Adaptive Brain Tumor Recognition Model using the Hybrid Tumor Recognition Approach

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Abstract

Objectives: The brain tumor recognition is an imperative part of the computing environment based robotic operation devices. The trend of the operation theatre robots is on the escalation due to the advancement in the technology, and necessitates the high precision of the tumor region for the automatic operations with the computerized interactions and without the intervention of the doctors. Methods Statistical Analysis: This paper presents the robust model that has been proposed for the brain tumor detection and classification using the SVM based tumor region recognition and classification algorithm. Findings: The proposed model has been defined with the set of the morphological operations for the reduction of the image, which is followed by the principle component analysis (PCA) based features for the tumor region classification with SVM. The proposed model has undergone the in-depth analysis under the results and discussion section, where the proposed model has been undergone the number of experiments. The proposed model has been tested on the basis of various performance parameters and has shown efficient results in the terms of performance parameters than the existing models. Application/ Improvements: The proposed model can be clearly considered better than the existing model on the basis of the obtained results from the simulation.

Keywords: Brain Tumor Localization, Hybrid Tumor Extraction Algorithm, Morphological Operations, PCA Features, SVM Classification

1. Introduction

Magnetic Resonance Imaging is the medical photo received through the special clinical device for the analysis of the human frame elements for the analysis of the numerous health related problems. MRI pix are acknowledged to offer the improvised contrast for the simple category of the unique types of the smooth tissues and different kinds of the objects than the alternative popularly acknowledged radiology technique known as Computed Technology (CT). The MRI and CT scan images are primarily utilized for the detection and assessment of the tumor region in the given image matrix by recognizing the target regions under the multilayered analytical scenarios. The vital image processing models such as bilateral techniques, deep classification, color illumination or differentiation, pattern differential methods, etc are utilized for the tumor region and its type recognition methods. The tumor recognition methods are usually based upon the odd one out pattern differentiation methods by combining the visually intelligent algorithm with threshold based segmentation, binarization or other similar methods to group the pixels in the multiple groups as per defined under the given method. Various comparatives studies have been studied under the literature survey for the assessment and motivation from the existing models for the realization of the robust and accurate methods.

2. Motivation

The existing model evaluates the 3-D MRI image with 3-D coordinates for blob based method for brain tumor extraction. The blob based method is not empowered with specific pattern recognition algorithm. The blob detection relies upon odd one out pattern, hence will not be
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Applicable in many cases with non-identical patterns. The existing model has been measured with approximately 90% of overall accuracy which must be checked and improved. The accuracy improvement can be achieved using the robust pattern recognition methods. The bilateral symmetry based pruning is effective in the cases of the divisible structures such as circle or sphere. The bilateral scheme is not applicable in the case of differently shaped tumors, which cannot be divided into equal sized halves of the tumor.

3. Experimental Design

The MRI scanning model has been popularly utilized for the diagnosis of the neurological, cardiovascular, musculoskeletal and oncological imaging. The MRI imaging does not utilize the ionizing radiation like CT, and works on the basis of the powerful magnetic field based analysis for the production of the magnetization of the hydrogen atoms in the water content in the human body. The heavy magnetic radiation causes the hydrogen nuclei for the production of the rotational magnetic field, which becomes detectable by the MRI magnetic radiation scanner. The particular manipulations can be made to the MRI scanners for the grabbing of the vital information from the human body. The areas with the tumor in the human body are considered to be equipped with the higher intensity than the other portions in the surrounding regions, which proves to be helpful in the case of the MRI images.

3.1 Algorithm 1

The proposed model workflow has been described in-depth in the following model (Figure 1):

Various morphological methods are improved or extended for the different types of gray-level images. For the simplified learning or color illumination, the restructuring or value incorporation method is deployed under the working module for the realization of the convex and bounded method for the gray scale conversion or analysis of image matrix \( A \). Gray-level dilation, \( DG(\cdot) \), is given by:

\[
DG(A) = \max_{j,k} \{ a[m-j,n-k] + b[j,k] \}
\]

Apply morphological operations on all gray levels individually. Each gray-level considered as 1, all other gray-levels 0. In final image, take the maximum or minimum gray-level for each pixel.

