

# BRAIN CANCER CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

R. Manimegala<sup>1</sup>, K. Priya<sup>2</sup>, S. Ranjana<sup>3</sup>

<sup>1,2,3</sup>Assistant Professor, Faculties of Humanities Science, Meenakashi Academy of Higher Education Research Chennai, TamilNadu, India

E-mail: manimegalar@maherfhs.ac.in<sup>1</sup>, priyak@maherfhs.ac.in<sup>2</sup>,  
ranjanas@maherfhs.ac.in<sup>3</sup>

## **Abstract:**

*A program has been planned and developed to diagnose and identify brain cancer. The program employs computer-based techniques in the detections of tumor fragments or tumors, and in photographs of various Astrocytoma brain tumor patients, it classifies the type of tumor utilizing Artificial Neural Network. For the diagnosis of the brain tumor, photographs of the patients afflicted by cancer were created utilizing image processing technique such as imaging segmentation, histogram equalization, image enhancement, morphologic surgery and feature extraction. Gray Level Co-occurrence Matrix (GLCM) is used for the detection of surface characteristics in the observed tumor. Such properties are contrasted with the functionality contained in the knowledge base. To order to identify various forms of brain cancers, a neuro fuzzy concept was eventually created. The entire system was verified in two stages: first, the phase of learning / training as well as second, the phase of recognition / testing. The device was equipped through documented MRI images from patients with impaired brain cancer from the Department of Radiology of Tata Memorial Hospital (TMH). Known brain cancer tests of impacted MRI scans are often obtained from TMH and used for device monitoring. The method has been shown to be effective in classifying these samples.*

**Keywords:** Brain Cancer, image classification, neural network.

## **1 Introduction:**

Health experts have been experimenting on cancer for decades because it requires time and resources to create novel therapies. Science may also identify the root cause of all cancers, so it may create healthier strategies to avoid brain tumors from developing so spreading, so it can be healthy. Around 40% of the main patients adequately diagnosed with surgery and radiation in certain cases. It seems that tumors are that, but without a specific cause. MRI has become a commonly used tool for medical imaging of high quality, particularly in cerebral imaging, where contrast and noninvasiveness of MRI's soft tissues are obviously advantages. MRI offers the human body an unrivaled perspective. Compared to any other imaging mode, the level of feature we can see is amazing. Reliable and fast brain cancer diagnosis and evaluation is of crucial scientific and cost-effectiveness for physicians.

Popular activities focused upon professional technicians are sluggish, barely accountable and challenging to measure.

The device developed is an effective method for brain cancer screening and classifying patients impacted by a specific MRI image. For medical sciences such as computer-aided treatment as well as mammography etc., the device often sees good application for cancer identification. Brain cancer is a complicated disorder categorized as 120 distinct forms. So-called non-malignant (benign) brain tumors can also be life-threatening as malignant tumors when normal brain tissue squeezes out and interferes with function. 44.4 percent of entirely brain tumors are in the glioma family of tumors. Astrocytoma glioblastoma is the most prevalent glioma with 51.9 percent and 21.6 percent in all brain tumor astrocytoma in other forms.

The primary source of cancer mortality of children under 20 years of age is brain tumors. This is the second most frequent cause of death for males aged 20-29. A cancer which extends from further parts of the body into the brain develops metastatic brain tumors. Approximately 10-15% of cancer patients will potentially grow metastatic brain tumors. There are several forms of brain cancer, but the most prominent and widespread is astrocytoma among numerous kinds of brain cancers. This thesis briefly describes the process of identification and analysis carried out. Section III explains the description and retrieval of pictures. Section IV and V shall establish the findings obtained during studies and conclusions drawn.

## **2 Related work:**

For the identification of the brain tumor in MRI images of cancer patients affected, the methods of image processing, for example histogram equation, imaging segmentation, image improvement, morphological operations as well as extraction function have been created. A Gray Level Co-occurrence matrix (GLCM) was used for exclusion of texture [1] features in the tumor observed. These attributes are related to the apps kept in the knowledge base. In addition, a Neuro Fuzzy Classifier was developed to classify different kinds of brain cancer. Data research final results very much rely on the vast number of genes that each experiment includes for a very limited amount of specimens. It is therefore necessary to choose the correct genes for potential unique markers of cancer. Several methods of selection of features have been proposed[2], but none of them are able to accurately classify any type of data, especially those of the multi-class datasets. Rather of conducting the mathematical comparison one-on - one, we plan to analyze the set of discrimination characteristics.

