A Time Variant Region Growth Analysis Model for Efficient Brain Tumor Classification Using CNN

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The issue of classifying brain tumor from MRI images is analyzed in detail. Number of schemes exists and uses texture, shape and mass features in classifying brain tumor. However, they struggle to meet the expected performance. To support the problem, an efficient Time Variant Region Growth Analysis Model (TVRGAM) is presented. The model applies Sliding Window Grey Approximation algorithm for preprocessing the image which removes the noise. The image has been segmented according to the mean gray value measured in the preprocessing. With the segmented image, concern texture features are extracted from the ROI identified. Further, the method trains the feature set with convolution neural network and the neurons computes Time variant tumor growth factor (TVTGF), with various class features. Based on the value of TVTGF, the method performs brain tumor classification. The method achieves expected performance hike in tumor classification.

Keywords: Brain Tumor, Image Classification, Deep Learning, CNN, TVTGF, TVRGAM.

1. Introduction

The modern society suffer with number of diseases which are identified at various phase of human life. The brain tumor is the one which appears on the brain tissues and affects the neurons of the brain. Such appearance of brain tumor functioning of various activities of the human body. It is a life threatening disease and cannot be cured at the later stage. By identifying or diagnosing the disease at the early stage help the person to get cured or managed effectively. Presence of brain tumor is identified from the Multi resonance Image (MRI) captured through device. The medical practitioner identifies the presence of disease by identifying a white mass present in the image. As the brain image represent different features and glands of the brain, if there exist mass value at the any of the glands, then it is concluded as brain tumor.

The medical practitioner would be challenged with the accuracy of prediction. This encourages the invention of automated brain tumor classification. The automated system would provide support for the medical practitioner in diagnosing the disease in efficient way. Image processing has been used in several medical problems. The same has been used in brain tumor classification, which involve in noise removal, segmentation and features extraction and classification. The preprocessing stage involve in removing the noise from the image which is performed with number of noise filters like Gabor filter. The segmentation is performed according to different features like grey scale value and other features using number of algorithms like K-means algorithm. Further, the method would extract number of features like texture, shape and so on. Finally, the classification is performed with different algorithms like decision tree, particle swarm optimization, support vector machine, neural network and so on.

Towards brain image classification, numbers of approaches are available which vary on the method of classification and the feature considered. However, the accuracy of tumor classification is greatly depending on the feature considered. If the shape feature is considered, then the method looks for the similar shape and the texture based approach monitors the appearance of same texture on classification. However, the accuracy of the method can be improved by using huge volume of brain images. The data mining approaches are not efficient in handling such huge volume of brain images. The deep learning methods are capable of handling huge volume of images and perform classification in a efficient way.

Convolution neural network has been used for image classification, which reduce the size of descriptor and convert the huge size of texture into small size of information. By having number of convolution layers and by enforcing set of normalization layers, the huge size of feature can be converted into small size of information covering all the features. This support the CNN to perform classification in more accurate way with least time. By considering this, an efficient time variant region growth analysis model is sketched here which extracts features from various regions in a region growth manner from images captured in different time stamp, CNN has been trained. Further, the method estimates Time variant tumor growth factor (TVTGF), to perform classification.

2. Related works:

Different methods on tumor classification is discussed here.

LCDEiT: A Linear Complexity Data-Efficient Image Transformer is presented in [1], towards brain tumor classification. The method used gated pooled CNN to feed information to transformer based student model to support classification.

A mutual informative MapReduce and minimum quadrangle classification (MIMR-MQC) is presented in [2], which preprocess the image with MIMR to remove redundant features for the data set and uses SVM towards classification. The fusion based multiple deep model [3], performs classification with Brain Hyperspectral Image. The method is focused to identify Glioblastoma Tumor. A detailed analysis of brain tumor detection and classification with the intelligent techniques is presented in [4]. A

Clinical Knowledge Driven Hybrid Transformer With Modality-Correlated Cross Attention

(CKD-TransBTS) [5], uses CNN with local features towards classification. A Hybrid Single Image Super Resolution (SISR) [6], enhances the features to support classification. The fractional chicken swarm optimization [7], classify the severity of tumor. A data complexity based evaluation model is presented in [8], which preprocess the data and applies cross validation on features to train CNN towards classification.