![Proposed model flowchart.](image)

Figure 1. Proposed model flowchart.
Gray-level erosion, \( E_G(A,B) \), is given by:

\[
E_G(A,B) = \min_{[j,k] \in B} \{a[m+j,n+k] - b[j,k]\}
\]

Erosion -

The duality between gray-level erosion and gray-level dilation--the gray-level counterpart of eq. --is somewhat more complex than in the binary case:

Duality : \( E_G(A,B) = -D_G(-A,B) \)

Where “\( -A \)" means that \( a[j, k] \rightarrow -a[j, k] \)

The definitions of higher order operations such as gray-level opening and gray-level closing are:

Opening - \( O_G(A,B) = D_G(E_G(A,B),B) \)

Closing - \( C_G(A,B) = -O_G(-A,-B) \)

In many situations the seeming complexity of gray level morphological processing is significantly reduced through the use of symmetric structuring elements where \( b[j,k] = b[-j,-k] \). The most common of these is based on the use of \( B = \text{constant} = 0 \). For this important case and using again the domain \( [j,k] \subseteq B \), the definitions above reduce to:

Dilation -

\[
D_G(A,B) = \max_{[j,k] \in B} \{a[m-j,n-j]\}
\]

Erosion -

\[
E_G(A,B) = \min_{[j,k] \in B} \{a[m-j,n-j]\}
\]

Opening - \( O_G(A,B) = \max_{B(A)} -B(\max_{B(A)} A) \)

Closing - \( C_G(A,B) = \max_{B(A)} -B(\max_{B(A)} A) \)

Where \( [j,k] \in B \)

In this paper, the proposed new algorithm has been described the brain tumor detection using MRI color model and brain recognition using SVM classification. Also explain the flow chart of proposed algorithm.

### 3.2 Algorithm 2

There are following steps for execution of character detection using skin color model and character recognition using SVM classification.

**Step 1**: Load training input image in the system in jpg format.

**Step 2**: Next step is apply MRI color model, this model identify skin region from given input image using pixel by pixel evaluation method.

**Step 3**: After identify the MRI tumor region, Measure and Mark rectangular bound box around similar skin region.

**Step 4**: Extract the character region with around rectangular box.

**Step 5**: Crop Mark character region.

**Step 6**: Crop image of character region is fed into character recognition system. This crop image is converted into gray scale.

**Step 7**: Next step is Feature extraction gray scale image and training image of brain tumor database using tumor region detection and correlation feature extractor method.

**Step 8**: After extracted features of training database of image is saved into feature vector matrix. This matrix contains angle of brain tumor and length and width of tumor.

**Step 9**: Next step is applied to fuzzy set for preprocessing of extracted features of training image Fuzzy set has been shortlisted more match able images (greater than min threshold value of matching feature).

**Step 10**: Next step is to obtained shortlist image fed into SVM classification model for brain tumor.

### 4. Result Analysis

The time based analytical comparison between the existing and proposed models clearly indicates the robustness of the proposed model in computing the result faster and quicker. The following Table 1 shows the time complexity results obtained from both of the models.

| Iteration Count | Existing Grayscale | Existing Colored Image | Proposed Grayscale | Proposed Colored Image |
|----------------|--------------------|------------------------|--------------------|------------------------|
| 1              | 0.3096             | 0.89978                | 0.0232             | 0.09508                |
| 2              | 0.3124             | 0.8564                 | 0.0233             | 0.08302                |
| 3              | 0.3087             | 0.8765                 | 0.0213             | 0.09212                |
| 4              | 0.3698             | 0.9644                 | 0.0232             | 0.09014                |
| 5              | 0.3310             | 0.8761                 | 0.0241             | 0.10200                |
| 6              | 0.3091             | 0.8315                 | 0.0210             | 0.08120                |
| 7              | 0.3265             | 0.9216                 | 0.0234             | 0.09200                |
| 8              | 0.3425             | 0.8917                 | 0.0233             | 0.09519                |

