



Hybrid Method for Brain Tumor Detection and Classification Using Convolutional Neural Networks

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Abstract: The most frequent and aggressive brain tumor is deadly because of its aggressive nature. This shows that treating a patient is one of the most important stages in improving a patient's quality of life. The different image methods, such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound, are used to examine the tumor in various parts of the body, are used to examine the tumor in various parts of the body, especially the brain, lungs, livers, breasts, and prostates. MRI pictures are very useful in diagnosing brain tumors in this study. However, because of the large quantity of data produced by an MRI scan, it is impossible to categorize tumor vs. non-tumor for a certain period manually. However, since it only provides reliable quantitative measures in a restricted number of photos, it does have certain limits. Therefore, a trustworthy and automated categorization technique is required to avoid human mortality. The surrounding area's large geographical and anatomical heterogeneity is inherent to a challenge that the automated brain tumor categorization presents. The HBTCNN detection method is developed in this study, employing Convolutional Neural Networks and SVM classification. Accuracy is used up in this scenario, resulting in 96.2% efficiency. The tiny kernel design of the deep architecture is done utilizing large kernels. The weight of the neuron is estimated to be around 1 milligram.

Keywords: CNN, SVM, Brain tumor, HBTCNN, MRI

I. INTRODUCTION

Data mining, which involves the complicated extraction of previously unknown patterns from large data sets, is referred to as non-trivial data mining. Gathering and analyzing relevant data to identify connections and patterns in the data is now popular. It employs statistics, visualization, machines, and other data processing methods and information extraction to generate insight [8]. Analytics is the most important buzzword in the IT and non-IT sectors since data grows quickly in the internet and smartphone era. Most data mining applications and deep learning techniques are focused on solving large data challenges, especially in the healthcare industry. Although the patients' growth rate is equivalent to their population growth and improved lifestyle, there is still a large need for data processing in healthcare [1].

The tumor is among the most frequent brain disorders and stands out from the others. According to the World Health Organization (WHO), worldwide, around 4.3 million people have cancer. Applying advances in imaging methods enables it to be used in a wide range of medical specialties, such as, for instance, computed tomography (CT) scans, pathology diagnosis, surgical planning, and long-term evaluation. [2] discussed that In surgical planning and cancer treatment, it is crucial to segment and measure a liver tumor's volume accurately. Because it would involve

automation, standardisation, and the incorporation of complete volumetric information, accurate automatic liver tumor segmentation would substantially affect the processes for therapy planning and follow-up reporting. MRI and CT are the most widely employed imaging tools in neurosciences and neurosurgery [3]. [7] discussed that Tumor segmentation required also the identical automatic initialization as regarding the liver. This phase was applied only in order to liver volume, obtained following automatic delineation of lean meats surface: this latter, used to original dataset quantity, was used as a new mask in order to be able to prevent processing overloads and even avoid errors related to be able to arsenic intoxication surrounding tissues delivering similar gray scale droit.

A primary goal of this study is to find the most effective model for predicting brain tumors using data mining methods. The process model shown in Figure 1 was used for this investigation.

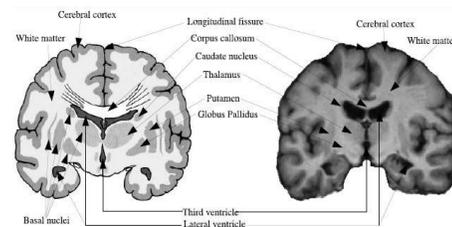


Figure 1: MRI Image architecture



[4] discussed that Liver tumor division in restorative pictures has been generally considered as of late, of which the Level set models show an uncommon potential with the advantage of overall optima and functional effectiveness.

