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Segmentation and Classification of Brain Tumor using Watershed, SVM and CNN Algorithms

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Abstract: The human brain is the primary controller of the humanoid system. A brain tumour is caused by abnormal cell growth and division in the brain, and so brain tumours can lead to brain cancer. Computer vision plays an important role in human health by reducing the accuracy of human judgement.CT scans, X-rays, and MRI scans are all common imaging modalities. Magnetic resonance imaging is the most reliable and secure method (MRI). MRI is used to detect every minute thing. The application of various methodologies is examined in our research. During this experiment, we used the Gaussian filter(GF)to remove noise from brain MRI for the identification of brain cancer.

Index Terms: BraTS,Classification, medical imaging, Segmen-tation, SVM, tumor detection,watershed.

I. INTRODUCTION

A Large number of cells make up the human body. When acell's growth becomes unchecked, the excess bulk turns into a tumour. CT and MRI scans are utilised to determine the tumor's location. The purpose of our research is to ac- curately detect and classify brain malignancies using a com- bination of approaches including medical image processing, pattern analysis, and computer vision for brain diagnosis en- hancement, segmentation, and classification. Neurosurgeons, radiologists, and other health-care professionals can benefit from our project. The classifier's performance, specificity, and diagnostic efficiency of brain tumour screening utilising industry standard simulation software tools are affected bythe imbalance of positive and negative cases in the trainingset. These methods entail preprocessing MRI scans gathered from numerous pathology labs as well as scans obtained from internet cancer imaging archives. After resizing the images, the proposed segmentation and classification methods are applied. The method is projected to improve the present brain tumour screening procedure while also potentially lowering health-care expenditures by reducing the need for follow- up operations. For accurate characterization and analysis of biomedical imaging data, several processing steps are required.

A. PROJECT IDEA

A tumor may be a development of cells within the brain or central epithelial duct that is abnormal. Because some tumors are malignant, they need to be recognised and treated as soon as possible. Because the actual source of brain tumorsis unknown, as is that the exact set of symptoms, people are also littered with them without realising it. Primary brain tumors will be either malignant (containing cancer cells) or benign (without containing cancer cells).

B. MOTIVATION OF THE PROJECT

When cells divide and develop abnormally, they form a brain tumor. When identified using diagnostic medical imaging tools, it seems to be a solid mass. There are two forms of brain tumors: Primary brain tumors and metastatic brain tumors. A primary brain tumour is one that develops in the brain and tends to stay there, whereas a metastatic brain tumouris one that develops elsewhere in the body and spreads tothe brain. The symptoms of a brain tumour are determinedby the tumor's location, size, and kind. It happens when a tumor compresses the surrounding cells and exerts pressure on them. Furthermore, it occurs when the tumour obstructs the movement of fluid throughout the brain. Headaches, nau- sea, and vomiting are common symptoms, as are difficulties balancing and walking. Diagnostic imaging methods such as CT scan and MRI can detect brain tumours. Depending on the type of place and the goal of the test, both modalities offer benefits in detecting. We prefer to use MRI scans in this paper since they are straightforward to inspect and provide accurate calcification and foreign mass placement.

C. LITERATURE SURVEY

The four separately trained SegNet models are post- processed to produce four maximum feature maps by combining

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the machine-learned feature maps from each trained mode's fully convolutional layers. This improves tumour segmentation even further.[1].

Preprocessing, feature extraction, picture categorization, and brain tumour segmentation are all part of this project. The MRI picture is smoothed and enhanced using the Laplacianof Gaussian filtering approach.[2].
The suggested technique can achieve good performancewith average Dice scores of 0.8136, 0.9095, and 0.8651 for tumour enhancement, according to the experimental resultson the BraTS 2018 validation dataset.[3].

The study used a real-time dataset with tumours of varying sizes, locations, shapes, and intensities. In thetraditional classifier section, we used six classic classifiersimplemented in scikit-learn: Support Vector Machine. AfterMLS approach is used in two ways. First, we used the best thresholding method, which processes the input brain image pixel by pixel. After that, watershed segmentation is used to separate multi-label regions of the thresholded objects that are close together, and finally, the morphological operation is used to precisely segment the Tumor defective area.
that, Convolutional Neural Networks was used.CNN achieved 3. Feature Extraction: Feature extraction retrieves features from a remarkable accuracy of 97.87 percent in this [4].

