

Improved Classification of Brain Tumor in MR Images using RNN Classification Framework

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ABSTRACT: Classification of brain tumor for medical applications is considered as an important constraint in computer-aided diagnosis (CAD). In this paper, we study the classification of brain tumor by considering the constraint as a classification problem in order to segregate the tumors among pituitary tumors, gliomatumor and meningioma tumor. This method adopts deep learning principle to extract the brain features from the MRI images. In this study, Recurrent Neural Network is used to classify the extracted features from brain. The experiments are carried out in terms of three fold cross-validation process over MRI brain image dataset. The results show that the proposed RNN classifier classifies the brain tumors effectively with 98% of mean classification accuracy than other existing methods.

KEYWORDS: Brain Tumor Classification, RNN, CAD, Classification

I. INTRODUCTION

Precise and quick diagnosis of brain tumors is essential if this disease is to be effectively treated. The choice of a method of treatment depends on the tumor stage, type and tumor grade at the time of diagnosis. In numerous ways, neuro-oncologists received support from computer-aided diagnosis (CAD) technique. Neuro-oncological CAD applications include the detection, classification and grading of tumors. A thoroughly studied issue is the cad-based classification of brain tumors into benign and malignant tumors [2][7]. Another research problem in this field is the classification of glioma, which is a major class of malignant tumors [1]. Magnetic resonance imaging (MRI) images of brain are used to produce the above-mentioned CAD systems. This is because of MRI's ability to provide a higher contrast to Computed Tomography (CT) images for soft tissues in the brain.

The limits of current studies on brain tumor classification into pituitary tumors, glioma, meningioma, which are summarized as follows. In view of the medical significance of the classification problem the efficiency of state-of-the-art methods is insufficient [11]. Previous methods relied before classification on manually delineated tumor areas. This avoided the complete automation. An influential performance improvement could not be achieved by the automatic algorithms developed using CNN and its variants. In addition, existing methods were tested on an unbalanced (in terms of tumor classes) dataset.

Thus it becomes significant to evaluate performance using metrics other than precision. Another fact is that there has been no related work dealing with the problem of in practice data scarcity.

This paper aims at the detection of tumor regions in brain, where it is difficult to monitor in case of MR images. Image processing has vital role at the initial stage. Grey Level Co-occurrence Matrix (GLCM) is used for the purpose of feature extraction on segmented brain regions and RNN Classifier is used to classify whether the brain is malignant or benign one.

II. LITERATURE SURVEY

Recent work on computer-aided diagnostics offers better performance due to the emergence of deep learning concepts. In the analysis of medical pictures deep learning strategies were used extensively.

Talo, M. et al. [3] proposed a deep-transfer approach to classifying normal and abnormal brain MR images automatically. The ResNet34 model is used as a deep learning model by Convolutional Neural Network (CNN). Current deep learning techniques have been used, such as data increase, optimal learning rate finders and finely tuned models. On 613 MR images, the proposed model achieved a 5-fold precision of 100% classification. Our system, which has been developed, is able to test large databases and can help radiologists screen MR pictures every day.

Swati, Z. N. K., et al. [4] have used a deep-CNN pre-trained model, and are proposing a block-based, transferal-level approach. On the T1-weighted contrasting magnetic resonance imaging (CE-MRI) benchmark dataset, the proposed procedure is evaluated. Our approach is more general, as it uses no handmade features, requires reduced pre-processing and can achieve an average 94.82% accuracy under fivefold cross-validation. In addition to traditional learning on machines, we compare our results with deep learning techniques using CNNs. Experimental results have shown that the CE-MRI dataset is classified more modernly by our proposed method.

Deep Neural Network classifier is used by Mohsen, H., et al. [5] to classify 66 MRIs into 4 classes of data, e.g., ordinary, glioblastoma, sarcomas and metastatic bronchogenic tumor. The classifier is combined with the discrete wavelet transformation (DWT), the powerful function removal tool and main component analysis (PCA), and the performance evaluation overall performance measurements was quite good.

Zhang, J. et al. [6] proposed a model of deep synergic learning to address the issue simultaneously with the use of multiple deep CNNs. Each pair of DCNNs is linked to a synergistic system that has a fully-connected structure which prevents the pair of

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input images belonging to the same class. Thus a mistake by the other DCNN results in a synergic failure that serves to update the model when one DCNN makes a correct classification. This model can be fully trained in monitoring DCNN classification mistakes and synergistic errors from each DCNN pair. Our experimental results for data sets show the state-of-the-art achievement of the proposed SDL model in these tasks.

