Received Date: 03/06/2020 Acceptance Date: 20/06/2020 Publication Date: 30/06/2020

GUI Based Multiclass Brain Tumor Classification

[1]Anchal Sharma, [2]Mr. Mukesh Kumar Saini, [3]Mr. Ghanshyam Singh
[1]M.tech Scholar, [2]Asstt. Professor, [3]Phd. Scholar
Department of Electronics & Communication Engineering,
Sobhasaria Group of Institutions, Sikar, India
E-Mail- [1]aanchalsharma1310@gmail.com, [2] mks.sikar@gmail.com, [3]gsingh.phd2016.etc@nitrr.ac.in

Abstract: Computer-aided design (CAD) applications have become very essential for clinical diagnosis of brain tumor. The systems increase the accuracy of the diagnosis and reduce the time required. Here a CAD system for the automatic detection and classification of brain tumor by images of brain magnetic resonance images (MRIs) is discussed in this paper. Mainly, dataset constituting of 11 Benign, 25 Gliomas, 30 Meningioma and 15 Metastases, are taken from 512 MR brain tumor slices marked by the radiologists using CBAC out of which 81 patients images from each category were taken into account which is available dataset from the website radiopedia.org. Proposed method follows three methods namely image enhancement followed by segmentation technique. These segmented images are then used for feature extraction. 84 relevant features were extracted from the segmented images were various machine learning algorithm were applied to get a feature matrices for further tumor detection and tumor classification. Quality evaluation of the proposed CAD has obtained positive results with an overall efficiency of 98% whereas F- score of 98.70 % and Precision of 98.80 % overall are obtained using ANN.

1. INTRODUCTION:

In the past few decades brain tumor has been one of the most deadly diseases. The National Brain Tumor Foundation (NBTF) has confirmed a rise in the number of people dying from brain tumors [1, 2]. Brain tumor is any mass arising from an irregular and uncontrolled development in the brain cells. The level of danger depends on a variety of factors such as the type of tumor, location, size and developmental condition [3]. Tumors in the brain may be either cancerous (malignant) or non- (benign). Benign brain tumors are low-, non- brain tumors that develop gradually, push away normal tissue but do not penetrate the normal tissue surrounding it. These are monoculture, delineated, excellently-defined and are categorized as non-metastatic tumors since no supplementary tumors are developed. However malignant brain tumors are cancerous brain tumors that develop quickly and penetrate the natural tissue surrounding them. These appear heterogeneous, not well defined, develop in a disorganized fashion, and are known as metastatic tumors because they promote development in distant organs with related tumors. Of the most lethal illnesses can be counted malignant brain tumors (or) cancerous brain tumors. Brain tumors can be categorized into the following categories according to the World Health Organization [4]:

Grade I: Pilocytic or benign, sluggish growth, with precise borders.
Grade II: Astrocytoma, sluggish growth, hardly ever spreads with a well defined border.
Grade III: Anaplastic Astrocytoma, rapid growth.
Grade IV: Glioblastoma Multiforme, malignant most invasive, spreads to close tissues and augments quickly.

While MRI appears to be effective in providing details on the location and size of tumors, it cannot identify types of tumors, thus the implementation of invasive techniques such as biopsy and spinal tap procedures, which are costly and time consuming methods [5]. Biopsy procedure is done where the surgeon makes a small incision in the scalp and cuts a small opening, called a burr opening, into the skull and puts a needle into the burr hole and takes a tissue sample from the brain tumor to test for cancer cells or the spinal tap approach where the doctor will take a sample of cerebrospinal fluid to search for cancer cells. This intrusive technique-related weakness involves the creation of new techniques of examination that seek to enhance the diagnostic capabilities of MR images. When classifying brain tumors, characteristics help to distinguish the tumors based on their particular pattern of severity or texture. The diverse structures on brain MR images of numerous tumors have helped to extract valuable traits features. Brain tumors are distinguished by radiologists on the basis of material homogeneity or heterogeneity or on the basis of iso-, hypo-, or hyper-intense parameters for differentiating between tumors. Such visually extractable features include instructions for choosing the most acceptable descriptors for mathematical features to build a CAD to differentiate between brain tumors. The objective of this study is to investigate the use of pattern classification methods for distinguishing different types of brain tumors, such as primary gliomas [6] from metastases, and also for grading of gliomas [7]. As suggested by Devasena and Hemalatha [8] a hybrid abnormality detection algorithm (HADA) based CAD method for the identification of odd sections in magnetic resonance imaging. The CAD method is composed of noise removal, smoothing, abstraction of features, elimination of features and grouping. Patil and Udupi designed an effective CAD for brain tumor identification [9]. They used reprocessing and square segmentation a part marking for image segmentation; extraction of features was achieved using texture features utilizing a co-occurrence gray level matrix (GLCM) [10]. Ultimately a probabilistic neural network (PNN) approach was used to identify the brain tumor that was found. Computer- diagnostic (CAD) programs suggested by Dandıl et al. [11] for classifying brain tumors between benign and malignant by utilizing Spatial-Fuzzy C-Means (FCM) method segmentation brain tumor. SVM was used to classify between benign and malign with a classification accuracy of 91.49%. In comparison, the literature includes many approaches for the diagnosis and segmentation of brain tumors [12-15]. This research introduces the conceptual architecture and technological application of a two-stage CAD hybrid framework for the identification and classification of brain tumors. The CAD system's goal is to identify and distinguish tumors into benign (Noncancerous) and malignant (Cancerous). In addition to a deep tumor division into benign and malignant from the MRIs, this research leads to the construction of a multi stage CAD method for tumor detection into four categories namely Benign, Gliomas, Meningioma and Metastases. The content of this research paper is structured as follows. The conceptual architecture and the CAD design processes are illustrated in the Section II. Implementation and performance assessment of the CAD program is reported in Section III. Next section IV is devoted to addressing the results and the discussion of the study. Finally, Section V points forth observations and conclusion.

