) published a description of the MRI brain tumor diagnosis method with automatic CAD recognition in 2010. Singh (2019) & Sayed et al. (2014) have studied and addressed the three-winged emergent cad system. The Japanese healthcare monitoring system uses this computerised method for brain diagnoses M. Saleck (2017). Yet more precision needs to be achieved. (Surya et al., 2021) explanation of the application of machine learning to MRI image processing is available here (Zargar et al., 2015). There are issues with this method, including ones with accuracy and imaging time. To acquire the necessary diagnostic information concerning tumors (such as the type, size, location, shape etc.), numerous medical imaging techniques are in use (Parveen, 2015; Aggarwal et al., 2023). The researchers used SVM and FCM algorithms (Sachdeva et al., 2014) to create a hybrid technique for classifying brain MRI data. Many authors contrasted naive Bays and neural network approach, this strategy has the disadvantage of being a conventional approach (Chaddad and Tanougast, 2016; Sahu and Singh, 2018; Sajjad, 2018). On the other hand (Mishra et al., 2014), (Singh and Singh, 2019) and (Rashid et al., 2020) proposed that machine learning might be used to categorise brain cancers. The model's accuracy, as measured by KNN and SVM, was 0.95%. Few authors suggested a method for more accurately identifying and classifying mental tumors by combining networks; nevertheless (Saba, 2020; Singh et al., 2018), despite the high accuracy, precision was not entirely adequate (Al-Ayyoub et al., 2014; Jain and Singh, 2020).

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

Parameters estimated

1. Mean square Error (MSE)
2. Peak Signal Noise Ratio (PSNR)
3. Correlation Coefficient
4. Structural Similarity Index measure
5. In contrast to noise ratio

A hybrid export MRI brain system has been used in this study for a quick and precise method. The method, however, has limitations in terms of categorization and noise. So, a new application has to be designed. 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.

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.

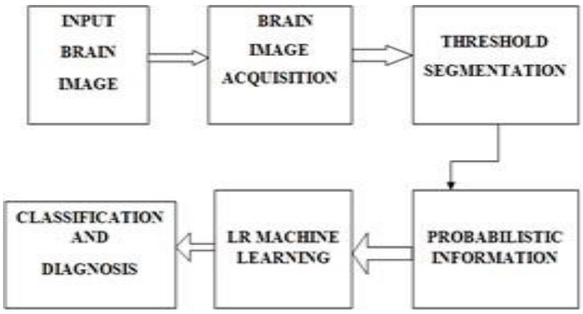

Figure 3. Proposed methodology

MRI brain pictures from a dataset are needed for this input brain image block. The process's second part was capturing images using histogram equalisation and adaptive median filter denoising techniques. This adaptive median filter has been constructed for denoising (Algorithm 1).

Algorithm 1

Step 1: Enter an image

Step 2: Grayscale conversion

Step 3: Bring in local data

Step 4: Calculate the threshold.

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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 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.