The basic flow diagram of BT detection and classification is shown in figure 2 [11]. The diagram consists of four modules Image Enhancement (Image pre-processing)

1. Image Segmentation
2. Feature extraction
3. Classification

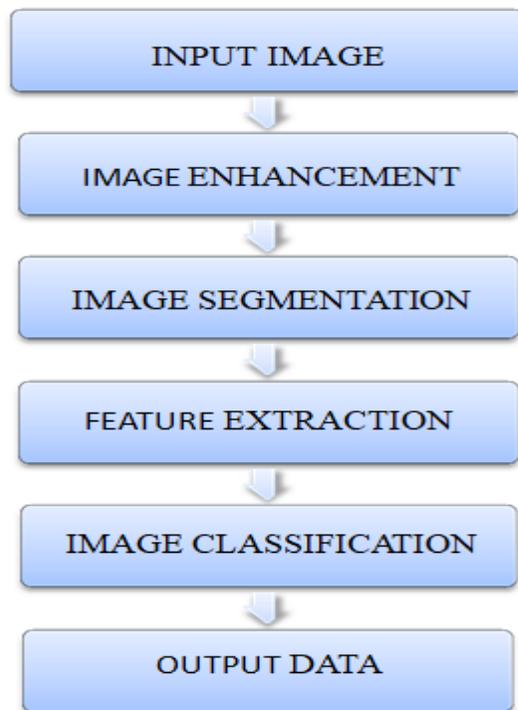


Figure 2: Generic flow diagram of brain tumor detection and analysis

II. LITERATURE SURVEY

Eman et al. (2015) describe the correct brain tumor detection approach in this paper. L, which means clustering, is the most common and easiest approach to locating the tumor component. This approach makes it possible to compute the tumor volume in the shortest time. But when a tumor is malignant, the presence of tumor cells will often be seen in groups or clusters, which decreases the likelihood of a successful diagnosis. A third tumor segmentation method is accomplished using Fuzzy C. With

noise-free pictures, the exact segmentation of tumors is achievable. To segment the tumor component, the process must be iterated several times. Additionally, the article presents the novel KIFCM methodology, which integrates the K means clustering with the Fuzzy c means clustering. Combining the two strategies mentioned above decreases the number of repetitions while improving accuracy, resulting in a better-established approach.

A novel approach for MRI brain imaging to describe tumor texture was suggested by Atiq Islam et al. (2013). The multi-resolution fractal model called multifunctional Brownian motion is used to assess the appearance of brain pictures (mBm). The supervised learning algorithm used the multi-fractal characteristics retrieved by the created algorithm and put them into the program to identify and segment the tumor area.

Andac Hamamci et al. (2012) suggested a technique for segmentation that required minimum user input. CA-based seeded tumor segmentation is used to perform segmentation on T1-weighted MRI images. Using this segmentation type, radiologists may design treatment plans for patients. It also employs tumor cut segmentation to divide tumor tissue into necrotic and augmenting sections. This is a highly quick and robust approach and improves segmentation and detection efficiency.

The model provided by Matthieu Le et al. (2016) might be somewhat difficult for researchers to tackle. It is important to determine the diffusion coefficient and proliferation rate for mathematical modeling. Diffusion approximation is problematic because of the lack of identifiable parameters, which causes the system to be confused and not be able to recognize complicated structures like tumors. Asymptotic qualities are used to obtain the diffusion equation using the Lattice Boltzmann Method.

Glioblastoma type tumor development on cerebral MR images was diagnosed using a novel convivial algorithm Lamia Sallemi et al. (2015). Global pixel value determines tumor growth. This particular strategy is made possible by cellular automata and rapid marching methods used to segregate tumor development. The treatment completely gets rid of the glioblastoma tumor. The suggested algorithm's primary purpose is to aid the radiologist in tumor diagnosis.

Christian et al. (2015) have created Robust, and fully automated picture segmentation was aided by MRI technology. A time-tested technique is used, in which a spatially weighted probabilistic algorithm is used for segmentation. The atlas-based EM approach is excellent for



investigating structures such as the hippocampus, thalamus, and putamen located in the subcortical regions of the brain.

Salim Lahmiri et al. (2017) provide a novel approach to removing noise by employing Wiener filtering. It runs till it reaches a specified condition to acquire an image calculation result. PSNR is used to measure the method's performance (Peak Signal to Noise Ratio). Without this denoising, sensors used by humans may be impaired. To make the picture less noisy, the author employed a Wiener filter.

Zhang Nan et al. (2011) provided a framework for a medical image analysis system that uses multi-spectral MRI data to segment and follow up on brain tumors and methods to remove false positives and outliers. Tumors of the brain may vary greatly in form and appearance and their levels of intensity. Complementary information from multiple spectra helps to clarify ambiguities. Additionally, they may be burdened with excessive extraneous information, resulting in more data processing time and segmentation mistakes.