2. CAD DESIGN

In this analysis, the nature of the proposed method provides the MRIs with correct identification and classification of brain tumor. Figure 1 depicts the conceptual device structure diagram.

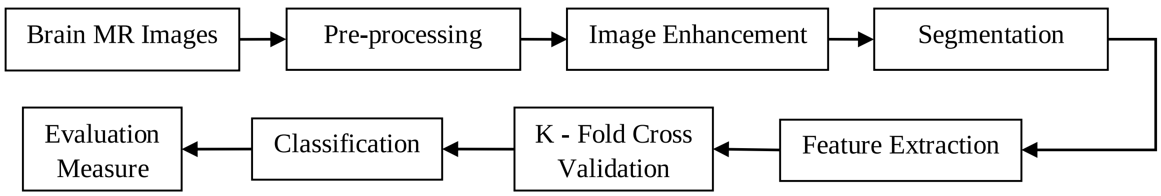


Figure 1: Overall Structure of the system

First phase has pre-processing and enhancement [16]. Followed by segmentation, abstraction of the feature, collection of features, classification, and analysis of results are compared and analyzed. Techniques of preprocessing and enhancement are being used to boost identification of abnormal regions within MRI. The technique of enhancement consists of three processing steps: first, the image is obtained from the MRI. Second, elimination of film artifacts on the MRI image such as labels and markings and eventually removal of the high frequency components. Segmentation explains the isolation of subject region from MRI image history.

2.1. Preprocessing

The gray scale image is handled in image processing utilizing various methods such as filtering, thresholding and contrast enhancing. Contrast renders the image as of which white objects are separated from dark objects by the gray and red artifacts. Therefore the identification of tumors in the MRI image becomes convenient by adjusting the brightness of the image. Thresholding segregates objects, holds those of interest to us and eliminates that are not. Another usage of thresholding is that it transforms the image from a grayscale image to a binary image (pixel values of 0 or l), with pixel values varying from 0 to 255. The control vision assistant window shows a description of the activity thresholds using the latest set of parameters. The pixels displayed in red have strengths which fall within the threshold range. Then the value of 1 is set through operator thresholds where the pixels exposed in gray exhibit values beyond the threshold value. The operator thresholds set their values to 0 [17]. In addition, filters can smooth, sharpen, transform and eliminate noise from an image so that we can obtain the details required to sharpen edges, count the edges of any particle holes and contrast the components with the foreground. The initial step in our research technique is the preprocessing of brain MR image. Preprocessing involves scanning of images and masking of the skulls for auxiliary processing. Our motto following preprocessing is to enhance the image eminence so that the tumor can be spotted with greater certainty and ease. The preprocessing steps involve conversion of gray scale followed by applying various filters like median filter of 3 x 3 masks in order to eliminate noise. This image thus achieved is then passing through a high pass filter mask [18] for the detection of edges. To obtain the enhanced image, the resulting image will be obtained by inserting edge seen in the original image and the obtained image. However, median filtering can only adjust the strength of the corrupted pixels on the damaged image to retain local image information. The CALHE technique is used for the purpose of image enhancement in our work.