The proposed model results have been obtained in the form of the time complexity obtained from both of the models. The proposed model works on the grayscale
and colored images faster than the existing model, which is clearly shown from the Table 2. The time complexity results have been obtained in the seconds, and there is the difference of almost 10 times less time than the existing model's calculated time.

| Iteration | 2-D Morphological Method | 3-D Blob | 3-D Proposed |
|-----------|--------------------------|----------|--------------|
| 1         | 1.5                      | 1.9      | 1.75         |
| 2         | 2.65                     | 2.3      | 2.2          |
| 3         | 2.48                     | 2.1      | 2.05         |

The Table 2 shows the results obtained from the existing tools based upon the tumor localization, which includes the existing 2-D morphological, 3-D blob and the 3-D proposed model. The proposed model has been marginally improved than the existing models on the second and third iteration, which signifies the stronger results obtained from the proposed model in accordance with the existing model.

The brain tumor object detection model is entirely based upon the supervised model based matrix appearance similarity, which selects the object with the highest similarity of the determination of the object position. The vehicle region selected in the earlier step is extracted as the region of interest (ROI) for the further evaluation. The deep neural network has been used for the network classification, which primarily classifies the data in two primary categories of Benign and Malignant. The computational complexity of the proposed model has been evaluated in the form of time complexity parameters. The time complexity has been evaluated for the object detection and classification separately. The obtained values of time complexity have been shown in the following table (Table 4).

| Index | Average time for classification | Average time for detection |
|-------|--------------------------------|---------------------------|
| 1     | 0.0323                         | 0.19                      |
| 2     | 0.041                          | 0.21                      |
| 3     | 0.029                          | 0.32                      |
| 4     | 0.0308                         | 0.25                      |
| 5     | 0.0291                         | 0.15                      |
| 6     | 0.0275                         | 0.13                      |
| 7     | 0.0258                         | 0.23                      |
| 8     | 0.0242                         | 0.18                      |
| 9     | 0.0225                         | 0.35                      |
| 10    | 0.0209                         | 0.31                      |
The following Figure 3 visualizes the values obtained under the Table 4. The average detection time is usually lower than the average classification time, whereas in some of the odd cases the classification model runs quicker than the detection model due to the smaller size of the vehicular objects in the given image.

![Time Complexity Analysis](image)

Figure 3. The average time complexity analysis of ten images.

The proposed model has been evaluated for its performance against the prominent existing models to estimate the performance enhancement. The proposed model results shown in Table 5, clearly indicate the improvement in the performance for the brain tumor classification over the input image data.

### Table 5. The comparative analysis of the proposed model

| TECHNIQUE         | RECALL VALUE |
|-------------------|--------------|
| HOG+SVM [19]      | 68.0         |
| DNN [2]           | 79.0         |
| Adaboost [21]     | 91.02        |
| LBP+SVM [20]      | 95.78        |
| Proposed          | 96.10        |

The proposed model has been designed to analyze the brain tumor regions in the given image. The image data has been kept in any of the image format and the loaded in the runtime memory using the MATLAB module for image document handling. The input image is segmented, localized and the tumor region is localized and then the localized ROI undergoes the tumor classification. The proposed model has been evaluated for the various performance parameters (Table 6), which show its effectiveness using the Recall and Precision values.

The Precision and Recall of the proposed model is quite higher making the proposed model highly efficient in the terms of brain tumor extraction and classification. The proposed model and existing model results (Table 7) have been measured using the Ling Zhao's system, which has described the proposed model’s effectiveness and accuracy to calculate the results of brain tumor on the dataset collected from the medical imaging sources. The proposed model has also been evaluated for the precision value which is the probability of the positive predictive value (PPV). The proposed model has been evaluated as the way efficient method than the existing model of tumor detection and classification. The new brain tumor classification model reflects the real performance of the proposed model.