IIMFCBM: Intelligent Integrated Model for Feature Extraction and Classification model is presented in [9], which performs automatic diagnosing by integrating a CNN for deep feature extraction and uses LSTM towards classification.

A machine learning based Multiclass Classification model [10], captures hidden features from vast features and applies Cumulative Variance method (CVM) in the selection of features to classify using KNN and m-SVM.

A Gaussian Convolutional Neural Network (GCNN) is adapted for classification in [11], into different classes. A Deep Probabilistic Sensing and Learning Model for Brain Tumor Classification model is presented in [12], which uses Fusion-Net and HFCMIK Segmentation and deep learning based probabilistic neural network (DLPNN) for classification.

A-depth review of the surveys on brain tumor classification is presented in [13]. A Secured Brain Tumor Segmentation and Classification with Recurrent U-Net (RU-Net) [14], extract features with black widow optimization-genetic algorithm (BWO-GA) scheme to support classification. Dendritic Squirrel Search Algorithm-based Artificial immune classifier (Dendritic-SSA-AIC) is presented in [15], which pre-process and segmentation the image using sparse fuzzy-c-means (Sparse FCM). Finally, Particle Rider mutual information (PRMI) is used towards the selection of features and PSO is used for classification.

3. Time Variant Region Growth Analysis Based Brain Tumor Classification Model with CNN:

The TVRGAM scheme fetches the brain image from data set and applies Sliding Window Grey Approximation algorithm for preprocessing the image which removes the noise. The image has been segmented according to the mean gray value measured in the preprocessing. From the segmented image, the method extracts the texture features. Further, the method trains the feature set with convolution neural network and the neurons computes Time variant tumor growth factor (TVTGF), with various class features. Based on the value of TVTGF, the method performs brain tumor classification.