2.2. Segmentation

Image segmentation is critical because large numbers of images are produced during the scan, and clinical experts are unlikely to manually separate these images in a reasonable amount of time. Segmentation of the image refers to segregation of the given image into many non-overlapping regions. Segmentation describes the image into pixel sets which are more important and easier to analyze. It is applied to locate the boundaries or objects in an image roughly, and the resulting segments collectively cover the entire image [19]. The segmentation algorithms operate on one of the two basic image intensity characteristics; similitude and discontinuity [20]. Segmentation has an important part to play in clinical diagnosis and can be useful in pre- planning and computer- surgery. Furthermore, various segmentation techniques are available that can be used widely, such as threshold-based segmentation, histogram-based methods, region-based methods (regional growth, splitting and merging methods), edge-based methods, and clustering methods. Clustering methods are the most effective processing technique for the medical images. Cluster analysis for other methods can be set as a pre- step, namely classifiers that would then run on selected clusters. We have also used K-mean clustering segmentation techniques in our method for tumor diagnosis and the measurement of tumor region in MRI images. A cluster is a group of objects identical to each other and different to the objects that belong to other clusters. It coincides with verdict order in an untagged dataset. The method of grouping objects into groups whose members are in by some means identical can be a vague concept of clustering. The algorithm of K-Means clustering is used for grouping objects into k number of classes based on attributes / features, k being a positive integer. The assemblage (clustering) is achieved by reducing the distance between the Euclidean data and the corresponding centroid clusters. K-Means clustering thus has the purpose of clustering the results. Commonly used methods of initialization are Random Partition [21]. The Forgy [22] scheme arbitrarily selects k definitions from the dataset and makes use of them for primary means. Moreover, random partition scheme initially applies each observation dynamically to a cluster and after that continues to the revise step, thus calculating the initial mean of being the cluster's centroid of randomly allocated points. His strategy intends to disperse the initial means as random partition places them all close to the data set core. As mentioned by Hamerly [23] usually the random partition approach is preferred for algorithms such as Fuzzy k-means and K-harmonic.

2.3. Feature Extraction

In this section of feature extraction a set of 84 relevant intensity and texture features are extracted from the SROIs. These features are: Histogram based features, gray level co-occurrence matrix (GLCM) [24], run length grey length matrix (RLGLM), Law's texture energy measure and Laplacian of Gaussian (LoG). Summarization of various intensity and texture features in mentioned in table 1 shown below.

Table 1: Summary of intensity and texture features

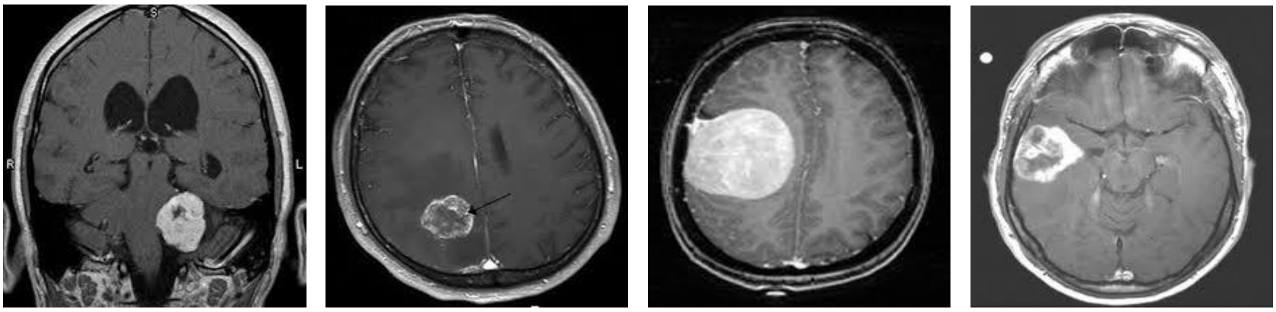
Feature category	**Features**	**Number of features**
Histogram Based Features	Five statistical parameters for histogram based features namely: (1) mean (2) variance (3) Skewness, (4) Kurtosis, (5) Energy	5 + 5 = 10
GLCM	At 0°, 45°, 90°, and 135° five statistical parameters of GLCM features are calculated namely: (1) mean (2) RMS (3) Smoothness (4) Skewness (5) Standard Deviation (6) variance (7) Kurtosis, (8) IDM	8 x 4 = 32
RLGLM	Total 7 features are considered namely at 0°, 45°, 90°, and 135° (1) SRE (2) LRE (3) GLN (4) RP (5) RLN (6) LGRE (7) HGRE	7 x 4 = 28
Laws Texture Energy	Five statistical parameters for the Laws Texture Energy namely: (1) mean (2) Standard Deviation (3) Entropy (4) RMS (5) variance	5 + 5 = 10
Log Edge Detection	The following four LoG filter performance parameters in the SROI region are retrieved at σ = 0.25, 0.50, 1, and 2 (1) mean intensity, (2) standard deviation, (3) Skewness (4) Kurtosis	4 x 4 = 4
Total number of features: 10 + 32 + 28 + 10 + 16 = 84		