III. BRAIN TUMOR DETECTION USING CNN

Another CNN is utilized to distinguish brains with tumors as benign or malignant. Levenberg-Marquardt is used to train the neural network. But the problem with this approach is that it looks for tumors if the detection system is at least 75 percent certain. The Berkeley wavelet transformation (BWT) is used to minimize complexity while accomplishing medical picture segmentation. To improve the accuracy of the SVM classifier, first and second-order statistical features are picked with a precision of 96.2 percent. With an accuracy of 86 percent, SVM is used to classify normal, benign, or malignant tumors. The dataset for this paper is derived from a publicly available collection of 3064 MR pictures. The characteristics discussed in this article were extracted using feature extraction and statistical image features on ROIs and images. This is accomplished by comparing the performance of two well-known classifiers: the Convolutional Neural Network (CNN) and the Support Vector Machine (SVM).

3.1 SYSTEM IMPLEMENTATION

3.1.1 Dataset Processing

To ensure that the model was robust and accurate, the dataset used was the BT Dataset, which included images of brains scanned at 233. There are three types of BTs: meningioma, glioma, and pituitary. 732 Meningioma, 1446 Glioma, and 928 Pituitary tumor pictures total.

3.1.2 Pre-processing

In MRI methods, we may adjust parameters such as radiofrequency pulses and gradients to get certain image appearances. There are a variety of MRI sequences, but T1 and T2 are the most used. Each MRI sequence offers data about tissues that transpired in the brain. The pictures utilized in this investigation are T1 for patients with normal anatomy. To provide an equal number of MR pictures of each normal subject, six sections were chosen at equal intervals from all of the normal subjects' MR pictures (person). Gadolinium-enhanced T1 MR images allow tumor boundaries to be better distinguished owing to the infusion of a contrast chemical called Gadolinium.

3.1.3 CNN Training:

CNN (convolutional neural network) is a neural network whose detection and classification are particularly useful for images. CNN is quite effective in discovering unique characteristics that are important for classifications. CNN is made up of neurons that can learn weight and bias. Neurons receive input; this is received and sent to the activation function, which produces an output. CNN implements consecutive convolution layers and a nonlinear ReLU function to extract particular characteristics with precise dimensions. The feature map is downsampled using the Max pooling layer. A Fully linked layer has every neuron in every preceding dense layer linked to each other. During training, backpropagation and gradient descent are both used. The softmax function restricts all class output values to 0 to 1 by using a probability distribution. Feature maps, also known as feature vectors, are provided by CNNs that enable the neural network to learn smaller features from images based on the depth of the hidden layers.

3.1.4 SVM Classification:

Supervised learning SVM classifier takes feature vectors from input pictures, analyses patterns, and uses this information to identify the maximum-separated hyperplane. The binary classification decision function is combined with this classifier to classify three distinct forms of cancers in the brain.

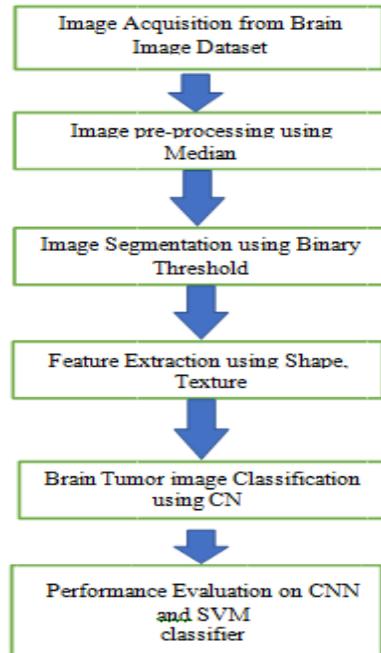


Figure 3: Architecture Diagram

Algorithm
3.1.5 CNN

This specific neural network is often employed in the medical imaging area. Many researchers throughout the years have attempted to construct a tumor model that can more effectively identify the tumor. We developed an example to classify the tumor in the 2D brain better with MRI data. The fully connected neural network could identify the tumor; however, we used CNN for our model because of sharing of parameters and the sparsity of connections.