Data research final results very much rely on the vast number of genes that each experiment includes for a very limited amount of specimens. It is therefore necessary to choose the correct genes for potential unique markers of cancer. Several methods for selecting features have been proposed,[3] but none of the methods can adequately distinguish all kinds of data, especially in multi class datasets. Rather of conducting the mathematical comparison one-, we plan to analyze the set of discrimination characteristics. This paper discusses a tumor blocking and labeling method that utilizes artificial neural network

algorithms in various patient photos to identify tumor blocks. The following techniques are used for MRI imaging. Various imaging [4] methods are used for the identification of brain cancers in the MRI pictures of people affected by cancer, such as histograms equalization, image segmentation, image stabilization, morphological procedures, as well as feature elimination.

Through this intra operative study, we have specifically differentiated normal brain with a sensitivity of 93% and a specificities of 91% from dense carcinoma as well as normal brain that is invaded by cancer cells. This Raman-based study allowed the identification of the previously undetectable diffuse-invasive cell-resolving brain cancer cells in 2-4 gliome patients. Therefore, this intra operative technique will identify the cell populations in real time and allows it an excellent tool for surgical resection as well as decision taking. The product of multiple classifiers is combined with this system. The functions are split into subsets and each sub-set includes SVM-RFE. The feature chosen for each subset is then listed separately. The Twin Support Vector (TWSVM) is used as an assist to minimize numerical uncertainty for the approach employed in each SVMRFE. That means increases filtering capability for each SVMRFE. Twin SVM's key goal is to consider two non-parallel, maximal hyperplanes when the normal SVM seeks the same ideal hyperplane.

We suggest a way of addressing all these problems using a rough-to-fine study of spatial features in pathology images. Anfirst survey process examines the variety of rough regions in the slide picture. This involves the extraction from tiled areas casing the slide of spatially located [7] characteristics of shape, color and texture. The reduction in dimension of the features assesses the variety of photos in the tiled regions and clusters build representative categories. In a second level, one representative tile from every category is evaluated in depth. For any symbolic surface, an Elastic Net classifier generates a diagnostic decision value. Computer and imaging technologies may be very helpful in the study of the location of the tumor. Throughout this article, features dependent on picture type and texture were examined and[8] brain tumors were identified. Use linear vector quantization after isolation of characteristics, brain tumors are categorized into malignant and benign forms.

The six-type spectrum resonance Raman (RR) in human brain tissues was studied using a confocal 532-nm micro-Raman-system. 43 RR spectra are studied from seven topics. It analyzes the spectral peaks of malignant meningioma, stage III (cancer), benign meningiomas (benign), meningial tissues (normal)[9], multiform cancer glioblastoma (IV grade), acoustic (benign) neuroma, and hysteria (benign). The resonance increased limit is found in all the tissue specimens with the 532-nm stimulation at 1548  $\text{cm}^{-1}$  (amide II) but not in the obtained spectra utilizing the non-r sonance Raman method. In the MRI images of multiple patients with astrocytome form of brain tumor this paper classifies the tumor forms utilizing the Network for Artificial Neurons (ANN).[10] Gray Level co-occurrence matrix (GLCM) is the extraction of texture features in the observed tumor. This essay suggests an abstract assessment method to diagnose regular or pathological MRI stimuli in the brain.

Apparently, brain tumor option and diagnosis was focused on signs and the presentation of radiology. The MRI is the primary guided instrument for the anatomical examination of brain tumors. Specific methods for the diagnosis of brain cancer were used in the present[11] research. Under such processes, preprocessing of pictures, image feature

extraction as well as subsequent classification of brain cancer is positively implemented. Some experimental approaches are exciting for the care of brain cancer patients, but the crucial obstacle is to recognize which therapy is better provided by a single individual. DNA micro-array technology has now started to discover patients that have not been historically identified and have specific survival systems [12], which allow for the simultaneous study of the expression of thousands of genes.

### 3 Proposed method:

The study included the collection into various kinds of brain tumors with MRI pictures that are influenced by brain cancer. For the diagnosis of tumor, the analysis of photographs such as histogram equalization, image segmentation, image improvement as well as eventual retrieval of characteristics using a gray level co-occurrence matrix. In the knowledge base, the derived function is processed. To identify various forms of brain cancer, a appropriate Neuro Fuzzy Classifier is created. MRI photographs taken at Tata Memorial Hospital are the photos used. Through developing a Graphical User Interface (GUI), the program is built to be user friendly.