2.4. Training Dataset and Classification

The data set used for the testing and information on the implementation of the program are given in the following subsections. Experiments were performed to evaluate different commonly used enhancement techniques for different type of diseased brain MRI images by the comparison we can find the best suited method for enhancement of Brain MRI image.

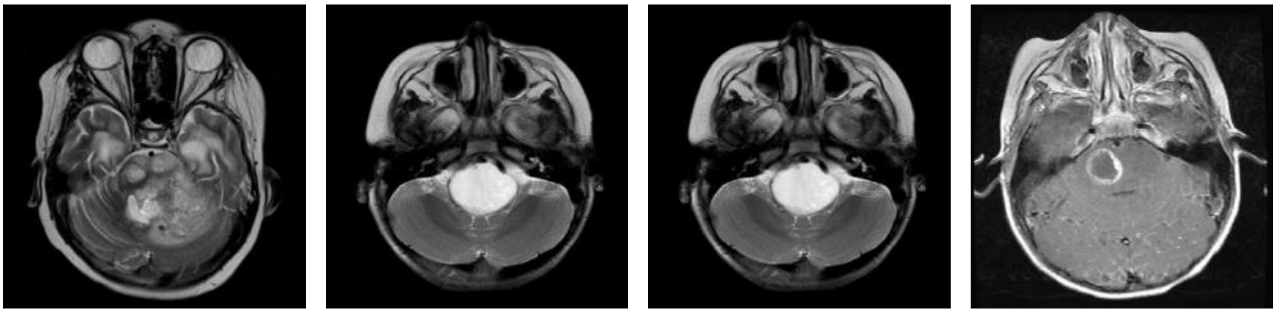
3. DATASET

In the current research, 81 patients dataset composing of 11 Benign, 25 Gliomas, 30 Meningioma and 15 Metastases, are taken from 512 MR brain tumor slices marked by the radiologists using CBAC out of which four images from each category is shown in the fig. 2 to fig. 5 respectively. These images are collected online available dataset from the website radiopedia.org.



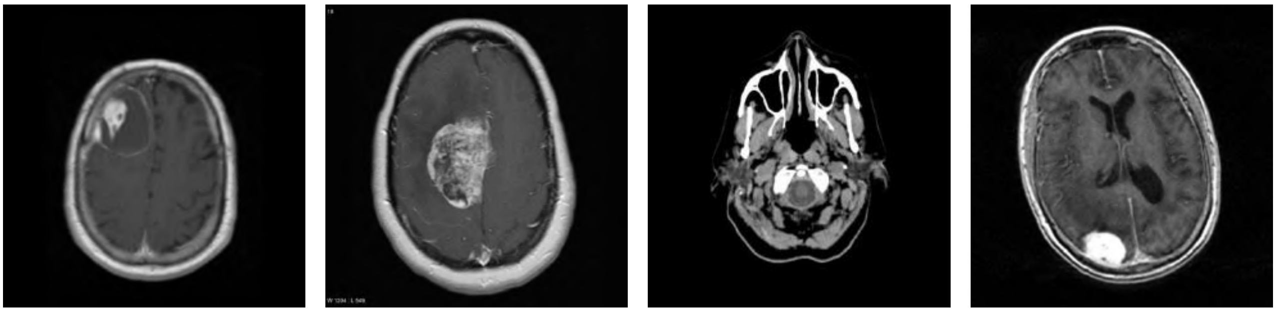
(a) (b) (c) (d)

