AUTOMATIC BRAIN TUMOR IDENTIFICATION USING NOVEL SELF ORGANIZING MAPS

[1]P. Mohan, [2]Dr. Vishal Bhatnagar
[1]Research scholar, Dept of C.S.E, Shri Venkateshwara University, Gajraula, Uttar Pradesh, India.
[2]Research Guide, Dept of C.S.E, Shri Venkateshwara University, Gajraula, Uttar Pradesh, India.

ABSTRACT:
The human brain is a remarkable part of the human nervous system, which regulates all bodily functions. Brain tumors develop from an abnormal mass of cells within the brain, and timely detection of these tumors often provides a wider range of treatment options. Identifying the infected area in brain tumor, MRI images is a crucial task since brain tumors are several illnesses resulting from an irregular cell growth in the brain. Early detection of tumors enhances patients' chances of recovery. The significance of precise brain tumor detection in brain MR (Magnetic Resonance) images cannot be overstated when medical image analysis and interpretation. Numerous techniques have been discussed in the past, but there remains a necessity to enhance the precision of the outcomes. Hence, an individual's chances of survival are significantly enhanced by early diagnosis and prompt treatment of brain tumors. Thus, this paper introduces automatic brain tumor identification using novel self organizing maps. In the context of medical image segmentation, a method employing the Self-Organizing Map (SOM) algorithm is presented. The SOM algorithm is instrumental in clustering, and the segmentation procedure plays a partitioning the preprocessed input image to extract characteristics like texture, color, shape, and intensity features. The application of the watershed algorithm in segmentation provides precise outline locations. For classification, an unsupervised neural network, called self-organizing maps, is utilized. The evaluation of this technique is based on metrics such as Accuracy, Sensitivity, and Precision. Implementing this approach is expected to yield improved outcomes for brain tumor identification.

KEYWORDS: Brain, Tumor, MRI (Magnetic Resonance Imaging), Self Organizing Map, Segmentation.
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I. INTRODUCTION

The human brain, an incredible component of the human nervous system, controls all bodily functions. In the human body, the brain is considered the most exceptional and dangerous organ. A mass of these abnormal cells develops into an uncontrolled growth of abnormal brain cells known as a tumor [1]. Detecting tumors early allows for a range of treatment options. Brain tumors can lead to brain cancer. Tumors are seriously endangering people's lives and according to the World Health Organization (WHO), more than 25% of cancer-related deaths occur in different countries. Proper treatment is often required for the early identification of brain tumors. These tumors can be categorized as either primary or secondary. Within the brain or its associated membranes, nerves, or glands, primary tumors can develop, and they are further classified as either Benign (non-cancerous) or Malignant (cancer-prone). Malignant brain tumors are particularly dangerous as they invade rapidly, causing swelling and destroying brain cells [2].

Brain tumors exhibit various speeds within the brain, depending on their location. The position of the tumor is also significant as it can impact the human nervous system. Treatment approaches for the tumor are determined by factors such as its size, location, and type [3]. Although the exact cause of brain tumors remains unclear, early screening of these conditions is essential to facilitate timely and effective therapy, which is supported by modern clinical imaging techniques. Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT) are the techniques which are more frequently used to examine brain tumors [4].

Image segmentation plays a significant role in both computer vision and the examination of medical pictures. It involves dividing an image into separate parts using homogeneity criteria. The visualization of their characteristics makes the segmentation of brain tumors very challenging [8]. Segmentation can depend on various features, such as grey scale, color, texture, depth, and motion, especially when dealing with brain tumors.

In MRI scans and other scans, brain tumors are recognized as abnormal blobs within the brain. These areas display distinct illumination from the surrounding brain tissue, usually brighter than the background. However, segmenting these tumors in MRI images is a highly complex task due to variations in size, texture, and location [5].

To improve treatment effectiveness and accuracy in the context of medical imaging, brain tumor identification and classification must be automated. Traditional methods of tumor detection often depend on subjective evaluations by doctors However, manual segmentation is time-consuming and subjected to inter- and intra-rater errors difficult to characterize. Thus, physicians usually use rough measures for evaluation. For these, accurate semiautomatic or automatic methods are required. However, it is a tough task, since the shape, structure, and location of these abnormalities are highly variable [10].

Tumor segmentation faces several challenges, including diverse appearances and inconsistent shapes. Manual segmentation performed by doctors can be a weary task, and variations arise when different doctors undertake the same segmentation task [6].

