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Identifying Grades of Glioma using Support Vector Machine Recursive Feature Elimination

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Abstract: The objective of this research is to classify glioma-a type of brain tumor, according to their grades by combining various classification methods and conventional magnetic resonance imaging. Determining Gliomas grades falls under the category medical image analysis. Image analysis includes the following: ROI definition (extraction), feature selection and classification. Feature selection till date is done using SVM-RFE algorithm. SVM-RFE stands for Support Vector Machine- Recursive Feature Elimination. But this algorithm can only classify glioma grade II, IV. The extracted feature of grade III is similar to the features of grade II or grade IV. Hence, they are either classified as grade II or grade IV. This paper aims at improving the existing classification method so as to identify grade III as well. Also in the existing systems the ROI extraction is done manually. Hence, the existing systems are semi-automatic. This work also aims at designing a fully automated system.

Keywords: conventional Magnetic Resonance Imaging, Classification Methods, ROI definition SVM-RFE

I. INTRODUCTION

Nervous system is the most complex system in a human body. It constitutes the central nervous system (CNS) and the peripheral nervous system. Central Nervous System consists of Brain and Spinal Cord. Brain is the most important component. It is responsible for any response to a stimulus. If the brain cells are damaged then this response is affected. The effects are shown in the form of convulsions, paralysis etc. Brain tumor often results in damaging not only the cells but also surrounding tissues [4]. The surrounding tissues are generally deformed. The location of brain tumor is one of the factors that determine how the brain tumor affects the individual's functioning and what symptoms the tumor causes. Unfortunately brain tumor cannot be identified at the initial stage. It can only be identified when various neurological symptoms have started. After the identification of brain tumor determining its type is also very important [5]. The location and type of brain tumor also plays a major role in formulating a treatment plan. Treatment of brain tumors differ from type to type.

Brain tumours are basically classified [1] into two types:

A. Primary brain tumour

B. Secondary brain tumour

Primary brain tumors include glial and non-glial tumors. Secondary brain tumors include metastases (tumors which originate in one part of the body and spread to the brain). Glioma is a type of glial tumor. They are also known as astrocytoma. WHO has assigned grades to them starting with grade I to grade IV; grade I being the least aggressive (benign) tumor while grade IV being the most aggressive (malignant) tumor. The "WHO GRADING OF ASTROCYTOMA" is the widely accepted grading system. This project aims at classifying gliomas according to the WHO grading system.

II. EXISTING SYSTEMS

Efforts have been constantly made to classify gliomas correctly.

Early works to classify tumor and non tumor regions:

The first methods that were used to identify tumors were either shape/boundary based methods or statistical methods.

Those methods had the following problems [7] [8]:

A. Selecting optimum boundary between tumor and non tumor region was difficult

B. Pixels are sensitive to local gradients; hence, that would make selecting the boundary more difficult

In order to solve these problems such systems were designed which used some form of already available information to identify tumors. The most common already available information is the anatomy of a normal brain tissue. On comparing of this information with the timorous MRI, the tumor could be identified. But availability of accurate clinical data is not always possible [3]. Moreover tumors may often deflect the anatomy of a normal tissue and that tissue may be mistakenly identified as tumor. Next the systems which required no prior knowledge were introduced. These were the classifiers. SVM [2] was used as a classifier. It was applied on a subset of features derived from a large set of available features.

But the system using SVM had two problems:

[a] The segmentation of desired ROI was not manual.

[b] If sufficient data set is not available then SVM may Misclassify the data.

Proposed system

The proposed system uses neural network as a classifier. It consists of two steps:

A. Phase-I

B. Phase-II

Phase-I

Data Description

The following MRI sequences were taken:

[a] Sagittal T1-weighted

[b] Axial T1-weighted

They were all pre contrast images. The quality of all the images was good and didn't require preprocessing.

Extraction of ROI

ROI refers to Region of Interest. In this case the tumor is the ROI. The ROI's are extracted by the process of thresholding. It is a segmentation technique which is based on gray level histogram of the image.

It is of the following types:

[a] interactive threshold

[b] Adaptive threshold

[c] Minimization method

In this work the minimization method is used. In this a particular value m is chosen as the threshold value.

the Thresholding Algorithm

[a] If pixels>=m then pixel=object

[b] If pixels<m then pixel=background

This produces a 2 level image called binary image. In this work the threshold value is the value which differen tiates the tumor and non tumor region.

The value in this case is a range.

The pixels falling within this range are identified as object or tumor and those outside the range are considered as background.

Classification: - Creating and Training the neural Network

A feed forward neural network is the classifier in the proposed system. To use neural network as a classifier the following steps are followed: The feed forward neural network is first created using the newff command.

a) Newff ([inputs], [number of neurons, number of outputs], {model of the neural network})

Where:

(a) Inputs= 0 or 1

(b) number of outputs=1 either a tumor or not

(c) Model of the network=log size has been used in this case.

Then it is trained using the training samples. The training samples are pairs of input/outputs. That is the axial or sagittal MRI scans are taken as inputs and the extracted ROIs are outputs. It is trained using the function **train ().**

b) Train (name of the network, inputs, targets)

PHASE-II

Classification: The Example MRI Scans Are Given to the Neural Network for Classification

Then the original image from which the tumor has to be detected is given for classification. When the original image is given for classification, the output obtained is the tumor part as well as some other parts.

The other parts are obtained because their intensities match that of the tumor region. It is so because intensities in one part of the brain may be normal for that region while tumor for other.

This can be solved by using brain atlases.