Figure 2: (a), (b), (c) & (d) are different types of Benign Brain MRI images



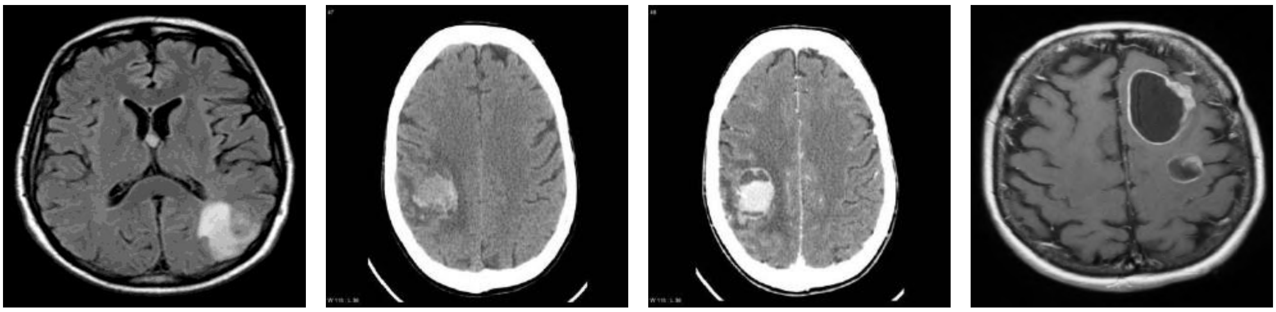
(a) (b) (c) (d)

Figure 3: (a), (b), (c) & (d) are different types of Gliomas Brain MRI images



(a) (b) (c) (d)

Figure 4: (a), (b), (c) & (d) are different types of Meningioma Brain MRI images



(a) (b) (c) (d)

Figure 4: (a), (b), (c) & (d) are different types of Metastases Brain MRI images

4. SOFTWARE IMPLEMENTATION:

These proposed methods are implemented in MATLAB 9.0 and are tested on various brain tumor MR images of size 400×400. The experiments were performed on PC having Intel™ i3 Processor 3.0 GHz processor with 4 GB RAM. The algorithm takes 3 min for training the samples. The most important stage of the proposed CAD program is training and classification. Multilayer perceptron (MLP) [25] is used for the training and classification of input functions. In MLP multilayer perceptron are layered feed forward networks. These networks are mostly used for classification of an image into different classes. Multilayer perceptron [26] are useful in number of applications, where statistical classification is required. Artificial neural networks are characterized by their architecture, activation function and learn paradigm. Multilayer Perceptron (MLP) is one of the mostly used ANNs and about 80 % of ANNs researches focused on [27]. It consists of a series of fully interconnected layers of nodes where there are only connections between adjacent layers. General structure is showed in figure 6. If there is several inputs [28] such as x_1, x_2, x_3….., x_n then these inputs will represent the first layer in the design of the MLP NN, the other layer which will be serve as a hidden layer is the weights (also called synapses) that corresponds to each input w_1, w_2, w_3….., w_n. In addition there is a bias parameter which refers to w_0 and can be interpreted as synapse that is associated with artificial input

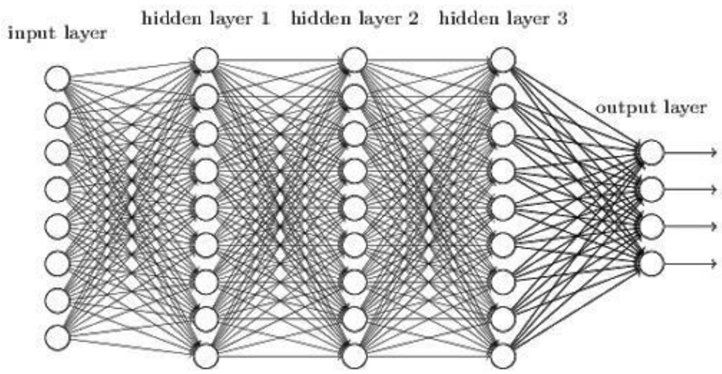


Figure 6: Multilayer perceptron neural network with three hidden layer.

that is x_0 = -1. The output neuron y will be the sum of the products of the input vector x_1, x_2, x_3….., x_n by the vector w_1, w_2, w_3….., w_n, that is:

$$\underline{x} \cdot \underline{w} = \sum_{i=0}^{n} x_i\, w_i \tag{1}$$

The output neuron can then be calculated by the means of activation function as equation (2) below

$$y = f_{net}(\underline{x} \cdot \underline{y}) \tag{2}$$

where a hyperbolic tangent function is usually adopted defined for a generic value a; however it is common to use other activation function in certain situations as shown in equation (3) below