Radiotherapy planning and tumor diagnosis depend heavily on brain tumor segmentation. Since several tumor segmentations have been demonstrated and improving the segmentation approach is still difficult due to a different factors including significant tumor appearance variability and confusing borders.

Early detection of brain tumors can greatly enhance treatment options and higher survival rates. However, manually identifying tumors or lesions is time-consuming and difficult, especially in light of the enormous volume of MRI images generated during normal medical procedures. In medical image processing, the segmentation of brain tumors from MRI data is crucial and requires significant data. Since brain tumors include soft tissue properties and ill-defined boundaries and accurate segmentation of these reduces, which is a challenging task. To address this issue, the use of Self-Organizing Maps (SOMs) as a type of unsupervised learning neural network has shown significant results in recent times for image segmentation.

Therefore, this paper introduces the presentation of automatic brain tumor identification using innovative self-organizing maps. The approach is based on a clustering-based Self Organizing Map (SOM) algorithm. The remaining part of the paper is structured as follows: A review of the literature is provided in Section II, followed by a description of the automatic detection of brain tumors using novel self-organizing maps in Section III, an analysis of the results of the suggested approach in Section IV, and a conclusion in Section V.

II. LITERATURE SURVEY

Dr.M.Latha, Dr.M.Senthilmurugan, Preetika B, Dr.R.Chinnaiyan et. al., [7] describes MRI Image based Brain Tumour Segmentation by using Machine Learning Classifiers. To establish the image characteristics, picture features are recovered using GLCM (Gray-Level Co-Occurrence Matrix), and effective tumor region segmentation is accomplished with reduced computational time. This is achieved by training these features in a specific manner. Thus, in the proposed system, the use of a triple process involving K-means, KNN (K-Nearest Neighbour), and FCM (Fuzzy C-means Clustering) highlights the accuracy and efficiency of the obtained GLCM-based features. The accuracy and error rate for brain MRI images are calculated using the triple method i.e., FCM and KNN triple technique.

MD Abdullah Al Nasim, Faisal Muhammad Shah, Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf, et. al., [12] by using Convolutional Neural Network, they describes Brain Tumor Detection. A real-time dataset with various tumour sizes, locations, shapes, and image intensities was employed in an experimental investigation. In the traditional classifier part, we applied six traditional classifiers namely: Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes, and Random Forest. The authors then replaced the traditional classifiers with a Convolutional Neural Network (CNN) using Keras and Tensorflow because it yields to a better performance. The considerably higher accuracy achieved by the CNN analysis made it highly compelling. This study's major goal was to identify normal and abnormal pixels using statistical and texture-based criteria.

G.Hemanth, M.Janardhan, L.Sujihelen et. al., [13] describes Design And Implementing Brain Tumor Detection Using Machine Learning Approach. The article presents a technique for automatically segmenting images using Convolutional Neural Networks (CNN) with small 3 x 3 kernels. Segmentation and categorization are made possible by this particular approach. CNN, a Machine Learning (ML) approach based on Neural Networks (NN), uses layers to categorise outcomes. The method covers a number of steps, including data collection, pre-processing, average filtering, segmentation, feature extraction, CNN-based classification, and identification. The data can be determined using Data Mining (DM) techniques to uncover important linkages and patterns. For the detection and prevention of brain tumors in their early stages, both Machine Learning (ML) and data mining are effective methods.

Khizar Abbas, Prince Waqas Khan, Khan Talha Ahmed, Wang-Cheoul Song et. al., [16] using Machine Learning to describe the Automatic Brain Tumor Detection in Medical Imaging. The main idea is to take the segmentation challenge as a multiclass classification task. Brain MRI sequences exhibit common characteristics and are locality and sparsity. In the initial stages, noise removal and image quality improvements are used. The classification score is then increased by computing and reducing different textural elements using PCA (Principle Component Analysis). The MICCAI (Medical Image Computing and Computer Assisted Interventions) 2013 dataset, which includes actual patient data with High-grade tumor and Low-grade tumor was used. They achieved a better Dice Score of 0.95 for whole tumour segmentation, outperforming the existing methods in terms of both Dice Score and time complexity.

Dr Lingaraju G M, Himaja Byale and Shekar Sivasubramanian et. al., [17] describes Brain tumors are automatically segmented and classified using machine learning techniques. The main goal of the study is to create an automated system for identifying brain lumps (masses of tissue) as benign (clump thickness) or malignant (marginal adhesion) using a classification method. To enhance classification accuracy, the model utilizes machine learning algorithms. This pre-processing for noise removal using an adaptive median filter, the system goes through four phases. The region of interest is then determined by segmenting data using the Gaussian Mixture Model (GMM). Several tumors are extracted utilising the Grey Level Co-occurrence Matrix (GLCM) feature extraction method. In the end, Neural Networks (NN) are employed for classification

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in order to identify and classify the tumor as benign or malignant.