The authors present a five-layer convolutional neural network used for tumor identification. The final model, which incorporates the hidden layers, provides the best tumor detection results.

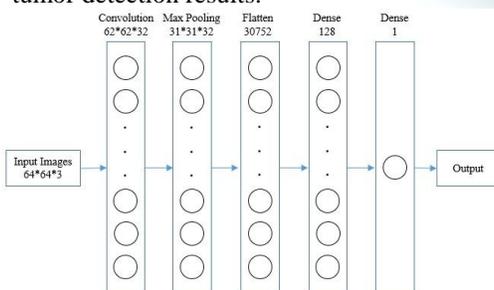


Fig. 4. Proposed Methodology for tumor detection using 5-Layer Convolutional Neural Network

Working Flow Devised for Proposed Methodology

1. Load the input dataset
2. Adding a Convolution Layer with 32 convolutional filter
3. Passing the Convolutional kernel into the Max Pooling layer
4. Pooled feature map is used to get the single column vector
5. Processing of the vector in dense layer with 128 nodes
6. Final dense layer applying Sigmoid as the Activation function
7. Validation stage and Performance evaluation

Fig.5. Working flow of the proposed CNN Model.

Algorithm: Process of CNN

```

1 loadImage();
2 dataAugmentation();
3 splitDate();
4 loadModel();
5 for each epoch in epochNumber do
6 for each batch in batchSize do
7 y=model(features);
8 loss=crossEntropy(y,Y);
9 optimization(loss);
10 accuracy();
11 bestAccuracy=max(best Accuracy, accuracy);
12 return;
    
```

3.1.6 SVM Classifier

Vapnik introduced the Support Vector Machine (SVM), which sparked considerable interest in the machine learning research field. Numerous recent research has shown that SVMs (support vector machines) typically outperform alternative data categorization techniques regarding classification accuracy.

Begin with the simplest scenario, which is one in which the training patterns are separable linearly. That is, there exists a linear function of the form $f(x) = w^T x + b$ (1) such that for each training example x_i , the function yields $f(x_i) \geq 0$ if x_i is from class +1, and $f(x_i) < 0$ if x_i is from class -1.

In other words, training examples from the two different classes are separated by the hyperplane $f(x) = w^T x + b = 0$, where w is the unit vector, and b is a constant.



While several hyperplanes may optimize the separation margin between two classes for a given training set, the SVM classifier is based on the hyperplane that maximizes the separation margin between the two classes. [10] discussed that Live wire with Active Appearance model (AAM) strategy is called Oriented Active Appearance Model (OAAM). The Geodesic Graph-cut calculation creates much better division results than some other completely programmed strategies distinguished in writing in the expressions of exactness and period preparing.

IV. RESULTS AND DISCUSSION

The proposed methodology has been implemented by using python programming language.

T1 weighted pictures, T2 weighted pictures, and PD weighted pictures are all found in each patient's data sets. The picture data collection is derived from Insight Journal and AAN Library websites. The scanners, each including an axial FSE (fast spin-echo) imaging sequence and a reduction in the susceptibility of the imaging system to non-uniformity of the magnetic field, are used to acquire the MRI scans. For the T1-weighted pictures, the number of slices is 124, whereas, for the T2-weighted pictures, the number of slices is 24. This does not mean that there is no correlation between the tissue location in the brain and the stored information. As a result, the experiment experiments by feeding the two MRI sequences as the input data to the experimental design.