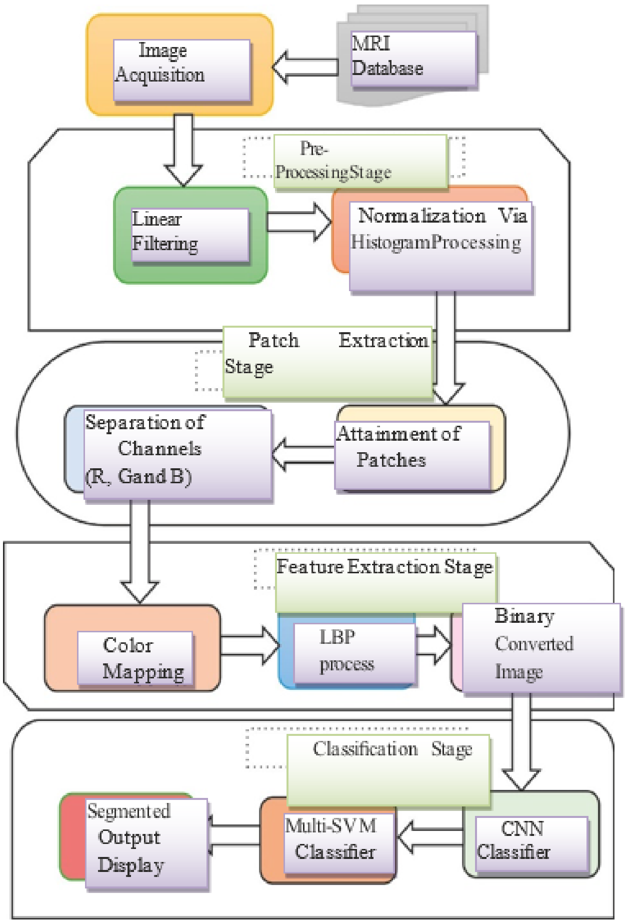

Figure 4. MRI brain tumor detection flowchart

This study merges a multilayered support vector machine (ML-SVM) technique with a convolution neural network (CNN). As illustrated in Figure 1, the steps, each block, and the subsequent results are discussed here. Images are imported throughout this procedure from a dataset. The suggested block diagram shows that 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 neighbourhood operation using weight adjustment processes is used to do linear filtering on the picture. This filtered picture has been adjusted for constant intensity.

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. 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 (Algorithm 2).

Algorithm 2

Step 1: MRI Image imported from the database.

Step 2: Gaussian-based linear filter applied.

Step 3: Normalize image using Histogram method.

Step 4: Extract the patches and separate them in RGB Channels

Step 5: Extract the features 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 in the image. The coordinates of the grey pixels are given.
iv. For P neighbor to be a central pixel, set the threshold.
v. If the value of the adjacent pixel is equal to 1, then assign 1; otherwise, 0.

Step 6: Now start the classification process on test images and, based on the results, transform 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.

Experimental Results

It demonstrates steps such as an image from a data set, pre-processing, in which the images are filtered to remove any undesirable artefacts and patch extraction, in which patches are achieved in relation to the RGB channels.

Filtering is done in this instance in two steps: first, the Gaussian filter kernel is used in linear filtering. The filtering produces a rotationally symmetric Gaussian low pass filter with a positive standard deviation value. The resultant image is normalized using histogram processing as the last step. The basic conversion procedure is then performed on this channel split picture using the grey thresholding approach. The resulting image must next be

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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.

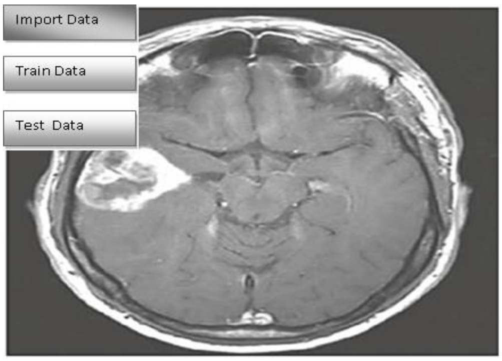

Figure 5. Brain Tumor Segmentation

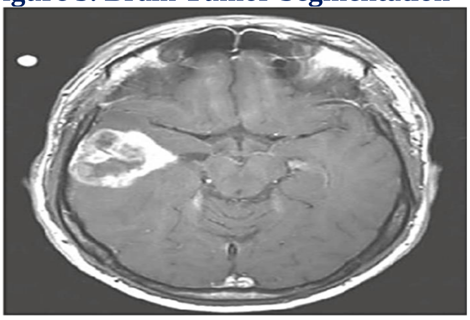

Figure 6. MRI image

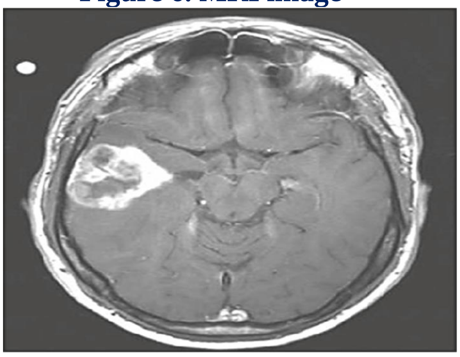

Figure 7. Filtered MRI image

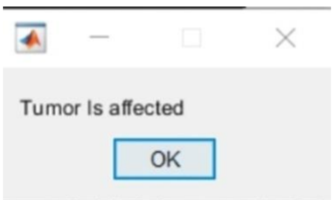

Figure 8. Final output from console

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"