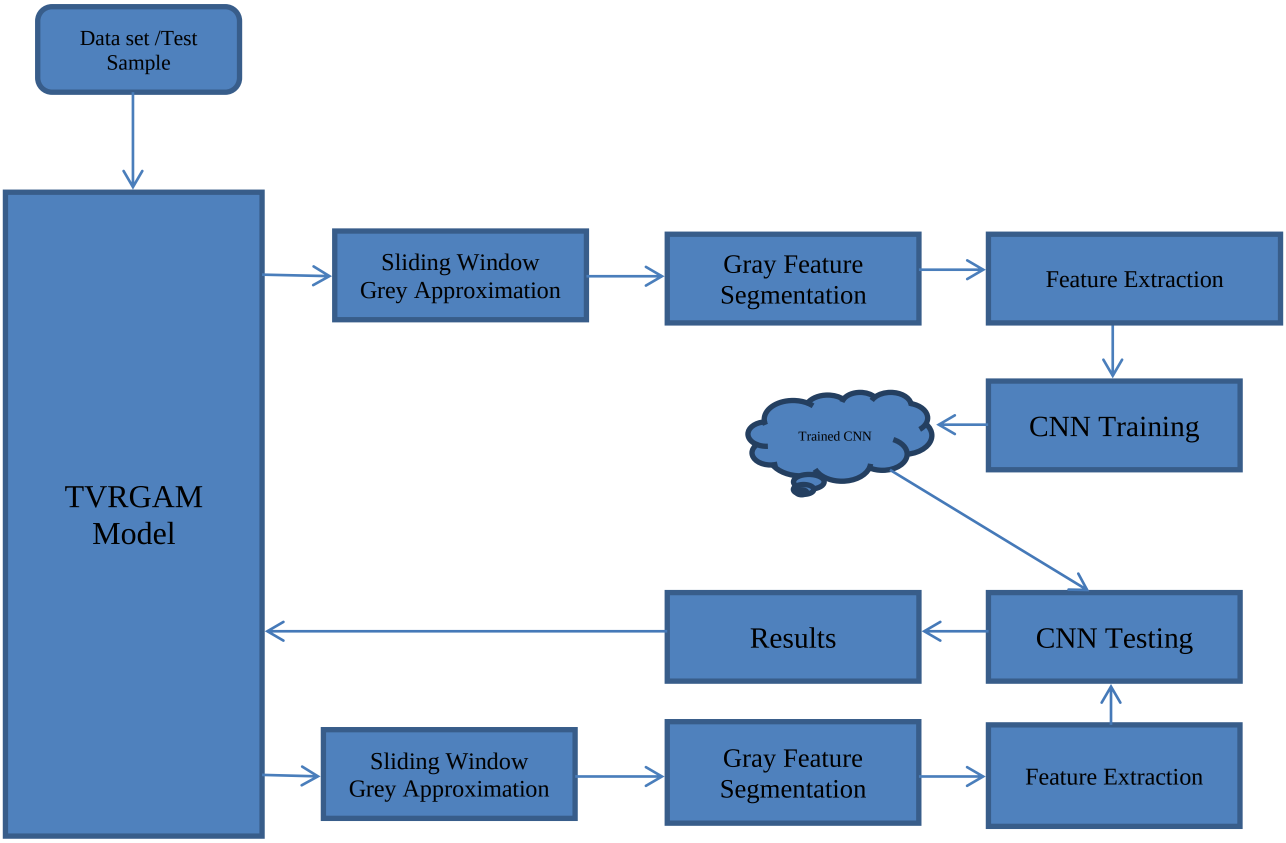

Figure 1: Architecture of proposed TVRGAM model

The working of the TVRGAM scheme is sketched in Figure 1, and each stage of the model is detailed here.

Sliding Window Gray Approximation:

The sliding window gray approximation algorithm uses a specific window size to normalize the image. The method applies the gray approximation on each window by traversing through the image. The scheme generates histogram of the window pixels, and identifies the two set of pixels from the histogram. Further, a subset of pixels are collected with higher gray scale value. Accordingly, the method computes the mean gray value and based on that the method adjust the pixel value which is less than the mean gray with the constant computed. This process is iterated at the entire window identified to normalize the image.

Algorithm:

Given: Brain image Bi

Obtain: Preprocessed image Pi

Start

Read Bi.

Initialize window size Ws=x

Window image ws = $\underset{i=1}{\overset{size(Bi)}{Crop(Bi, ws, i)}}$

For each window image w

Hs = Generate Gray Histogram (w)

Gray pixel set Gps = $\sum_{i=1}^{size(Hs)} Hs(i).grayvalue > 50$

Compute mean gray set Mgs = $\frac{\sum_{i=1}^{size(Gps)} Gps(i)}{size(Gps)}$

For any pixel pi

If w(pi)<mgs && pi∈ gps then

W(pi) = Mgs

End

End

End

Stop

The above algorithm preprocesses the image to normalize the image with noisy pixels and normalized image is used to perform segmentation.

Gray Feature Segmentation:

The segmentation algorithm initializes two groups of pixel clusters. According to the mean gray value measured in the previous stage, the method classifies the pixels into to clusters and adds the pixels with higher value in a group and other pixels under another group. Such segmented image is passed towards classification.

Feature Extraction:

Feature extraction phase involve in reading the segmented image and extract the features. The method extracts the texture region which contains the tumor details. Extracted texture has been used to perform brain tumor classification.

CNN Training:

The CNN is trained with the image data set given. Each image present in the data set has been preprocessed and segmented. The texture regions are extracted. Extracted texture set has been used to train the convolution neural network. The CNN is designed to have a input layer and have two convolution layers and one output layer. The first convolution layer generates four mass orientation value. Second convolution layer generates the single mass orientation value. The max pooling layer computes the orientation value.

Algorithm:

Given: Brain image set bis

Output: CNN

Start

Read Bis

For each brain image b

Pi = Perform sliding window gray approximation (b)

Si = Segmentation (Pi)

Texture t = Feature Extraction (si)

Add to texture set Ts = ($\sum$ Texture $\in$ Ts) $\cup$ T

End

Initialize CNN.

For each bi

Generate a neuron n.