The new MNC-based multi-grade brain tumor classification system was proposed by Sajjad, M., et al. [8]. First, a deep learning method divides tumor regions from an MR image. Secondly, extensive increases in data are used to effectively train the proposed system to ensure that the MRI for multi-grade brain tumor classification does not contain a number of data problems. Lastly, a pre-trained CNN model is finalized with increased data for the classification of brain tumors. Experimentally evaluated, the proposed system shows convincing performance in comparison to existing methods, on both augmented and original data.

III. METHODOLOGY

The work proposed contains three phases for the detection of the brain tumor regions. RNN is one of the deep algorithms traditionally used for classification purposes.

- Low-level processing: pre-processing operations including image reading and enhancing the contrast nature of an image.
- Intermediate level processing: Segmentation using K-means clustering of tumor regions in brain.
- High level processing: Extraction of features and classification using RNN deep learning model that helps in classification of tumor state.

The detailed architecture is given in Figure 1,

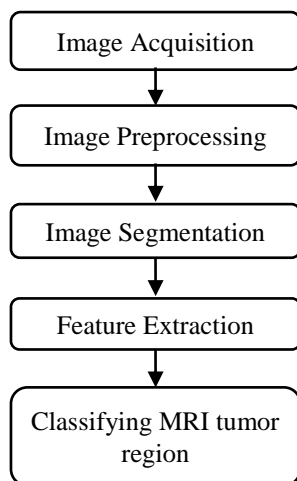


Fig.1. Architecture of proposed system

A. Image Acquisition

Image Acquisition is using hardware such as digital camera, mobile phone, etc. to collect an image from some source. The image acquisition stage is the first stage of every vision system. Following the capture of the image, different processing techniques can be used to perform a specific task on the image. The sample images that are required to train the systems are collected in this stage. High precision MRI devices is used for capturing the image

regions of brain it is used for training and testing and for the purpose of classification, a standard PNG format is used.

B. Image Preprocessing

Preprocessing is the step towards improving the image quality and doing some operation on the MRI brain image. Read the image from the path and resize the pixel image (800×500).

C. Image Enhancement

For better visualization, the min-max contrast extended algorithm is used. The linear contrast extended the following transformation,

$$DN_{st} = 255 \times [(DN - DN_{min}) / (DN_{max} - DN_{min})] \quad (1)$$

where

DN is regarded as the pixel number,

DN_{st} is regarded as the enhanced output image corresponding to DN

DN_{max} is regarded as the maximum DN value in original image and

DN_{min} is regarded as the minimum DN values in the original image.

D. Segmentation

Image Segmentation is the process by which tumor regions are classified into separate groups. The clustering of K-means is used for the grouping of brain objects. The outcome of the clustering algorithm k-means is used to segment the area of the tumor on the entire brain area. The Euclidian Distance Formula is generally presented as follows:

$$L^2 = \sum_{i=1}^n (x_i - y_i)^2 \quad (2)$$

where, L is regarded as the distance between the co-ordinate (x₁;x₂) and the coordinate (y₁;y₂), and (x,y) represents the two pixel points.

$$L = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \quad (3)$$

If the data points are the closest to the cluster, they will stop and move to the next data points, if they are not closest to the cluster.

E. Conversion of Gray Scale and Binary Image

For functional extraction, a segmented image can be converted to gray and binary images. Gray scale is that the image takes on the gray shadow colours. The gray intensity value is stored as an 8-bit integer and 256 different gray shades are possible from black to white. Binary images have only two possible values of 0 or 1, Black or white for each pixel. The pixel is stored in one bit.

F. Feature Extraction

The GLCM (Gray Level Co-Occurrence Matrix) has been proven to be the best statistical method of extracting images. It is called the spatial dependency matrix at gray level otherwise. Shape, color, texture are the important types of feature extractions. The statistical value is changed for each input picture, based on these types.



Texture feature that measures pixel values using image query statistical methods,

- Contrast is used to evaluate the local variations in GLCM.
- Correlation is used to evaluate the probability occurrence of a specified pixel pairs.
- Energy is used to evaluate the sum of squared elements in GLCM
- Homogeneity is used to evaluate the nearest distribution of elements in GLCM.

$$\text{Energy} = \sum_{i,j=0}^{N-1} (P_{ij})^2 \quad (4)$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij} (i-j)^2 \quad (5)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (6)$$

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij}) P_{ij} \quad (7)$$

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (8)$$

where, P_{ij} is regarded as the elements of GLCM (i, j)
 N is regarded as the total number of gray levels in the image

μ is regarded as the mean of GLCM

σ^2 is regarded as the variance of reference pixel intensity.

