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APPLICATION OF SEMANTIC SEGMENTATION NETWORKING BASED SEGMENTATION AND GOOGLENET CNN FOR MRI IMAGES OF BRAIN TUMOR

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ABSTRACT

In the medical field, BRAIN Tumor Segmentation is a quite challenging task due to different types of tumor appearances and also owing to alter characteristics like locality, and contrast. BRAIN cancer is generally diagnosed by a specialist called a neurologist. Imaging tests which are performed using a Magnetic Resonance Imaging (MRI) and Computed Tomography Scan uses computer technology to produce detailed pictures of the BRAIN. During the last decade, MRI was used to identify the BRAIN abnormality, to determine the location and size of the tissues. The segmentation process of medical image separates the image into a non-overlapped, consistent region, which is homogeneous according to the properties like intensity, color and texture. The property of segmentation is to make partitions in image which consist of complex in nature into a series of non-overlapping and constituents based on some characteristic features such as shape, gray level, color, texture and size. Accurate segmentation of brain tumor is an indispensable component for cancer diagnosis and treatment. To improve the tumor detection and identify the tumor accurately with less execution time and also a multi-objective classification scheme Semantic segmentation networking based segmentation and GoogLeNet CNN is applied for classifying the BRAIN tumor.

KEYWORDS : Magnetic Resonance Imaging, GoogLeNet, CNN, Segmentation, Tumor

1. INTRODUCTION

One of the most common Brain diseases is Tumor. The diagnosis and treatment of this Brain disease have become a significant factor for more than 4 lack people per year in the world (as per the World Health Organization (WHO) estimate). In recent years, developments in medical imaging techniques are helping us in many dominions of medicine. Computer Aided pathological diagnosis, planning the surgical procedures and treatment and time series examinations.

Brain cancer has been identified as on the deadliest and adamant one. These tumors can be found in many areas of the Brain that are important to run the body's important tasks. The tumor cells spread to other parts of the Brain and create extra tumors that are very small to diagnose with the normal imaging techniques. Sometimes, it is difficult to diagnose the Brain cancers location and this makes it difficult to cure in those patients who have to suffer with this disease. In recent years, the number of cancer cases has increased compared to previous years. In primary stage of the tumor, it is difficult to recognize. Once it is diagnosed, the course of treatment like radiation, chemotherapy etc.

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can be planned but late diagnosis of tumor is fatal for the patients.Usually the symptoms of infections in Cancer is found little late, but Computer Supported Technology in diagnosing the tumor has been a wonderful step in medicine, like already applied in Neuro surgery.

2 . PROBLEM STATEMENT

This research study on cloud storage retrieval and tumor of Brain aims at effective usage of advanced technology for medical related problems and also to discuss the upcoming developments and methodologies in the field of cloud storage. Some likely to happen problems in cloud storage retrieval and Brain tumor segmentation are i) High security and less computation cost of the auditor in a multi user setting is provided by the protocols like public key infrastructure. ii) Presence of more number of pixel coincidence which collide with each other in an input image taken for segmentation and it provides a tough partitioning during the time of segmentation. iii) As understanding the process of pixel filling and orientation existence is little difficult, this may lead to an un-optimal solution for the system. iv) In some medical cases, serious problems in segmentation of images may arise due to the unmatched irrelevant and wrong patterns. v) An ordered sequence or regularization mechanism has to found in the image segmentation as a robust system requires number of repetitions and time for matching the variations between the dispersed particles leading to high complex classified images.

It is important to give the user an intuitive edge to specify a query region (on a study of a patient or on a Brain atlas), which may consist of complex statements to specify a complete query region.To find similarity between the selected query region and the Region of Interest (ROI) such as the tumor or edema, the voxel set of the segmentation is stored in the database. Each voxel set of a segmented ROI belonging to a particular study contains about 20,000 voxels. The Database model has to be designed in such a way that the retrieval of data is efficiently done. This can be achieved by indexing the data tables so that retrieval of thousands of data is done fast in a short time. This reduces the search time in retrieval of required data.The main aim is to use deep learning methods to identify the locations of tumor cells, so that the radiologists can refine the radiation therapy used to treat Brain tumors, by comparing the previous patients with similar tumors to a present patient. This helps in knowing how the previous patient got cured with the treatment and to decide how to treat the present patient. This similarity based query plays a vital role in the medical training, treatment decision making and future research.