Krishnappa H.K, Dheeraj, Digvijay Reddy, Kiran and Bhavana.V et. al., [18] describes this paper, this focuses on using image segmentation techniques to detect brain tumors. From the supplied dicom Magnetic Resonance Image (MRI), it seeks to isolate tumor cells. To do this, the image's noise is removed using a pre-processing procedure. The image is then subjected to k-means clustering, and the skull is removed using morphological techniques to make it possible to identify tumor cells. To successfully extract tumor cells, picture thresholding is then used and followed by level-set segmentation. The accuracy of the results is evaluated using performance metrics such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), precision, and recall.

III. AUTOMATIC BRAIN TUMOR IDENTIFICATION

This section presents the automatic brain tumor identification using innovative self-organizing maps. Figure 1 displays the block diagram representing the presented approach. The MRIs utilized in this analysis are obtained from open-source databases and websites. Different types of tumors are present in the MR images on which the algorithm is tested. Skull stripping is a critical process in the analysis of brain image.

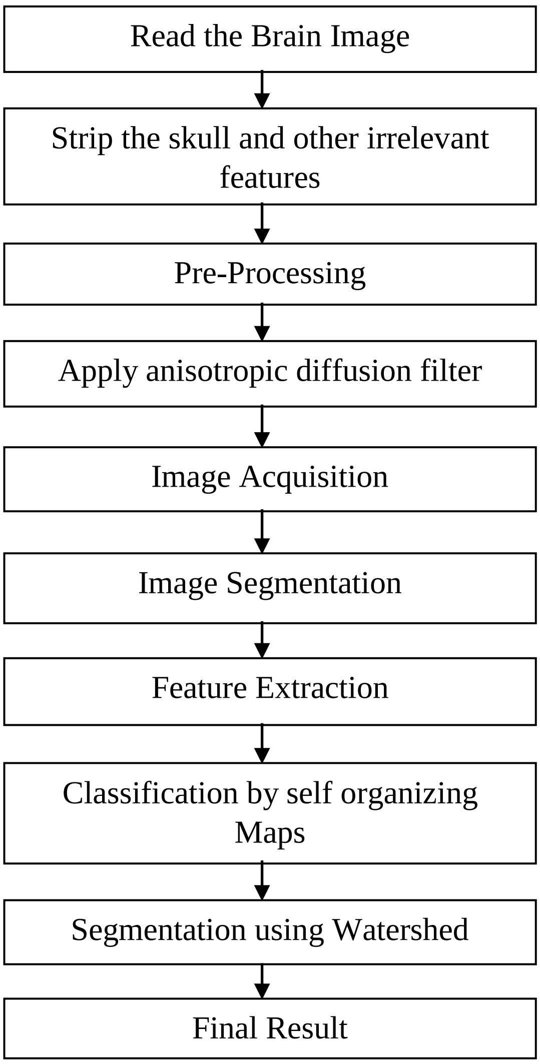

Fig. 1: Block Diagram of Automatic Brain Tumor Identification

Accurate separation of the brain area from non-brain tissues like skin, the skull, and the eyes is crucial for a number of applications, including cortical surface reconstruction, pre-surgical planning, and brain morphometry. This segmentation is based on both picture intensity and brain anatomy. To get better results, the method combines morphological procedures with adaptive threshold estimation. The image histogram can be used to calculate the threshold value. This process is automatic and requires no user input to choose the settings for brain matter extraction.

Pre-Processing: Data reduction is applied to optimize different parameters. To remove unwanted noise and background from the MRI picture, preprocessing is done in the early stage. Various techniques like edge detection and the canny edge detector are employed for noise removal. This step is essential to reduce memory consumption for each image. In the preprocessing stage, a Gabor filter is utilized, which is effective for edge detection and is similar to the human visual system.

Anisotropic Diffusion Filter (ADF): The noise in brain MRIs is diminished using Anisotropic Diffusion Filtering (ADF). It is articulated as piecewise constant smoothing of the given image, ADF is described. It is simpler to understand MRI data successfully when piecewise constant or progressive intensity changes are taken into consideration because MRI data contains smooth zones separated by discontinuities which represent the different tissue classes. ADF successfully represent different image textures by applying the rule of diffusion to pixel intensities. The use of a suitable threshold function will restrict smoothing over edges.