Image pre-processing comprised bias field correction and normalisation of each MRI sequence's intensity histograms. During multiplication or addition of FMs of various sizes, they employed convolution without padding, and thereforechopped the centre part of the largest one.[5].

They devised a two-stage verification-based tumour segmentation method that improves detection by segmenting the tumour area from the MR image and then using another algorithm to compare the segmented portion with the ground truth image. This new algorithm was named as watershed- matching algorithm[6].

To partition the image and use the classification technique, effective segmentation techniques are used. Through this we discovered that the best categorization tool is the SupportVector Machine[7].

D. OVERVIEW OF SYSTEM MODULES

The suggested CNN classification approach consists of pre- processing, segmentation, feature extraction, and classificationprocess for the categorization of tumours as malignant or non-cancerous from brain MRI. The first step is preprocessingwhich includes smoothening, sharpening, shrinking imagesand reducing the noise of input in the image analysis process. Segmentation is used to separate the targeted objects and once the interesting or targeted objects are isolated from the input, certain features are made which are then used to classify the objects into particular classes.

1. **Preprocessing :** The first step in improving the quality of an image before processing it into an application is to employan image preprocessing technique. We employed Gaussian, high pass, and median filtering techniques to eliminate noise from the source image during image preprocessing. The useof a Gaussian filter reduces noise in MRI brain pictures; high pass filtering removes undesired frequencies from the image; and median filtering improves image quality.

2. **Segmentation:** The brain image is segmented to isolate different items like grey matter, white matter, cerebral spinal fluid, skull, Tumor, etc. from each other, and the backdrop,as well as individual Tumors, are labelled as part of an image classification approach. The MLS approach is createdin this paper by integrating optimal thresholding, watershed segmentation, and morphological procedures. The proposed segmented brain tumours, and because the CNN approach is presently the go-to model for any image related problem,it's used for feature extraction within the CNN process. the foremost significant advantage of CNN over its predecessors is that it discovers crucial traits without the necessity for human intervention. It may also share parameters, allowingus to run the CNN model on any device. Furthermore, this method requires less information for faster training and searches for traits at their most fundamental level. The convolution layer extracts the features of an input image while learning image features to preserve the link between pixels. Longer features may be discovered by increasing the quantity of filters within the convolution layer, but this comes at the value of more training time. By employing a subsampling process, the pooling layer minimises the amount of parameters while keeping critical data. The feature map matrix was became a vector via a totally connected layer, which is similar to a neural network. The characteristics vector is combined to make a model that's then classified because the target item employing a softmax technique.

3. **Classification:** The final phase in the image analysis approach is classification, which includes organising feature data inan image into distinct classes. After segmenting a suspicious region, a feature extraction and selection strategy is utilised to extract the important information from the region; next, based on the available features and Tumor classes, a classification technique is employed to produce the best results.

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II. METHODOLOGY

Tumor identification is a difficult task. The position, form, and structure of tumours differ greatly from one patient to the next, making segmentation a difficult task. We have exhibited some photos of the same brain slice from different patients in the figure above, which clearly indicate the tumour diversity. The location of the tumour is clearly different in each of the eight images/patients presented below. To make matters worse, all eight patients/images have diverse shapes and intra-tumoralstructures. In reality, as the photos below show, the tumour canbe divided into multiple regions. This does, in fact, illustrate the difficulty of automatic segmentation.

A. Convoluted Neural Networks

The deep learning algorithm analyzes information in the same way as the human brain, but is much smaller due to the complexity of the brain. Image classification extracts features from an image to identify patterns in the dataset.