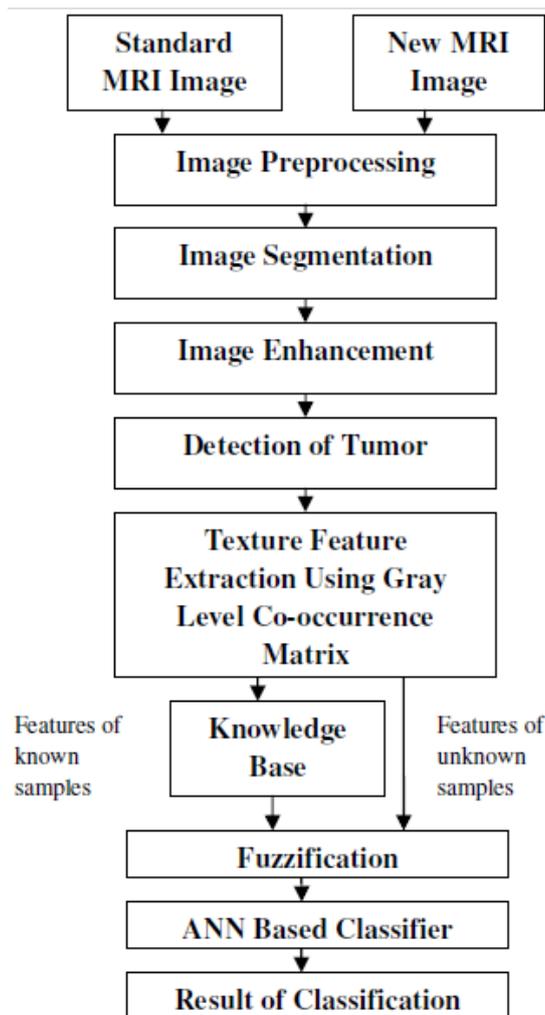


Figure 1. System Architecture

The program is planned and built in two stages, namely the process of learning / training and recognition / testing. The ANN is equipped during the study / training process to identify various forms of Astrocytoma in the brain. First, the identified MRI images are handled through specific image processing processes including Histogram Equalization, Thresholding, Sharpening Filters, and so on; then textural characteristics can be take out using a Gray Level Matrix. The extracted features are used for the efficient classification of unknown items in the information base. These features are standardized between -1 and 1 and presented as a function input to the Classification Artificial Neural Network. The unidentified MRI images pretentious by cancer of type Astrocytoma are used for difficult in Recognition/Testing Phase.

### III. IMAGE CLASSIFICATION STAGES

#### A. *Stage zero: Pathological Detection:*

The system has automatically classified all the slices processed as abnormal. Astrocytoma tumor established on a radiologist disease explosion is known to contain.

#### B. *Stage 1: Tumor Segmentation.*

The first move is to separate the tumor area from the rest of the image. Numerous methods for picture analysis are used to isolate the tumor area. The pre-processing of photographs comprises predominantly of histograms. The principal challenge in the identification of tumor edge is that on a very ambiguous image, the tumor appears very black. Histogram Equalization has been done to solve this problem. Segmented pictures subdivide into their elements or artifacts. The degree of transport of this section depends on the issue being set, i.e. when it is possible to identify the tumor tip, the segmentation will stop and the primary purpose is to discrete the tumor from its background.

The limits have been used to separate the tumor and gray level 0 to generate a binarized picture of gray level 1, which reflects a background color. This is the most appropriate for this method. The segmentation is defined by a single parameter named the Intensity Threshold in basic implementations. Every pixel in the picture is equivalent to this level in a single step. The pixel in the output is set to white, if the intensity of the pixel is higher than the threshold. It is set to black if it is less than the Threshold. The following equation A explains the operation.

$$T = \frac{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} e_{i,j} * M_{i,j}}{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} M_{i,j}}$$

The main change is to render the whole brain and tumor more contrast. Contrast can be present between the brain as well as tumor region just below the human vision threshold. Thus, a sharpening filter for the digitized MRI is added to improve the contrast between the regular brain as well as tumor area and thereby contributes to a major increase in picture contrast. The dilation operator is used to cover the damaged holes at the borders and to ensure cohesion at the borders. A filling operator is added to the dilated image to fill the contours similarly. Centroses are determined to identify areas after the activity on an picture.