Disc Similarity coefficient (DSC) =

$$\frac{2TP}{FP+2TP+FN} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Jaccard Similarity Index (JSI) =

$$\frac{TP}{TP+FN+FP} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

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 identifying and classifying 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 similarly provided in Table 1.

Table 1. Parametric evaluation and comparison

Classification Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
CNN	96.45	92	95	94.82
CNN+SVM	95.63	93	95	92
Proposed Algorithm(Thresholding+Multi SVM+CNN)	99.5	95.73	97.8	97.3

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

In this case, the accurate tumor region of interest classification rateis 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.

$$\text{Accuracy(ACC)} = \frac{TP+TN}{(TP+TN)+(FP+FN)} \times 100 \ldots\ldots\ldots\ldots\ldots(3)$$

$$\text{Sensitivity(SE)} = \frac{TP}{(TP+FN)} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

$$\text{Specificity(Sp)} = \frac{TN}{TN+FP} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$\text{Precision(PR)} = \frac{TP}{TP+FP} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

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 99.5%, sensitivity by 95.73%, specificity by 97.8% (equation 5), and precision by 97.3%.

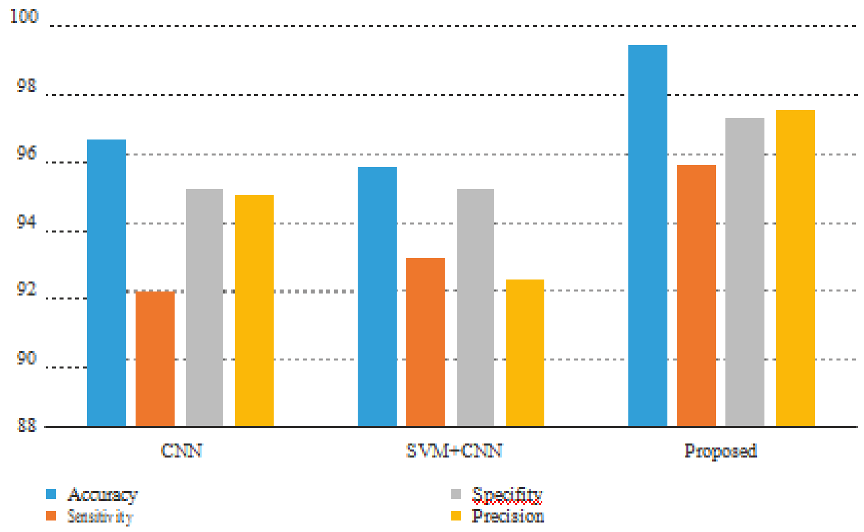

Figure 9. Graphical plot of sensitivity, accuracy, specificity and precision

Conclusion

The integration of convolutional neural networks (CNNs) with threshold segmentation in the brain tumour detection model signifies a notable development within the realm of medical imaging. This case serves as a demonstration of the capacity of artificial intelligence to transform the healthcare sector through the provision of precise and efficient diagnostic instruments. With the ongoing advancement of technology and the growing accessibility of data, this particular model possesses the capability to significantly influence the timely identification and management of brain tumours, hence enhancing the quality of patient care and overall results.

Many techniques for diagnosing and classifying brain tumors have been published and studied in the literature to expand the range of treatment options and patient endurance. In this study, pre-processing, training, testing and classification were used to advance the segmentation and identification of brain tumor. CNN's main advantage over its forerunner is that it automatically recognises elements without human assistance. The suggested method proved to be best with a 99.5% accuracy rate; hence it's a better approach for early brain tumour diagnosis.

Conflict of interest

We do not have any conflict of interest in this article.

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