The doctors use the similarity based retrieval to specify diagnosis, identifying tumor growth and possible treatment options. This is done by comparing the images of a new patient or self-selected query from a database of previous patients. Hence, it is very necessary to support interactive queries of the tumor dataset by the doctors and cancer researchers. An interactive query gives a chance to do queries based on text data and to combine the cases to image based similarity queries. This is the basis for important analysis. Storing both the text based and image based Brain tumor date in a database is required here.

3. PROPOSED APPROACH

This approach consists of three steps: (A) Brain image preprocessing, (B) Brain tumor segmentation, and (C) Brain tumor classification. The input of the approach is the brain images and the output is the respective type of the brain tumor. Figure 1 shows the flowchart of the proposed approach. The details of the steps of proposed approach are described in the subsections below. Brain image preprocessing is an important step, which has a positive effect on the result of brain image analysis and the quality of brain feature extraction. After reading the input brain images, these images have large values which are outside of the range [0, 255], including negative values. Therefore, this step in our approach transforms the brain images into intensity brain images in the range [0,1] by using min-max normalization rule as given in the equation below: Brain tumor classification is the final step of the proposed approach, that is used to identify the type of brain tumor based on the GoogLeNet CNN classifier. GoogLeNet CNN is a feed forward neural networks (FNNs), composed of input and output layers, as well as a single hidden layer. Initializing the weights and biases of the input layer is randomly selected before going to compute the weights of the output layer. The concept of GoogLeNet CNN to classify multi class problem in more

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detail. In this step and during the training phase, the GoogLeNet CNN classifier model is trained on the brain features obtained from the previous step. Subsequently, the trained GoogLeNet CNN model is utilized to classify the type of brain tumor in an effective manner. A number of experiments are conducted based on holdout and 5-folds cross validation techniques. In the holdout technique, we divided the dataset into two sets: a training set which contains 70% of the dataset, and a testing set that contains 30% of the dataset. On the other hand, in the 5-folds cross validation, the dataset is divided into five sets; one of them is selected for testing and the remaining four sets are used for training, and this is done for five times. For evaluation, the confusion matrices of the actual and classified brain tumor classes are computed among the testing phase.

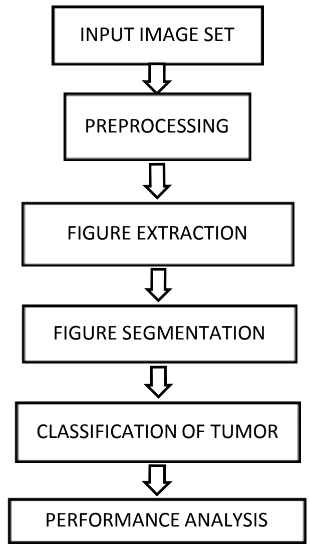

Figure 1. Proposed Work Flow

3.1 Steps for Proposed Algorithm

Step 1 : Image acquisition
Step 2 : Pre-processing
Step 3 : CNN based semantic segmentation
Step 4 : GoogLeNet classification

4. RESULTS AND DISCUSSION

For the implementation of proposed work to improve user interaction with the research application, the graphical user interface has been prepared. It consists of a number of axes to store the input and output image, a few buttons to perform the proposed image processing and a few boxes to display patient information and calculated efficiency parameters. It is generally accepted that the learning ability of the network will improve by increasing the complexity of the network. In this study, we demonstrate that the coarse segmentation using semantic network achieves higher Sensitivity, and the fine segmentation using semantic networking can effectively refine the segmentation results. Furthermore, the visual effects of the segmentation results. The results in the third row after the refinement using semantic segmentation are significantly better than those in the second row, not only obtains more accurate tumor areas, but also effectively removes the false positive areas. In summary, coarse-to-segmentation framework, the tumor profile with higher accuracy is obtained by using the proposed MCCNN due to the advantages of multiple cascaded combinations and multi-scale feature fusion. And CRFs to refine the segmentation results by considering the spatial and appearance consistency of segmentation results. Both the quantitative results and visual effects demonstrate the performance of the proposed coarse-to-segmentation framework. Figure 2 to 5 shows the Input Image, Iteration Graph, Pre Processing of Input Images and Segmentation Result.

