Brain Tumor Detection Using Neural Network

Pankaj Sapra, Rupinderpal Singh, Shivani Khurana

Abstract: The segmentation of brain tumors in magnetic resonance images (MRI) is a challenging and difficult task because of the variety of their possible shapes, locations, image intensities. In this paper, it is intended to summarize and compare the methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI) used in different stages of Computer Aided Detection System (CAD). Brain Image classification techniques are studied. Existing methods are classically divided into region based and contour based methods. These are usually dedicated to full enhanced tumors or specific types of tumors. The amount of resources required to describe large set of data is simplified and selected in for tissue segmentation. In this paper, modified image segmentation techniques were applied on MRI scan images in order to detect brain tumors. Also in this paper, a modified Probabilistic Neural Network (PNN) model that is based on learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI-scans. The assessment of the modified PNN classifier performance is measured in terms of the training performance, classification accuracies and computational time. The simulation results showed that the modified PNN gives rapid and accurate classification compared with the image processing and published conventional PNN techniques. Simulation results also showed that the proposed system out performs the corresponding PNN system presented and successfully handle the process of brain tumor classification in MRI image with 100% accuracy.

Index Terms*: Magnetic Resonance Image (MRI),Computer** **Aided Detection System (CAD), Probabilistic Neural Network (PNN)*, Edge detection

I. INTRODUCTION

In today's digital era, capturing, storing and analysis of medical image had been digitized. Even with state of the art techniques, detailed interpretation of medical image is a challenge from the perspective of time and accuracy. The challenge stands tall especially in regions with abnormal color and shape which needs to be identified by radiologists for future studies. The key task in designing such image processing and computer vision applications is the accurate segmentation of medical images. Image segmentation is the process of partitioning different regions of the image based on different criteria. Surgical planning, post-surgical assessment, abnormality detection, and much other medical application require medical image segmentation. In spite of wide number of automatic and semi – automatic image segmentation techniques, they fail in most cases largely because of unknown and irregular noise, in homogeneity, poor contrast and weak boundaries which are inherent to medical images. MRI and other medical images contain complicated anatomical structures that require precise and most accurate segmentation for clinical diagnosis. Brain image segmentation from MRI images is complicated and challenging but its precise and exact segmentation is necessary for tumors detection and their classification, edema, hemorrhage detection and necrotic tissues. For early detection of abnormalities in brain parts, MRI imaging is the most efficient imaging technique. Unlike computerized Tomography (CT), MRI image acquisition parameters can be adjusted for generating high contrast image with different gray level for various cases of neuropathology. Therefore, MRI image segmentation stands in the upcoming research limelight in medical imaging arena. In the field of neuroscience, mapping of functional activation onto brain anatomy, the study of brain development, and the analysis of neuron anatomical variability in normal brains requires the identification of brain structures in MRI images. Apart from this, segmentation of MRI images is essential in clinical diagnosis of neurodegenerative and psychiatric disorders, treatment evaluation, and surgical planning. Brain cancer is a very serious type of malignancy that occurs when there is an uncontrolled growth of cancer cells in the brain. Brain cancer is caused by a malignant brain tumor. Not all brain tumors are malignant (cancerous). Some types of brain tumors are benign (non-cancerous). Brain cancer is also called glioma and meningioma. Brain cancer is one of the leading causes of death from cancer. There are two main types of brain cancer. They include primary brain cancer, in which the brain cancer originates in the brain itself. Primary brain cancer is the rarest type of brain cancer. It can spread and invade healthy tissues on the brain and spinal cord but rarely spreads to other parts of the body. Secondary brain cancer is more common and is caused by a cancer that has begun in another part of the body, such as lung cancer or breast cancer that spreads to the brain. Secondary brain cancer is also called metastatic brain cancer. Brain cancer is most treatable and curable if caught in the earliest stages of the disease. Untreated and/or advanced brain cancer can only spread inward because the skull will not let the brain tumor expand outward. This puts excessive pressure on the brain (increased intracranial pressure) and can cause permanent brain damage and eventually death. This process results in symptoms, such as headache, and other neurological problems. For more details on other key symptoms and complications, refer to symptoms of brain cancer. People at risk for developing brain cancer include people with a family history of brain cancer and people who have had radiation therapy of the head.