Logically, for the extraction of the large area in a given MRI picture the final area is removed.

### **B. Stage 2: Feature Extraction**

The research consists of extracting essential face recognition characteristics. The extracted features give the textural property and are retained in the database. The extracted features are contrasted with the Unknown sample Image features. Gray level matrices (GLCM) characteristics are used to distinguish between regular and pathological brain tumours, or more precisely, grey level matrices. Five matrices are formed with four horizontal, right diagonal, vertical as well as left diagonal orientations in spatial direction [5, 6] (0, 45, 90, and 135). The sum of the four preceding matrices is a fifth matrix.

### **D . Stage 3: Knowledge Base**

Knowledge is any material that categorizes efficiently between one community and another. For this scenario, the tumor may have other characteristics that are not recognized by certain brain tissues. Two main sources of information are accessible in the area of MRI volumes. The first is the strength of the pixel in the element, which defines the fabric properties of the imaging device. The second is image / anatomical volume, with predicted tissue type and location in the body, such as the possibility that CSF is within the ventricle. Tumor existence restricts the use of anatomical information, since it can take any shape as well as occupy any region of the brain [3, 7] as honeycomb.

### **E. Stage 4: Nero-Fuzzy Classifier**

For the identification of nominee circumscribes tumor, neuro-fuzzy classifier is used. ANN 'S are data networks that are linked, typically referred to as nodes. The input of a single node is the weighted sum of all the related nodes 'output. The result value of a node is typically a non-linear feature of its input value (known as activation feature). The multiplication weighting factor amongst the node  $j$  as well as the node  $I$  performance is named the  $w_{ji}$  weight.

An Adaptive, often nonlinear network that can execute a data task (input / output map) is an artificial neural network. Adaptive implies that device parameters, generally known as the learning / training process, are modified during service. Following the training process, the neural network parameters are set as well as the program is applied to solve the problem. In the analysis, context propagation ANN consists of one layer of data, one or two hidden layers as well as one output layer [8,9].

The input information (Extracted Features) is sent periodically to the Artificial Network with back-propagation; each analysis contrasts the outcome of the neural network with the expected performance (Tumor Grade) and calculates an error. This error is then returned to the Artificial Neural Network (back propagated) and used to change weight such

that for each iteration the error reduces as well as the neural model closes itself to created the required output. This process is called training. The development of these networks is to map a set of input values to a set of output values [15]. The mapping takes place via the modification of weights of the wji; the most common of which is a prevalent delta rule is a learning algorithm. If the weights on the training set have been changed the value is defined, and unknown input images are identified by ANN [8]. The generalized delta rule needs a minimum of [9, 10] error word.

$$E_p = \frac{1}{2} \sum_j (t_{pj} - o_{pj})^2$$

The index p in this equation is one input vector and the vectors t<sub>pj</sub> as well as o<sub>pj</sub> refer to the target and observed output vectors p respectively.

#### 4 Result and discussion:

The program is designed to efficiently identify Brain Cancer's input MRI image into a form of tumor classification. During the Recognition / Testing process, MRI photographs of patients with Brain Cancer are used. The machine shows the area of tumors removed from the outer skull for the reference picture used for processing. The extracted features in this field are linked to the retained features in the knowledge base.

The system developed then classes the picture into a tumor degree for brain cancer type astrocytoma.

Sr.No	TestImage	Original grade ofImg	Classified grade ofimg
1	Img 1	grade 1	grade 1
2	Img 2	grade 2	grade 2
3	Img 3	grade 3	grade 3
4	Img 4	grade 4	grade 4
5	Img 5	grade 1	grade 1
6	Img 6	grade 2	grade 2
7	Img 7	grade 3	grade 3
8	Img 8	grade 4	grade 4
9	Img 9	grade 1	grade 1

Table 1 offers descriptions of the tumor type Astrocytoma grade originally created by the method formed in this picture, which affects the picture and outcome of classification. Figure 2 indicates the location of the tumor removed from the outer skull. The grade III type tumor affects the provided picture in Figure 3.