Algorithm:

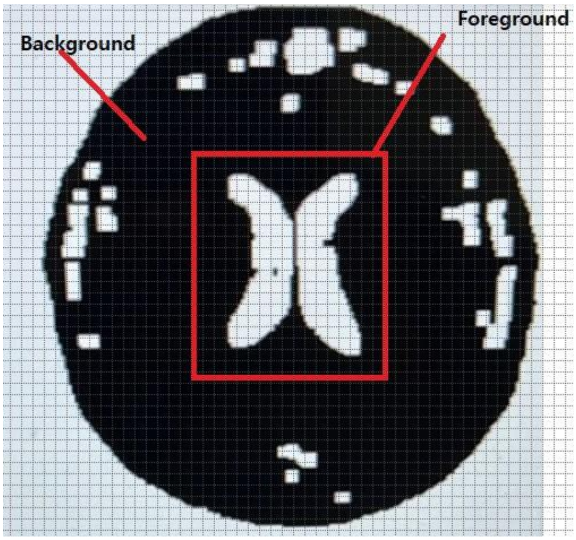

Fig. 1. Location of tumor

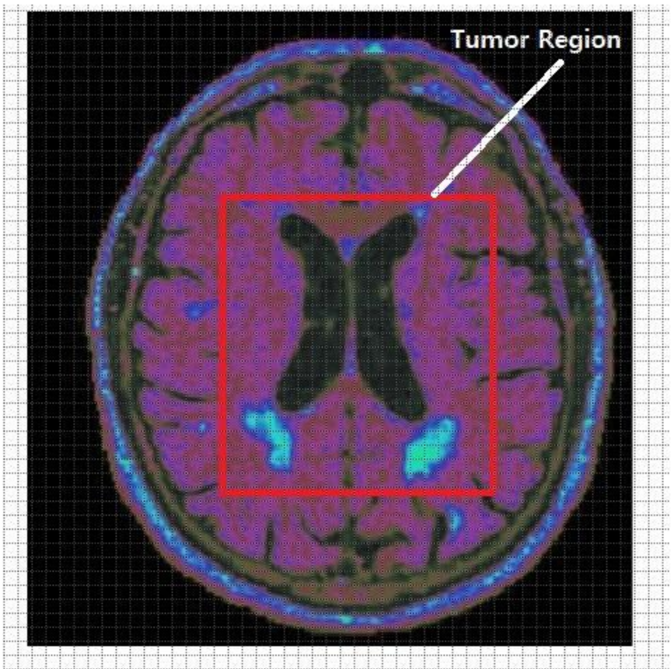

Fig. 2. Highlighted region of tumor

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Using for image classification is very computationally intensive because the parameters that can be trained are very large.
Practical Step by Step GuideStep 1: Select a data set.
Step 2: Create a training data set.Step 3: Gather data for training. Step 4: Rearrange the data.
Step 5: Labels and Features are assigned.
Step 6: Converting labels to categorical data and normalisingX.

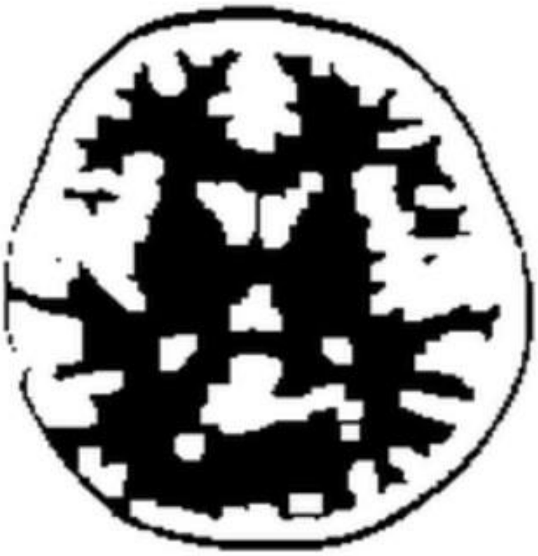

Fig. 3. Image with no tumor

Step 7: Separate X and Y for CNN to their intended function.

B. Support Vector Machine

When we train a machine learning model with labelled data,it's called supervised learning. It means we have data with the appropriate classification already attached to it. When using supervised learning, we'll need to rebuild the models whenever new data comes in to ensure that the predictions you obtain are still correct. Labeling photos of food is an example of supervised learning. An algorithm is nothing more than a programmable arithmetic function. That's why most algorithms feature cost functions, weight values, and parameter functions that can be swapped around depending on the data you're dealing with. Machine learning is just a set of math equations that must be solved.'