Diagnosing brain cancer begins with taking a thorough personal and family medical

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history, including symptoms and risk factors for brain cancer. The diagnostic process also includes completing a thorough physical and neurological exam. A neurological helps to evaluate the brain and nervous system and such functions as reflexes, sensation, movement, balance, alertness, coordination, vision, and hearing.

A diagnosis of brain cancer is generally made by a specialist called a neurologist. Imaging tests that may be performed include MRI and/or CT scan which use computer technology to create detailed pictures of the brain. A procedure called a brain angiogram may also be done to illuminate blood vessels in the brain that feed blood to a brain tumor. Another procedure that may be performed is a spinal tap or lumbar puncture. In this procedure, a small sample of spinal fluid is removed from the spinal cord and examined under a microscope for the presence of cancer cells. Diagnostic testing also includes a biopsy. In a biopsy a sample of cells or tissues are taken from the brain during surgery performed on a brain tumor.

II. PROPOSED SYSTEM

Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There is an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges.

The purpose of edge detection in general is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image processing. Several algorithms exists, and this worksheet focuses on a particular one developed by John F. Canny(JFC). Even though it is quite old, it has become one of the standard edge detection methods and it is still used in research.

The Canny Edge Detection Algorithm

The algorithm runs in 5 separate steps:

1.Smoothing: Blurring of the image to remove noise.

2.Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.

3.Non-maximum suppression: Only local maxima should be marked as edges.

4.Double thresholding: Potential edges are determined by thresholding.

5.Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

An edge in an image may point in a variety of directions, so the Canny algorithm uses four filters to detect horizontal, vertical and diagonal edges in the blurred image. The edge detection operator (Roberts, Prewitt, Sobel for example) returns a value for the first derivative in the horizontal direction (G_x) and the vertical direction (G_y). From this the edge gradient and direction can be determined:

$$\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$$

$$\mathbf{\Theta} = \arctan\left(\frac{\mathbf{G}_y}{\mathbf{G}_x}\right).$$

The edge direction angle is rounded to one of four angles representing vertical, horizontal and the two diagonals (0, 45, 90 and 135 degrees for example)

Performance of Edge Detection Algorithms

- Gradient-based **algorithms** such as the Prewitt filter have a major drawback of being very sensitive to noise. The size of the kernel filter and coefficients are fixed and cannot be adapted to a given image. An adaptive **edge-detection** algorithm is necessary to provide a robust solution that is adaptable to the varying noise levels. Gradient-based **algorithms** such as the Prewitt filter have a major drawback of being very sensitive to noise. The size of the kernel filter and coefficients are fixed and cannot be adapted to a given image. An adaptive **edge-detection** algorithm is necessary to provide a robust solution that is adaptable to the varying noise levels of these images to help distinguish valid image contents from visual artifacts introduced by noise.
- The performance of the canny algorithm depends heavily on the adjustable parameters, σ, which is the standard deviation for the Gaussian filter, and the threshold values, 'T1' and 'T2'. σ also controls the size of the Gaussian filter. The bigger the value for σ, the larger the size of the Gaussian filter becomes. This implies more blurring, necessary for noisy images, as well as detecting larger edges. As expected, however, the larger the scale of the Gaussian, the less accurate is the localization of the **edge**. Smaller values of σ imply a smaller Gaussian filter which limits the amount of blurring, maintaining finer edges in the image. The user can tailor the algorithm by adjusting these parameters to adapt to different environments.
- Canny's edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator. However, the Canny's edge detection algorithm performs better than all these operators under almost all scenarios.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not.

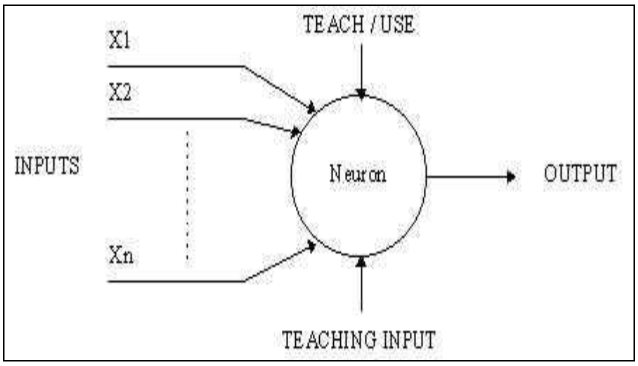

Figure1.A simple neuron

Firing rules

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the ones on which the node was trained. A simple firing rule can be implemented by using Hamming distance technique. The rule goes as follows: Take a collection of training patterns for a node, some of which cause it to fire (the 1-taught set of patterns) and others which prevent it from doing so (the 0-taught set). Then the patterns not in the collection cause the node to fire if, on comparison, they have more input elements in common with the 'nearest' pattern in the 1-taught set than with the 'nearest' pattern in the 0-taught set. If there is a tie, then the pattern remains in the undefined state.