N = Texture(bi)

End

At convolution layer one.

For each neuron

For each quarter texture Qt

Compute mass orientation Mo = $\frac{\sum_{i=1}^{size(Qt)} Count(Qt(i).value > Qt.meangray)}{size(Qt)}$

End

Mass orientation mo(1) = $\frac{Mo(1)+Mo(2)}{2}$

Mass orientation mo(2) = $\frac{Mo(3)+Mo(4)}{2}$

End

Perform max pooling

At convolution Layer two.

For each neuron

$$\text{Mass orientation mo} = \frac{Mo(1)+Mo(2)}{2}$$

$$\text{Mass orientation mo(2)} = \frac{Mo(3)+Mo(4)}{2}$$

End

Perform max pooling.

Stop

The training scheme computes mass orientation value on the given image towards various images in the class to identify the class.

CNN Testing:

To start with, input brain image is preprocessed and segmented to extract the texture. The texture features are used in training CNN. Extract features are pass through the convolution network. The CNN layers convolve the features by computing mass orientation. The last layer of max pooling estimates the mass orientation similarity (MOS) against various images orientation value. Based on the MOS value, the method identifies the class of image.

Algorithm:

Given: Brain Image B, CNN

Obtain: Class C

Start

Read B, CNN.

Pi = sliding window gray approximation (B)

Si = Segmentation (Pi)

Texture T = Feature Extraction (Si)

Pass through CNN.

At convolution layer 1

Extract quadratic mass values and compute mass orientation.

Perform pooling.

At convolution layer 2

Compute mass orientation.

Perform pooling

At output layer

For each class

For each orientation

$$\text{Compute MOS} = \frac{\sum_{i=1}^{size(c)} Distance(C(i).Mo, Mo(B))}{size(C)}$$

End

End

Class C = choose the class with maximum MOS

Stop

The testing involves in measuring mass orientation similarity towards various classes of brain images to identify the class.

4. Results and Discussion:

The time variant region growth analysis model is implemented with Matlab. Performance of the model is evaluated and compared in this section.

Table 1: Environment Details

Parameter	Value
Tool	Matlab
Data source	BRATS 2019
Tumor classes	2
Total images	3000

The environment details considered for evaluation is given in Table 1.

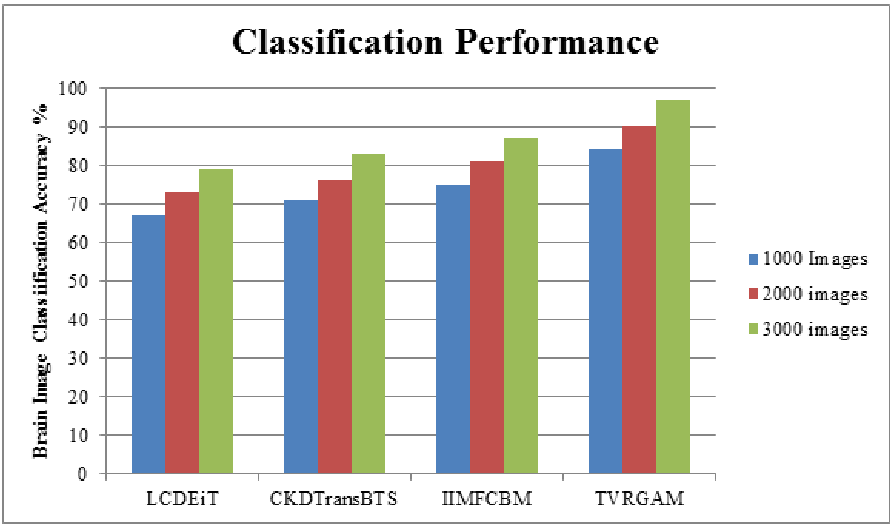

Figure 2: Classification Accuracy

The accuracy of brain image classification is counted and displayed in Figure 2, and the proposed TVRGAM scheme delivers higher accuracy.