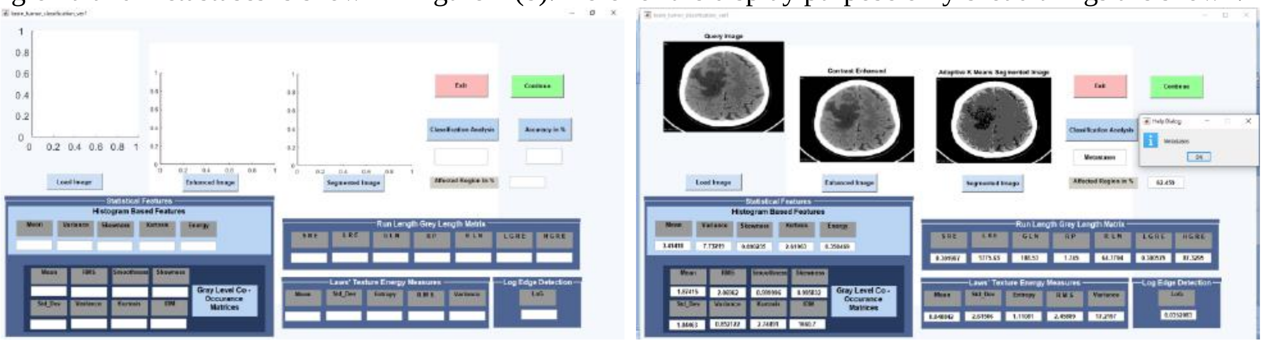
$$f(a) = \frac{1- e^{-a}}{1 + e^{+a}} \tag{3}$$

One can easily realize that the architect of the multilayer perceptron involves: - Input layer - Hidden layer (s) - Output layer. Multi layer perceptron supervised learning algorithm is used in the artificial neural network to address regression problems [29, 30]. As mentioned by Sachdev [31], the sum of Eigen vectors retained for better classification shall be 49. For weight estimation (training phase), momentum weight and bias-based learning, gradient descent back propagation with momentum algorithm is being utilized. The network proposed in the CAD system is using momentum constant of 0.2 and the learning rate of 0.3. During network preparation, tenfold cross-validation is used to prevent overtraining and boost the network's generalization capability. Hit and trial approach was used to determine the topology of the network. It is observed that a fair trade-off between precision and speed is accomplished by the use of 44, 5, and 20 neurons respectively in the first, second, and third hidden layers.

5. PERFORMANCE AND EVALUATION:

5.1. GUI Interface Description:

A multifunctional graphical user interface (GUI) CAD prototype for the detection, segmentation and classification of brain tumors has been developed. The CAD system is designed to access MRIs in various formats commonly available in image formats. It shows the overall view of the interface in figure 7 (a). The interface offers as many five buttons namely; first button is for loading MRI image is in the GUI which selects the target MRI image. Second button for enhancing the image using CLHAE followed by third button used for segmentation of the test image being enhanced in the second button pressing using k- mean clustering technique. Once the CAD system finds the features of the image, many features appears in the GUI (for the display purpose only we have restricted the front to the type of features we have calculated though in the back end features are calculated according to the table 1 above. One button is dedicated for applying the classification on the feature obtained after segmentation followed by classification accuracy. The GUI system with all its features and parameters is being utilized to classify tumors into benign, gliomas, meningioma and metastases is shown in figure 7 (b). Here for the display purpose only broad things are shown.



(a) Overall view of GUI (b) Tumor Classification

Figure 7: Proposed system GUI for brain tumor classification

5.2. Testing Environment:

Evaluation of the proposed CAD system is done using a graphical user interface (GUI) where the performance is calculated in terms of various parameters including [32]; Sensitivity, which reflects the proportion of actual positives found correctly; Specificity, that shows the fraction of the negatives found correctly; and lastly Accuracy, which is the fraction of actual positive as well as true negative. These parameters are explained the following equations (4), (5) and (6) correspondingly.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Negative} + \text{True Positive} + \text{False Negative} + \text{False Positive}} \text{ X } 100 \qquad (4)$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \qquad (5)$$

$$\text{F} - \text{Score} = \frac{2 \text{ x Precision x Recall}}{\text{Positive Real Cases} + \text{Real Negative Cases}} \qquad (6)$$

There is a total of 81 MRIs in the non-standard assessment database, which has been divided into separate sets as per the experiment performed below. There are four sets of experiments carried out to assess ANN's efficiency and robustness.

Experiment 1: The classifier based on ANN is implemented using the databases with all the extracted features, without a balancing technique.

Experiment 2: Using the databases with the most relevant features, the classifier based on ANN was applied, by applying remove duplicate filters.

Experiment 3: In the third experiment, Resample with replacement of data has been used. In with replacement selection, images from the same subject patient will not appear in testing.

Experiment 4: For the fourth experiment the system is evaluated on a dataset that is fully unseen by the system to eliminate bias.