For example, a 3-input neuron is taught to output 1 when the input (X1, X2 and X3) is 111 or 101 and to output 0 when the input is 000 or 001. Then, before applying the firing rule, the truth table is;

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0/1	0/1	0/1	1	0/1	1

Figure2: the outcome of 3-input neuron

As an example of the way the firing rule is applied, take the pattern 010. It differs from 000 in 1 element, from 001 in 2 elements, from 101 in 3 elements and from 111 in 2 elements. Therefore, the 'nearest' pattern is 000 which belongs in the 0-taught set. Thus the firing rule requires that the neuron should not fire when the input is 001. On the other hand, 011 is equally distant from two taught patterns that have different outputs and thus the output stays undefined (0/1). By applying the firing in every column the following truth table is obtained;

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0	0/1	0/1	1	1	1

Figure3. the other outcome of the neuron system

The difference between the two truth tables is called the *generalisation of the neuron.* Therefore the firing rule gives the neuron a sense of similarity and enables it to respond 'sensibly' to patterns not seen during training.

A more complicated neuron

The previous neuron doesn't do anything that conventional conventional computers don't do already. A more sophisticated neuron (figure 2) is the McCulloch and Pitts model (MCP). The difference from the previous model is that the inputs are 'weighted'; the effect that each input has at decision making is dependent on the weight of the particular input. The weight of an input is a number which when multiplied with the input gives the weighted input. These weighted inputs are then added together and if they exceed a pre-set threshold value, the neuron fires. In any other case the neuron does not fire.

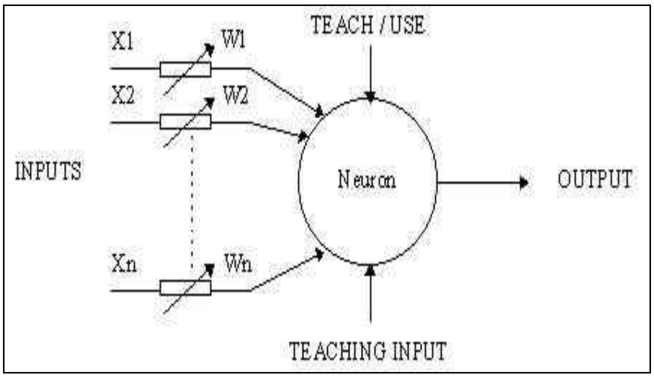

Figure 4. An MCP neuron

In mathematical terms, the neuron fires if and only if;

$$X1W1 + X2W2 + X3W3 + ... > T$$

The addition of input weights and of the threshold makes this neuron a very flexible and powerful one. The MCP neuron has the ability to adapt to a particular situation by changing its weights and/or threshold. Various algorithms exist that cause the neuron to 'adapt'; the most used ones are the Delta rule and the back error propagation. The former is used in feed-forward networks and the latter in feedback networks.

The following are the various outcomes of the proposed system.

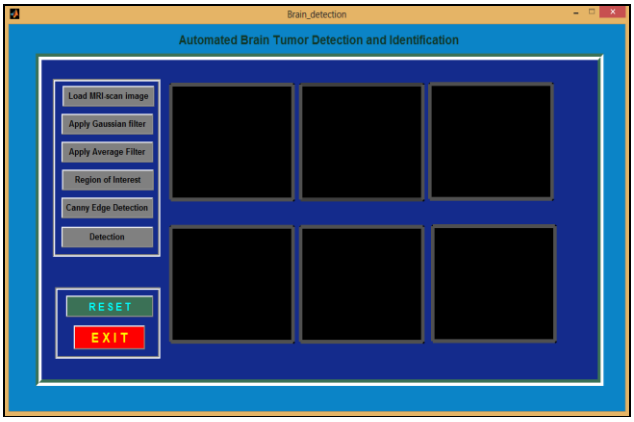

figure 5. The basic layout of the proposed system.