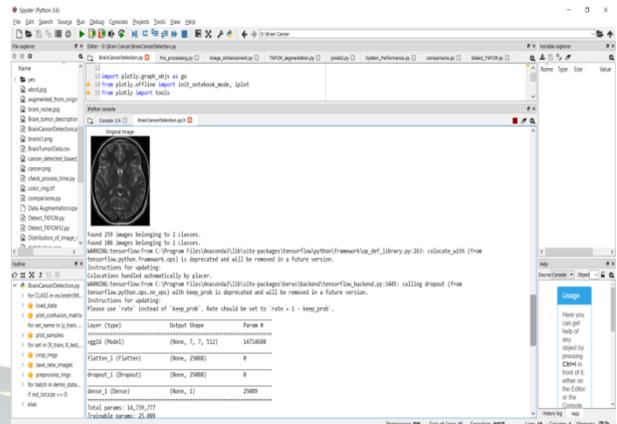


Figure 7 using CNN the layers found and selecting the original image

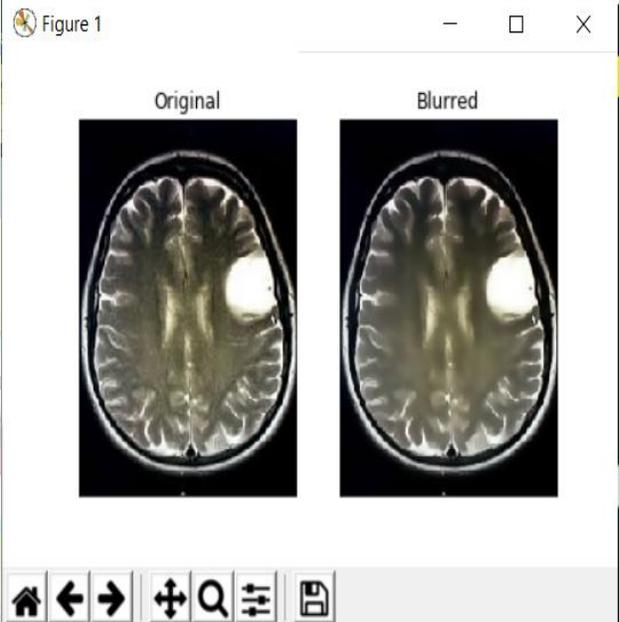


Figure 8 Classified in an original and blurred image

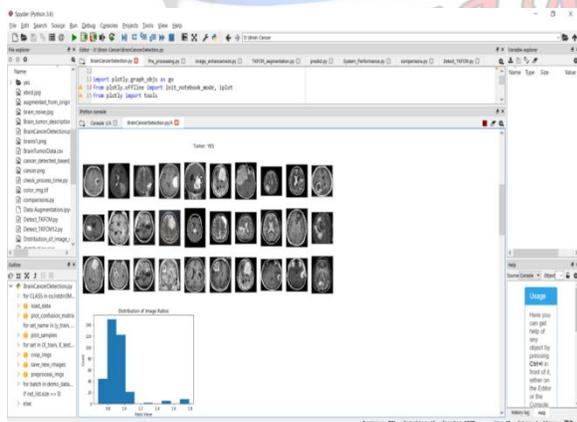


Figure 6 Tumor images and Distribution of image ratios

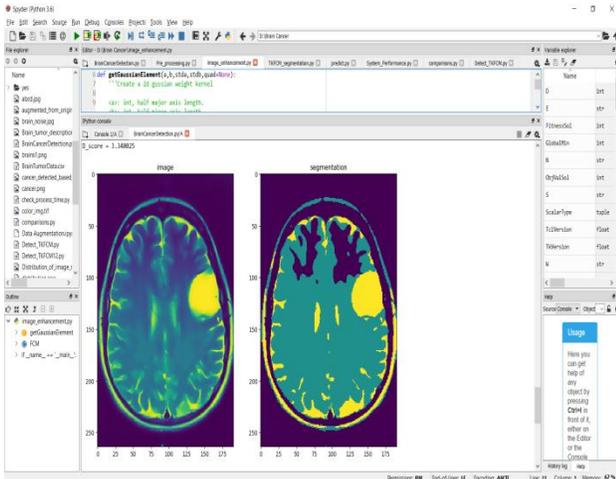


Figure 9 Image segmentation

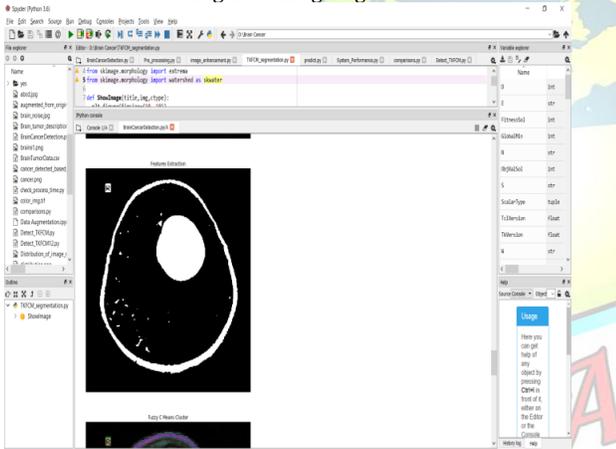


Figure 10 Feature Extraction

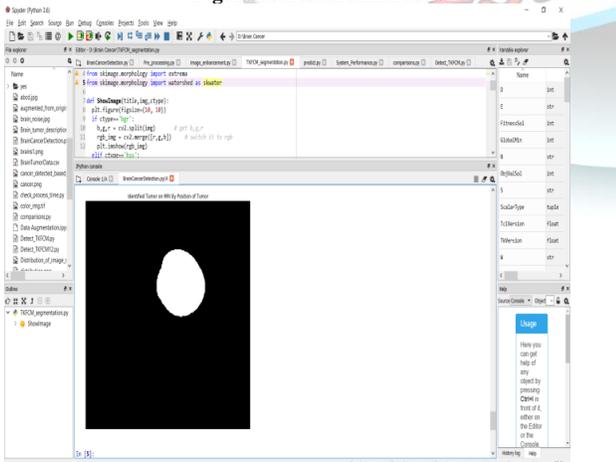


Figure 11: Identified Tumor on MRI by a portion of the tumor

Table 1: Table of Precision and Recall Rate

Methods	Precision	Recall
Linear SVM[50]	0.925	0.04
FFNN[50]	0.875	0.05
Fuzzy-SVM[50]	0.95	0.025
Proposed	0.96	0.092

The precision and recall values obtained from the classification results of our proposed system have been plotted using a graph as shown in Figure 12, and the values are represented in Table 1.

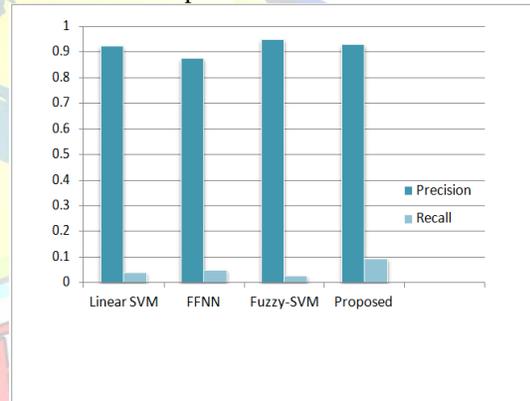


Figure 12: Performance Evaluation in Terms of Precision and Recall

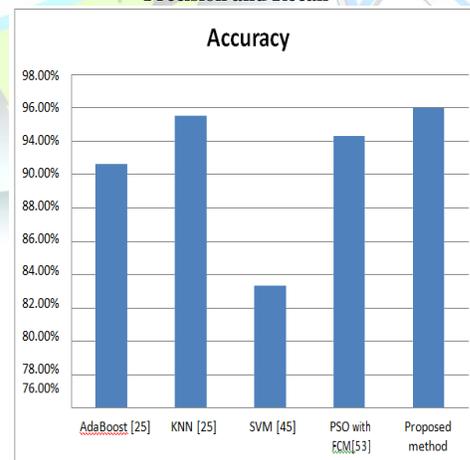


Figure 13: Bar graph for Performance Analysis



V. CONCLUSION

Brain tumor identification is a challenging and delicate process that helps radiologists guide their scans to find brain tumors. Two different tissue analysis methods are employed in this experiment to find the location of brain tumors. For HBTCNN, it has been recommended to use a CNN-based technique for segmenting brain tumors in MRI images. Numerous solutions, including some recently described algorithms, are currently available for brain tumor segmentation and SVM classification to detect the tumor. Various methods are available for detecting brain tumors, and they vary in their application possibilities. They developed a Convolutional Neural Network (CNN) classifier to overcome these inherent flaws. An SVM-based classifier was used to find the best classifications for the test data compared to the training data, resulting in a classification rate of 96.2%. To improve the performance of prediction using 3d images.

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