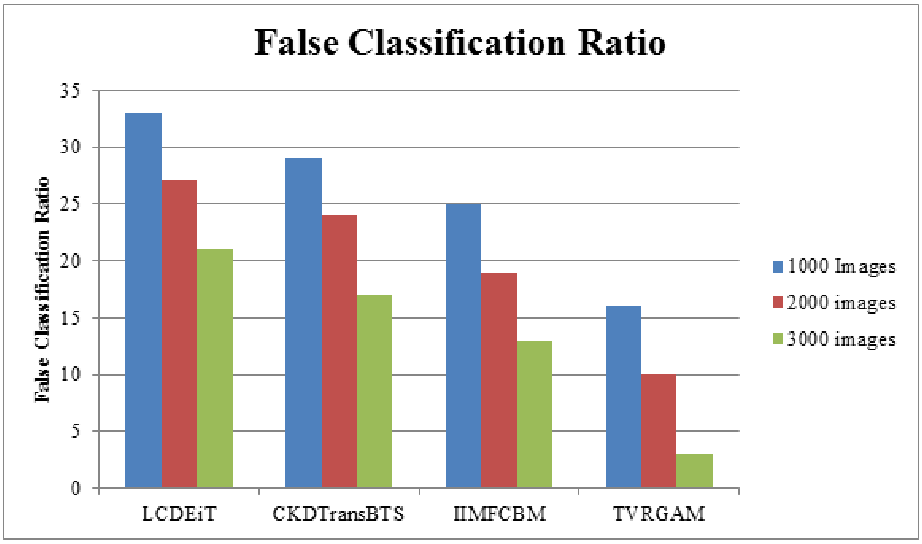

Figure 3: Analysis on False classification ratio

The false classification ratio of methods are considered and given in Figure 3, and TVRGAM model introduced less false ratio than others.

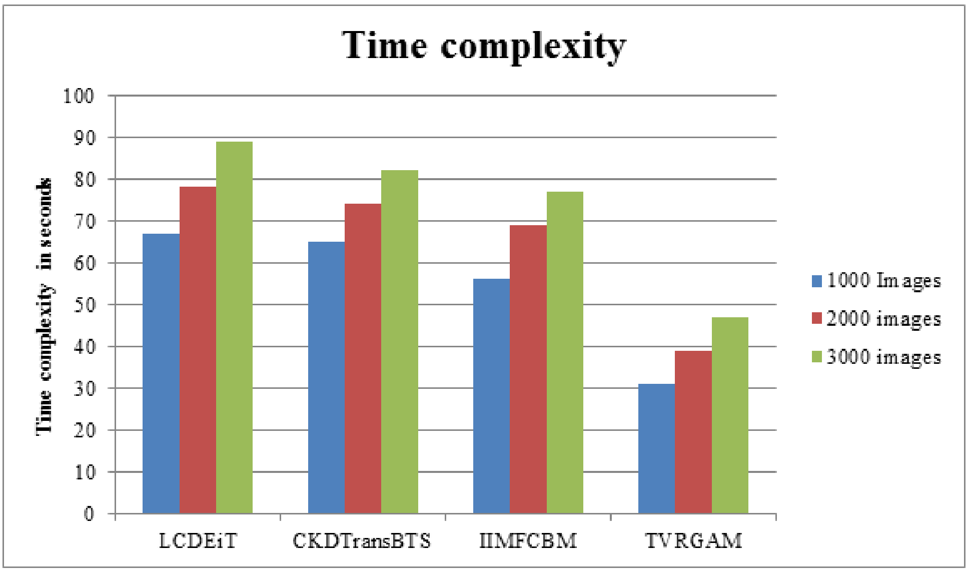

Figure 4: Time complexity

The time complexity introduced by methods are counted and given in Figure 4, where the TVRGAM model introduces less time complexity than others.

5. Conclusion:

A time variant region growth analysis model is presented towards classifying tumor from brain images. The method preprocesses the image with sliding window mass approximation to eliminate the noise from the image. Further, the image has been segmented according to the gray approximation values. Third, the features are extracted to train the CNN model. At the test phase, the neurons compute mass orientation similarity towards various classes of images. With the value of MOS, the class of image is identified. The proposed method improves the performance of brain image classification than others.

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