In the proposed system the image is firstly loaded as shown in the following figure.

Figure 6. The image is loaded.

After the image is loaded the various filters are applied on the input image such as the Gaussian filter and the average filter.

Figure 7. By applying the various filters on the input image.

After the filtering process the image (region), is detected by the Canny Detection, to detect whether the following case is abnormal or normal.

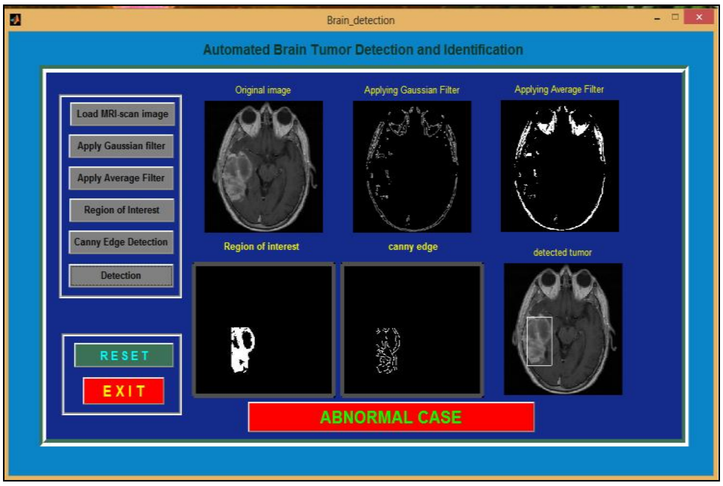

Figure 8. The abnormal case.

Figure 9. The normal case.

III. CONCLUSION

The paper prose's a method for classification of tumor in a brain image. The main objective of this step is to differentiate the different abnormal brain images based on the optimal feature set. This classification is performed on proton Magnetic Resonance Spectroscopy images. But the classification accuracy results are different for different datasets which is one of the drawbacks of this approach. Experiments are conducted on various real-world datasets and the results concluded that the proposed algorithm yield good results when compared with the other classifiers. The results revealed that the proposed hybrid approach is accurate, fast and robust. In this paper, we proposed two approaches for Brain tumor detection, identification and classification. The first approach is based on an integrated set of image processing algorithms, while the other is based on a modified and improved probabilistic artificial neural networks structure. The proposed integrated image processing algorithm is based on a modified canny edge detection algorithm and implemented using MATLAB. However, simulation results using this algorithm showed its ability to accurately detect and identify the contour of the tumor, its computational time and accuracy were much less than its corresponding algorithms that use the parallel distributed processing nature of neural networks to reduce computing time and enhance the classification accuracy. This leaded us to propose a modified and improved probabilistic artificial neural networks structure. The modification is based on automatic utilization of specified regions of interest (ROIs) within the tumor area in the MRI images. Form each ROI, set of extracted features include tumor shape and intensity characteristics are extracted and normalized. Each ROI is then given a weight to estimate the PDF of each brain tumor in the MR image. These weights are used as a modeling process to modify the conventional PNN. This method is based on learning vector quantization (LVQ) which is a supervised competitive learning technique. This model is successfully tested by using a set of infected brain MRI-scan images to classify brain tumor. In our experiments, a database of 64 MRI-scan Gray-scale images was used; each image size is 220×220 pixels.

Out of the 64 subjects a group of 18 random patients MRI images were selected as a test set, while the rest of the dataset was used for training. Training data was used to feed into the neural networks as inputs and then knowing the output, the weights of the hidden nodes were calculated.Many trials were performed on the same Neural Network, selecting 18 subjects randomly every time for testing and the remaining subjects for retraining to find accuracy of neural network prediction. Simulation results showed that the proposed system outperform the presented system and successfully handle the process of MRI image classification with 100% accuracy when the spread value is equal to 1.In this paper, we propose two approaches for Brain Tumor Detection based on artificial neural networks. The networks were categorized into feed-forward neural networks and Back propagation neural Network. The purpose is to develop tools for discriminating malignant tumors from benign ones assisting decision making in clinical diagnosis. The proposed approach utilizes a combination of these two neural network techniques and is composed of several steps including segmentation, feature vector extraction and model learning. These two methods can then be used to filter out non-suspecting brain scans as well as to point out suspicious regions that have similar property as the tumor regions.

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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