***(a) Brain atlases*:** a brain atlas is a template which has been prepared by experts. They provide the probability of gray matter at a location, as well as every other location. It is helpful as it can specify what intensities to expect in the MRI scans and accordingly decide whether tumor is present or not.

(b) Drawback of atlases*:* Unfortunately, these locations will typically be different - e.g., position (18, 200, 52) in the template might correspond to, say, (19, 207, 55) in the patient - as the patient's head may not be the 'typical' size and shape, and moreover it may have been tilted when the image was captured.

Other way to solve the problem is use of ***morphological operations.*** Thus intensity plus morphological operations provides accurate training to the classifier and hence, the neural network can identify the tumors accurately.

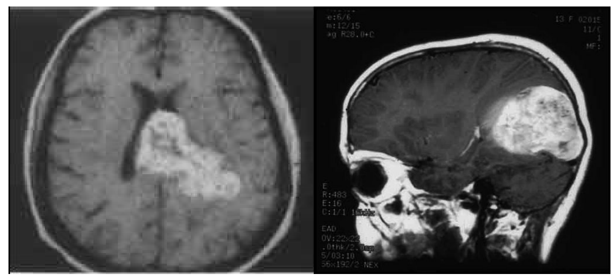

Figure 1. The axial and sagittal sequences

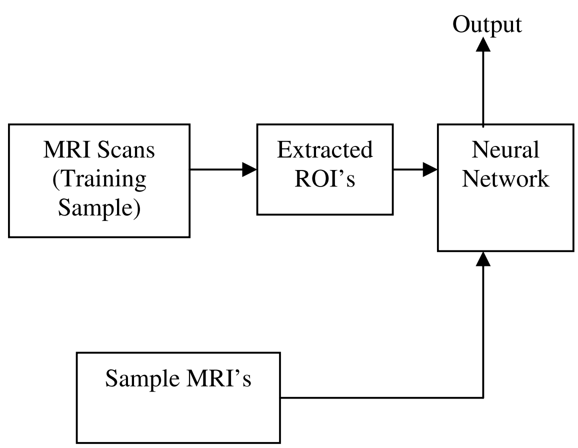

Figure 2: the proposed system

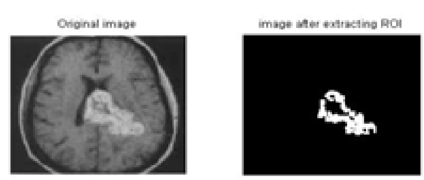

Figure 3: the extracted ROI

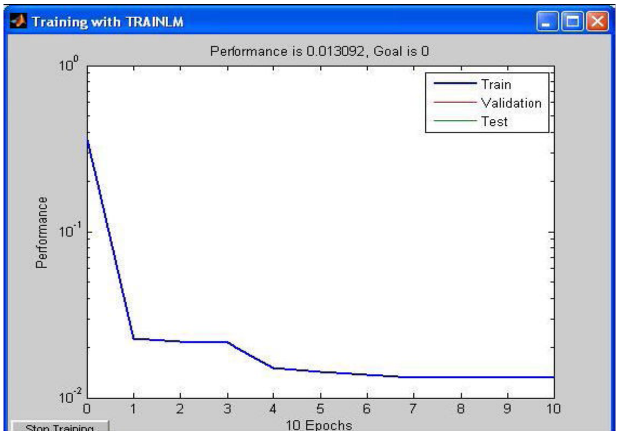

Figure 4: the training graph

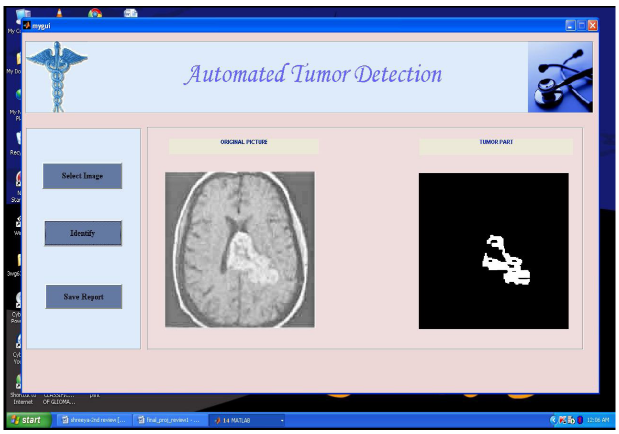

Figure 5: the identified tumor

III. CONCLUSION

The neural network uses the training samples and learns to distinguish between tumor and non tumor region. It does so by adjusting the weights or connections between the neurons. The tumor if present is properly classified. Also for images not having any tumor it shows a blank white output. Fig4. Shows the training graph of the system. The X axis shows the performance and the Y axis shows the number of epochs. It shows an acceptable range of errors. The lower the curve is, the better and more accurately the network is trained. This leads to better classification of the images.

The system has the following advantages:

A. The ROI in the system is not obtained manually. It has been obtained by segmentation. Thus the system does not require manual intervention and is fully automatic.

B. Since neural network is used as a classifier so even small number of tumor pictures give good results. This system can help a doctor to identify a tumor better. Since all the other background objects are removed the shape and size of the tumor is better visible. This will help a surgeon to remove the tumor accurately.

IV. FUTURE WORKS

Recent studies have shown that tumor is a genetic disease. Different tumors modify different genes. Even tumors of same kind modify different genes. So a new system of classification is being designed. This system can be extended to classify tumors according to that system.

Till now in this work only the tumor and non tumor regions have been classified. Grading will be done using perfusion MRI which provides information about the relative cerebral blood flow (rCBF). The rCBF is used to differentiate between low grade glioma and high grade glioma.

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