### Table 6. The table of comparison between existing and proposed model

| Sr. No. | System                                      | Recall Value | Precision |
|---------|---------------------------------------------|--------------|-----------|
| 1.      | Liang Zhao, Bjoern H. Menze et. al. (Multimodal Brain Tumor [BRATS]) | -            | 82%       |
| 2.      | Proposed model                              | 96.10%       | 95.08%    |

The Table 7 shows the comparative analysis of the proposed model against the existing models based upon the brain tumor localization accuracy, which determines the performance of the pixel region selection in the provided sections. The proposed model has marginally improves the performance by approximately 3-5% on the basis of each category of brain tumor data. The brain tumor classification errors have been also studied for the evaluation of the proposed model as per shown in the Table 8.

The proposed model has been based upon the new brain tumor classification model, which is further evalu-
Adapted deeply and analyzed for the performance against the existing models. The proposed model has recorded with null value for the classification error, whereas shows the marginal improvements in the algorithmic error and syntactic parsing errors. In the base paper, the 3-D blob based method has been utilized for the tumor detection along with the segmentation in the MRI images. The proposed model has been compared to the existing model as shown in Table 9, on the basis of the detection rate, recall and precision. The following Table 9 elaborates the comparison between the existing and proposed model.

**Table 8.** The comparison between proposed and existing model on various errors

| Parameter Type | Existing | Proposed | Correct | Incorrect | Correct | Incorrect |
|----------------|----------|----------|---------|-----------|---------|-----------|
| No. of A-P Collections | 390 | 118 | 425 | 93 |
| Error type 1: Algorithm error | 15.64 | 17.8 | 10.21 | 14.3 |
| Error type 2: Syntactic parsing error | 12.31 | 27.12 | 8.86 | 25.02 |
| Error type 3: Classification error | 0 | 20.34 | 0 | 17.54 |
| Analysis of Correct Results | 72.05 | 34.75 | 81.95 | 28.62 |

**Table 9.** The comparative results between the existing and proposed model

| PARAMETER 3-D BILATERAL BLOB DETECTION | PROPOSED MODEL |
|--------------------------------------|----------------|
| Precision | 94.51% | 95.08% |
| Recall | 46.17% | **96.10%** |
| Detection Rate (Accuracy) | 95.30% | 96.41% |

**5. Conclusion**

The proposed model has been designed on the basis of the combination of the several algorithms for the realization of the robust tumor region localization model, which includes the morphological operators, Principal Component Analysis (PCA) along with Support Vector Machine (SVM) based classification. The proposed model has been designed for the high accuracy based brain tumor detection, which has been realized by using the latter hybrid model. The performance of the proposed model has been analyzed under the variety of the experiments, where the proposed model has been found with 95.08% precision, 96.10% recall against the 94.51% and 46.17% in the existing model based upon the 3-D BILATERAL BLOB DETECTION, which was suffering from the false negative cases. The problem of false negative cases has been removed in the proposed model which is clearly indicated from the latter results. The proposed model's overall accuracy for the different types of the tumors has been assessed under this study, where the benign, malignant and normal or undetected (non-classified) cases has been discussed. The proposed model has been recorded with the overall accuracy of 94.14% and 93.75% in the proposed model for BENIGN and MALIGNANT tumors, which is better than the Pantelis's model with 91.43% and 93.48% accuracy respectively and Woo Kyung's 90.2% and 90.25% respectively. This shows the robustness of the proposed model in the terms of overall accuracy. The proposed model has been also compared against the Liang Zhao's model, where it has outperformed the existing model with 96.10% against the value of 95.08% of the recall parameter. The overall accuracy of the proposed model has been recorded higher than the LBP+SVM (95.78%), Adaboost (91.02%), DNN (79.0%), HOG+SVM (68.0%) against 96.10% in the proposed model.

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