6. RESULTS & DISCUSSION

Accuracy analysis of the proposed CAD system accomplish 98.77 % as highest for the experiment 1 and least in the experiment 4 which is but obvious as it is for untrained data. Hence it can be also being concluded that to increase the accuracy for the system more number of training is required. Performance of the proposed system is shown in the table 2.

Table 2: Performance Parameter of Classification Results

	Accuracy	Sensitivity	F - Score
Experiment 1	98.77	98.80	98.70
Experiment 2	98.18	98.20	98.20
Experiment 3	96.29	96.30	96.10
Experiment 4	77.77	77.80	76.40

Table 3: Confusion Matrix of the Classification Results

	Benign	Gliomas	Meningioma	Metastases
Experiment 1	10	0	0	1
	0	25	0	0
	0	0	30	0
	0	0	0	15
Experiment 2	10	0	1	0
	0	18	0	0
	0	0	15	0
	0	0	0	11
Experiment 3	8	0	3	0
	0	29	0	0
	0	0	25	0
	0	0	0	16
Experiment 4	4	4	1	2
	1	18	5	1
	0	1	28	1
	0	1	1	13

This paper develops a CAD system which includes the segmentation, extraction of features and multiclass classification of four brain tumor groups into benign, gliomas, meningioma and metastases and the confusion matrix of the same is shown in the table 3. However, such tumors might have comparable characteristics in their pattern of intensity and texture; but they may differ in location, scale, and form. The system performance is assessed on a dataset of 81 MR images using ANN method with different setting. The labelled segmented images extract 84 texture and intensity features. Various experimental combinations are conducted to obtain the feature structure trial output as well as multi-class brain tumor classification using multilayer perceptron. Nevertheless, the incorporation of additional patients per tumor class and the introduction of astrocytome subclasses—low-grade astrocytomas and high-grade astrocytomas as well as the generalization efficiency of the proposed approach will increase.

7. CONCLUSION

The study conducted in this paper demonstrates an automated system that classifies brain tumor into four types which are benign, gliomas, meningioma and metastases based on an artificial neural network using back-propagation algorithm in MLP. The results were optimal based on accuracy, precision and F-score obtained are highly acceptable and thus the network was able to successfully classify the new MR images given as testing inputs. This system can be improved to detect and classify more than four types of brain tumor in future work, and for an even more optimal result, this software can be included in the MRI hardware to obtain an instantaneous output. Moreover, extensive preparation should be able to further enhance the efficiency of the proposed MLP approach. The methods developed to enhance, segment, feature extraction, and classification of brain tumors can be combined to create a CAD system. Radiologists will benefit from this system for accurate localisation, detection and analysis of brain tumors on MR images.

REFERENCES:

1. Logeswari, T., and M. Karnan. "An improved implementation of brain tumor detection using segmentation based on hierarchical self organizing map." *International Journal of Computer Theory and Engineering* 2.4 (2010): 591.
2. El-Dahshan, El-Sayed A., et al. "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm." *Expert systems with Applications* 41.11 (2014): 5526-5545.
3. Selvanayaki, K., and M. Karnan. "CAD system for automatic detection of brain tumor through magnetic resonance image-a review." *International Journal of Engineering Science and Technology* 2.10 (2010): 5890-5901.
4. John, Pauline. "Brain tumor classification using wavelet and texture based neural network." *International Journal of Scientific & Engineering Research* 3.10 (2012): 1-7.
5. Bandyopadhyay, Samir Kumar. "Detection of brain tumor-a proposed method." *Journal of Global Research in Computer Science* 2.1 (2011): 55-63.
6. Dogra, J., S. Jain, and M. Sood. "Glioma classification of MR brain tumor employing machine learning." *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* 8.8 (2019): 2676-2682.
7. Zacharaki, Evangelia I., et al. "Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme." *Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine* 62.6 (2009): 1609-1618.