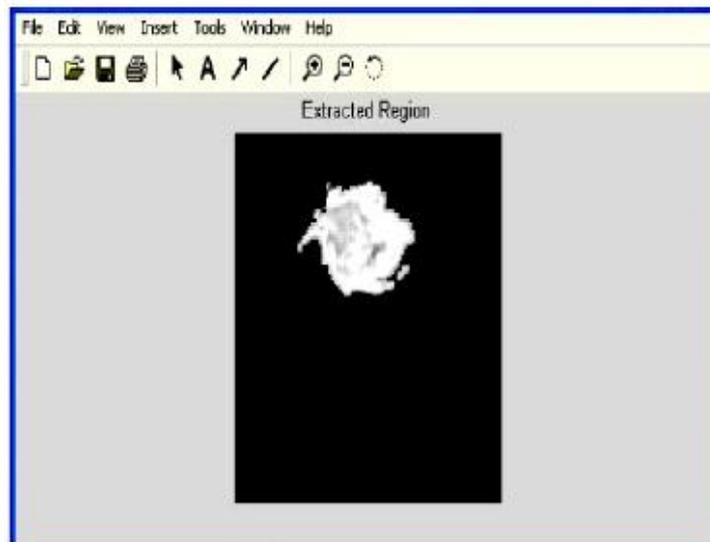


Figure 2. Extracted region without outer skull

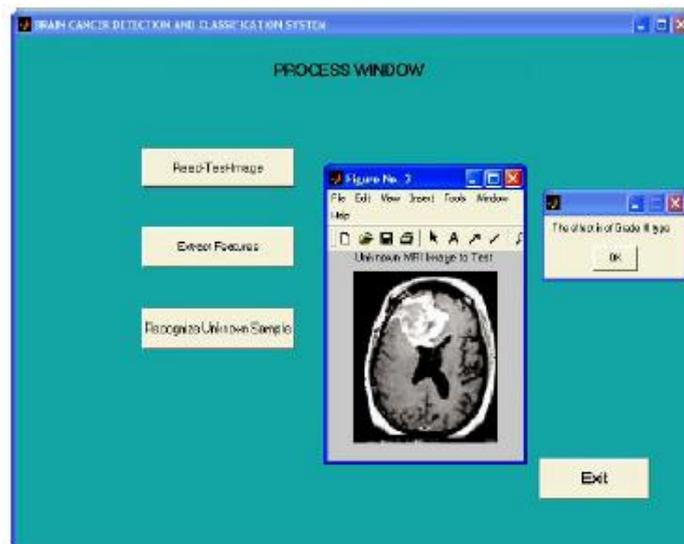


Figure 3. Classification result

The findings mentioned above demonstrate that the device performs effectively in brain cancer diagnosis and classification. Tests of Undisclosed brain cancer Diagnosis Undisclosed photographs of cancer specialist from TMH were seen and debated. The findings of the examinations conform to the view of the doctors and are accompanied by a cancer examination. The devices currently accessible can only identify tumor position and size but have little awareness of the tumor type. A collection of suspicious tissues has now been collected and checked after other types of cancer (biopsies) have been identified. In order to assess the extent of normalcy and illness, pathologists see the abnormal tissues, usually through bright field microscopes.

This cycle requires time and is tiring. Diagnostic errors may contribute to the induced fatigue produced by this method. The device defined in this project automated classification

and description of pathological tissues. By classified the unknown picture as suitable astrocytoma type of cancer, the developed and deployed device offers accurate identification and real-time monitoring, hence no pathological tests are needed.

## 5 Conclusion:

Using the Artificial Neural Network to apply the brain cancer diagnosis and classification system. The framework for the diagnosis and recognition of tumours has been developed focused on image processing methods, artificial neural network and interactive user interface. The conceptually clear classification approach uses the Neuro Fuzzy principle to identify and recognize cancer in the brain. In the preparation of the artificial neural network, Texture properties are used.

In various ways, co-occurrence matrices are calculated and Gray Level Co-occurrence Matrix characteristics (GLCM) are extracted from matrices. In brain images obtained under different clinical circumstances and technological requirements, the latter technique accurately classifies the tube forms, with elevated variations that are specifically defined as abnormalities in the region of brain disease. Images from MRI samples taken from the Tata Memorial Hospital Department of Radiology are collected in this report. The detailed diagnosis and classification of cancer type Astrocytoma is given in this framework.

And with the above explanations Photos was the machine checked. The program may be configured for certain cancer forms and very little modifications. By including certain forms of photos (e.g. Cat, MRS, CTS), the device variety may be further increased. Many patient details are required to increase the quality of the program. It is important. Additionally, physiological and developmental data as well as structural features of the brain should be applied to the framework

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