Algorithm

1) Step 1: Data Pre-processing.
2) Step 2: Fitting the SVM classifier model.
3) Step 3: Predicting the test set result.
4) Step 4: Produce a confusion matrix.
5) Step 5: Imaging the training set result.
6) Step 6: Imaging the test set result.

C. Watershed algorithm

In some complex photos, the Watershed method is utilised for segmentation. If we use simple thresholding and contourdetection, we won't be able to deliver accurate results. The Watershed algorithm works by extracting certain backgroundand foreground information. Then, with the help of markers,perform a watershed run and determine the exact limits. In general, this technique aids in the detection of touching and overlapping objects in images. image. It can be user definedfor markers, such as manually clicking and collecting theresults, markers' coordinates, as well as employing some
pre-defined methods like thresholding or any morphological operations. We are unable to apply the algorithm directly dueto the presence of noise. We then compute the watershedtransformation of the modified segmentation function.

Algorithm:

1) Step 1: Convert a colour image to grayscale by importingit.

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2) Step 2: The Segmentation Function will be the GradientMagnitude.
3) Step 3: Select the foreground object.
4) Step 4: Calculate background marking.

IV. RESULT

Test Cases and Test Results

extraction phase	precision	recall	f1-score	support
1	0.88	1.00	0.93	7
0	1.00	0.67	0.80	3
Accuracy	-	-	0.90	10
macro avg	0.92	0.88	0.87	10
weighted avg	0.91	0.89	0.90	10

TABLE I OUTPUT OF SVM AND WATERSHED

III. EXPERIMENTAL SETUP

A. Data set

The dataset is available on Kaggle. It contains 98 images of a healthy brain (without tumor). 155 images of the tumorousbrain. The dataset is divided into the following two parts.80 percent is used for training.The remaining 20 percent is usedfor testing.

B. Performance Parameters

Following are the performance parameters:

Classification score:

When we say the model's accuracy, we usually mean theclassification score. It is defined as the number of correct predictions divided by the total number of input samples. When the number of samples in each class is nearly equal, this metric produces good results in multi-class classification.

Confusion matrix:

Confusion matrix of CNN and Watershed algorithm:6 0
1 3
Outcome Values:
6 0 1 3

Confusion matrix of SVM and Watershed algorithm:7 0
1 2
Outcome Values:
7 0 1 2

Model accuracy and loss curves:

Model accuracy and loss curves, also known as learning curves, are commonly used for models that learn incrementally over time, such as neural networks. They represent an evaluation of the training and validation data, indicating how well the model is learning and generalising. The model loss curve represents a score (loss) minimising function, implying that a lower score leads to better model performance. The model accuracy curve represents a maximum score (accuracy), so a higher score indicates thatthe model performed better.

F1-Score:

The F1 Score is calulated as 2*((precision*recall)/(precision+recall))
The F1-Score of our system is as follows: 1. CNN andwatershed

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TABLE II

extraction phase	precision	recall	f1-score	support
1	0.86	1.00	0.92	6
0	1.00	0.75	0.86	4
Accuracy	-	-	0.90	10
macro avg	0.93	0.88	0.89	10
weighted avg	0.91	0.90	0.90	10

TABLE II OUTPUT OF CNN AND WATERSHED

The accuracy achieved by CNN and Watershed algorithm is 90%. The SVM and Watershed algorithm achieved the accuracy of 90%The console shows the confusion matrix and classificationreport which includes accuracy, precision, recall, f1-score.

Test Cases:

Description of Input	Expected Output	Observed	Status
1.Test MRI with tumor	Detects tumor	Detects Tumor	Pass
2.Test MRI with no tumor	Shows no tumor	No tumor	Pass
3.Grayscale image input	Works successfully	Works successfully	Pass
4.RGB image as input	Works Successfully	Works Successfully	Pass

TABLE III TEST CASES

V. CONCLUSION

So, in this proposed system, CNN, Watershed and SVM algorithms were used to detect tumor, which are extremely important for image processing, tumor detection and classification.

VI. FUTURE WORK

By training the model with a larger number of images, wecan improve its accuracy. Identifying and labelling tumor subregions.

ACKNOWLEDGMENT

It gives us great pleasure in presenting the preliminary project report on 'Segmentation and Classification of Brain tumor using CNN, SVM and Watershed Algorithms'.

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