G. Classification Phase

The last step of this work is the Classification Phase. In this approach, RNN deep learning classifier is used over segmented tumor regions and also in benign regions with the label as malignant or benign. The dataset has been divided into two phase for training and testing process to evaluate the tumor regions in brain. The process of this stage is training the dataset feature vectors and their corresponding classes, whereas the output is the decision that will determine the type of input image whether it is malignant or benign. To achieve good results, RNN is trained and tested using RBF kernel functions. In this paper, RNN algorithm is used for classification of brain tumor regions.

In the RNN architecture [9] the information in the words before step t is also used as an input while the word is processed in step t . The fundamental RNN architecture consists of cells repeated one by one.

Previous cell data is taken from a cell and word is given as inputs. Some references trace the recursive representation over a single cell. Some other references are the sequence cells of the architecture. The architectural structure of the RNN is shown in Fig.2.

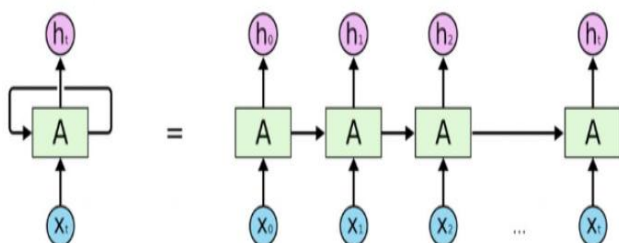


Figure 2: RNN Architecture [10]

In natural language processing problems, the amount of text contained in every data instance does not appear to be a certain value. The dimensions of the sequence are reduced to a value in order to process all text. The sequence is filled to the value if the sequence size is smaller than the value specified. The excess is discarded if the sequence size exceeds the specified value.

The algorithm shown below,

Algorithm: Classification of Blueberry Leaf Images

Start

Step 1: Read the input MRI brain image

Step 2: Improve contrast nature of original MRI image using contrast stretched min-max algorithm

Step 3: Convert the contrast stretched binary image into grayscale.

Step 4: Segment the gray scale image using KM clustering.

Step 5: Extract the features from segmented MR image using GLCM

stats = graycoprops(glcms, 'Contrast Correlation Energy Homogeneity');

Step 6: Evaluate 40 images (20 - training and 20 -testing).

Step 7: RNN classifier to classify the state of brain regions.

Step 8: Compare Ground truth image to check if the region is malignant or benign.

Step 9: Set the classifier label as 0 and 1, then

Apply state

if (result == 1)

helpdlg ('tumor is found in brain')

disp ('Malignant')

else

helpdlg ('No tumor is reported in brain')

disp ('Benign')

end

if (choice == 3)

close all

return

end

Step 10: Return the results.

Stop

IV. EXPERIMENTAL RESULTS

The comparison shows that our technique goes beyond all the cutting edge methods. In the third column of the table the whole data set used for training is specified. When 80% of images are used for training, the proposed method recorded the best result. We present results instead if 56% of the dataset is used for training. This shows the efficiency of our method with much higher than related works.

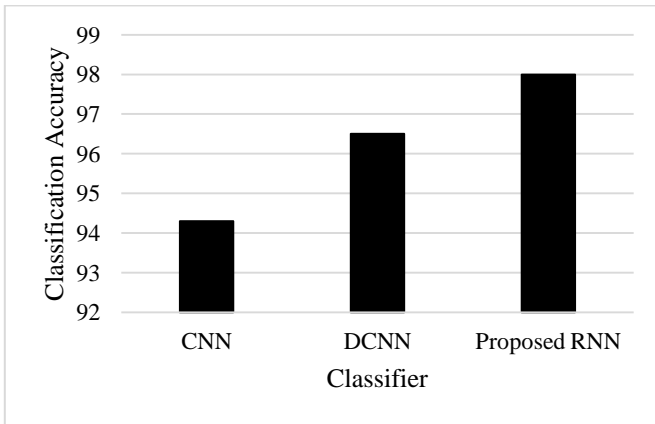


Figure 3: Classification Accuracy between proposed RNN framework and existing CNN or DCNN

The conclusions about the system are made on the basis of the performance assessment and detailed analysis. When using RNN instead of the classification layer the accuracy of the system improved. This meant some of the classifications failed using CNN or DCNN classifiers.

V. CONCLUSION

In this paper, the brain tumor classification is carried out using a series of steps like pre-processing, segmentation and classification to segregate the tumors among pituitary tumors, glioma tumor and meningioma tumor. This method adopts deep learning principle to extract the brain features from the MRI images. In this study, Recurrent Neural Network is used to classify the extracted features from brain. The experiments are carried out in terms of three fold cross-validation process over MRI brain image dataset. The results show that the proposed RNN classifier classifies the brain tumors effectively with 98% of mean classification accuracy than other existing methods.

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