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Figure 2 : Input Image

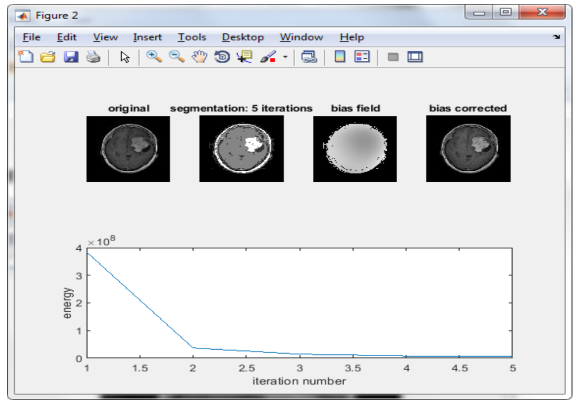

Figure 3 : Iteration Graph

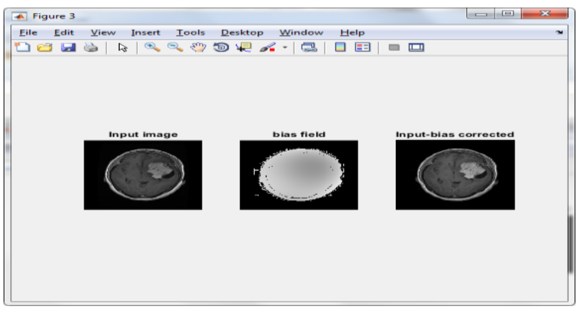

Figure 4 : Pre Processing of Input Images

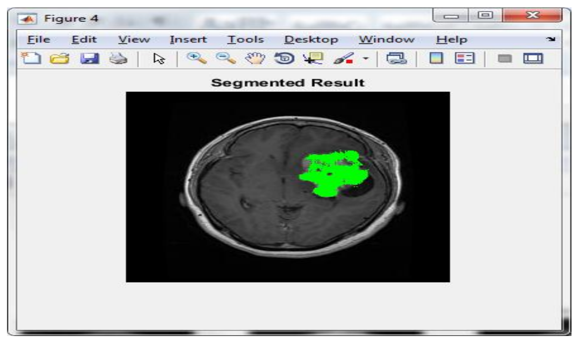

Figure 5 : Segmentation Result

The brain tumor part has been identified and segmented from the input image. Table 1 shows the Segmentation performance. The brain tumor has been identified and classified from the MRI images provided. Table 2 shows the Classification performance. Table 3 shows classification performance of other tumor types. Table 4 shows the comparison results of existing work and proposed work.

Table 1 Segmentation performance.

Parameters	
Accuracy	0.9906
Sensitivity	0.9153
Specificity	0.9928
Precision	0.7929
Recall	0.9153
False Positive Rate	0.0072

Table 2 Classification performance.

Parameters	
Accuracy	99.7826
Sensitivity	100
Specificity	99.7171
Precision	99.0698
Recall	100
F-Measure	0.9953

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Table 3 Classification Performance of other tumor types

	Meningioma tumor		Glioma tumor		Pituitary tumor	
	Existing	Proposed	Existing	Proposed	Existing	Proposed
Precision	0.9580	0.9861	0.972	0.9885	0.952	0.9682
Sensitivity	0.955	0.9771	0.944	0.9885	0.934	0.9726
Specificity	0.987	0.9957	0.9510	0.9897	0.97	0.99
Accuracy	97.54	99.1304	95.81	98.91	96.89	98.587

Table 4 Comparison results of existing system and proposed work

Parameters	Existing Work	Proposed Work
Sensitivity	0.9074	0.9153
Specificity	0.9918	0.9928
Computation time	1.5-3 mins	29.133 sec
False Positive Rate	2.24	0.0072
False Negative Rate	1.84	0.0847

5. CONCLUSION

The results show that Semantic segmentation and GoogLeNet CNN Classification can successfully segment a tumor provided the parameters are set properly in MATLAB environment. This approach algorithm performance is better for the cases where the intensity level difference amongst the tumor and non-tumor regions is higher. It can also segment non homogenous tumors providing the non-homogeneity is within the tumor section. This work proves that methods aimed at general purpose segmentation tools in medical imaging can be used for automatic segmentation of Brain tumors. The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging. Among the clustering methods investigated, the fuzzy c-means and Hybrid SP clustering is marked out best out of all others. The user interface in the main application must be extended to allow activation of the segmentation and to collect initialization points from a pointing device and transfer them to the segmentation module. Finally the main program must receive the segmented image and present the image as an opaque area. It has only one limitation that the method is semi-automatic.

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