8. C. Lakshmi Devasena and M. Hemalatha, "Efficient computer aided diagnosis of abnormal parts detection in magnetic resonance images using hybrid abnormality detection algorithm," *Central European Journal of Computer Science*, vol. 3, no. 3, pp. 117–128, 2013.
9. Abd-Ellah, Mahmoud Khaled, et al. "Design and implementation of a computer-aided diagnosis system for brain tumor classification." *2016 28th International Conference on Microelectronics (ICM)*. IEEE, 2016.
10. Latif-Amet, A., Aysin Ertüzün, and Aytül Erçil. "An efficient method for texture defect detection: sub-band domain co-occurrence matrices." *Image and Vision computing* 18.6-7 (2000): 543-553.
11. Dandıl, Emre, Murat Çakıroğlu, and Ziya Ekşi. "Computer-aided diagnosis of malign and benign brain tumors on MR images." *International Conference on ICT Innovations*. Springer, Cham, 2014.
12. Ulku, Eyup Emre, and Ali Yilmaz Camurcu. "Computer aided brain tumor detection with histogram equalization and morphological image processing techniques." *2013 International Conference on Electronics, Computer and Computation (ICECCO)*. IEEE, 2013.
13. Gordillo, Nelly, Eduard Montseny, and Pilar Sobrevilla. "State of the art survey on MRI brain tumor segmentation." *Magnetic resonance imaging* 31.8 (2013): 1426-1438.
14. Abdel-Maksoud, Eman, Mohammed Elmogy, and Rashid Al-Awadi. "Brain tumor segmentation based on a hybrid clustering technique." *Egyptian Informatics Journal* 16.1 (2015): 71-81.
15. Amien, Magdi BM, Ahmed Abd-elrehman, and Walla Ibrahim. "An intelligent-model for automatic brain-tumor diagnosis based-on MRI images." *International Journal of Computer Applications* 72.23 (2013).
16. Dimililer, Kamil, and Ahmet İlhan. "Effect of image enhancement on MRI brain images with neural networks." *Procedia Computer Science* 102 (2016): 39-44.
17. Lakshmi, A. Pavani, and P. Samata. "Optimization of visual presentation of MRI image for accurate detection of tumor in human brain using virtual instrument." *The 5th 2012 Biomedical Engineering International Conference*. IEEE, 2012.
18. Telrandhe, Swapnil R., Amit Pimpalkar, and Ankita Kendhe. "Brain Tumor Detection using Object Labeling Algorithm & SVM." *International Engineering Journal For Research & Development* 2 (2015): 2-8.
19. Janani, V., and P. Meena. "Image segmentation for tumor detection using fuzzy inference system." *Int J Comput Sci Mobile Comput (IJCSMC)* 2.5 (2013): 244-8.
20. Qurat-Ul-Ain, Ghazanfar Latif, et al. "Classification and segmentation of brain tumor using texture analysis." *Recent advances in artificial intelligence, knowledge engineering and data bases* (2010): 147-155.
21. Vijay, J., and J. Subhashini. "An efficient brain tumor detection methodology using K-means clustering algoriftnn." *2013 International Conference on Communication and Signal Processing*. IEEE, 2013.
22. Hamerly, Greg, and Charles Elkan. "Learning the k in k-means." *Advances in neural information processing systems*. 2004.
23. Schmidt, Mark, et al. "Segmenting brain tumors using alignment-based features." *Fourth International Conference on Machine Learning and Applications (ICMLA'05)*. IEEE, 2005.
24. Shree, N. Varuna, and T. N. R. Kumar. "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network." *Brain informatics* 5.1 (2018): 23-30.
25. Veer, Shubhangi S., and Pradeep M. Patil. "Brain Tumor Classification Using Artificial Neural Network on MRI Images." International Journal of Research in Engineering and Technology 4.12 (2015): 218-226.
26. Achkar, Roger, et al. "Brain Tumor Classification Using Back Propagation Algorithm in MLP." 2019 Fourth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA). IEEE, 2019.
27. Ncibi, Kais, et al. "A multilayer perceptron artificial neural networks based a preprocessing and hybrid optimization task for data mining and classification." Int. J. Econom. Financ. Manag. Int. J. Econom. Financ. Manag 5.1 (2017): 12-21.
28. Omar, Raid Adnan, Jassim Mohammed Najim, and Imad H. Abood. "Classification of brain tumors using the multilayer perceptron artificial neural network." Iraqi Journal of Physics 16.36 (2018): 190-198.
29. Jain, Anil K., Robert P. W. Duin, and Jianchang Mao. "Statistical pattern recognition: A review." IEEE Transactions on pattern analysis and machine intelligence 22.1 (2000): 4-37.
30. Duda, Richard O., Peter E. Hart, and David G. Stork. Pattern classification. John Wiley & Sons, 2012.
31. Sachdeva, Jainy, et al. "Segmentation, feature extraction, and multiclass brain tumor classification." Journal of digital imaging 26.6 (2013): 1141-1150.
32. Zacharaki, Evangelia I., et al. "MRI-based classification of brain tumor type and grade using SVM-RFE." 2009 IEEE International Symposium on Biomedical Imaging: From Nano to Macro. IEEE, 2009.