Image Acquisition: The dataset contains medical images obtained from a public health library, with image dimensions of 460x307 bitmap images. Each image is represented by pixels and used for subsequent processing.

Image Segmentation: Every digital image undergoes segmentation into multiple segments. Segmentation is mostly used to change the visual representation into a more useful and understandable form. It is primarily utilized for object localization and boundary detection. A collection of segments from image segmentation together cover the entire image. Each region's pixels possess specific characteristics, such as color intensity and texture.

To achieve image segmentation, knowledge of the object's shape and size within the image is required. The segmentation is performed based on desired characteristics like size and shape and often utilizing the concept of thresholding in the selection of appropriate thresholds.

Feature Extraction: Feature extraction involves deriving values from an initial set of major data. When the input data is extensive and suspected to contain redundancies, a reduced set of features can be obtained through a process called feature selection. These chosen features include relevant information from the input.

A collection of components known as map nodes or neurons constitutes a Self-Organizing Map (SOM). Each map node contains a weight vector, and for the enhanced feature representation, pseudo-Zernike moments are employed. These moments demonstrate invariance under image rotation, and the enhanced feature representation of the weight vector is attributed to the multilevel moments of an image. The nodes are organized in a rectangular grid, and though they are not directly linked to one another, all the nodes are connected to each input node.

Self-Organizing Maps (SOMs) serve as a data visualization technique that reduces data dimensions through self-organizing neural networks. Each map node possesses a unique coordinate, simplifying node referencing and distance calculation. The connections are only with the input nodes and leaving the map nodes unaware of their neighbors' values. A map node updates its weights only based on the information from the input vector. The weight vector consists of two components: the data part, which has the same dimensions as the sample vectors, and the natural location, representing the pixel's position in the image.

Self-organizing map technique is applied for the identification of tumor images. The process starts with initialization, where initial weight vectors are set to random variables. In this paper, SOM is utilized to reduce dimensionality and cluster an image. With the SOM algorithm, tumor images are accurately identified with high precision in this paper.

Training using the Self Organizing Maps (SOM): It represents one of the leading neural network models, that supports competitive learning networks. It operates without requiring human involvement and thus referred to as unattended learning. The map units agglomerate knowledge and evaluate the input file's class memberships to help in feature detection. The SOM discretely maps the input space using a set of neurons represented as Y ϵ Sn. The weights "w1, w2, and wN" are initially initialised with small random numbers, where "wj" denotes the weight vector connected to neuron "j," and "N" is the overall number of neurons.

The algorithm is carried out in accordance with the steps in Algorithm 1, where (u, v, t) denotes the collection of neuron indexes used in the neighborhood function. The coefficients *{α (t), t≥ 0}* known as the adaptation gain decreases monotonically and satisfies the following property:

$$\lim_{n\to\infty}\sum \alpha(t) \to \infty \qquad (1)$$

Repeat: The first phase involves taking the winner using an input y(t) at time t.

$$u(t)argmin\, n\, y(t) - wv(t)\;\; n\; (2)$$

ii) The weights of the winning neuron undergo repeated updates until the map converges.

$$wv(t) = \propto (t)n(u,v,t)[y(t) - wu(t)]\; (3)$$

The segmentation primarily relies on gradient-based techniques and is commonly referred to as the watershed algorithm. In this method, the mountains within the landscape correspond to ridgelines (high intensity), while valleys represent structure basins (low intensity). The watershed algorithm ensures complete image contouring and is preferred for its reliance on edges rather than color. This region-based method, which treats the background as a separate object and makes use of picture morphology and requires choosing at least one marker (or "seed" point) within each object in the image. Watershed algorithms find significant application in image processing, especially for brain tumor segmentation in MRI images. It effectively separates different objects, enabling object counting and next analysis of the segmented objects. Finally, this technique identifies either a patient have brain tumor or not.

IV. RESULT ANALYSIS

In this section, automatic brain tumor identification using novel self organizing maps is implemented. Before pre-processing, the skull is first stripped once the brain pictures have been initially read. Skull stripping eliminates non-cerebral regions inside the brain since they are not areas of interest for us. Preprocessing is then conducted to remove noise and unwanted data. Self-Organizing Maps (SOMs), an unsupervised neural network, are employed for the visualization and exploratory data analysis of high-dimensional datasets. The Watershed algorithm is utilized for brain tumor segmentation. The performance of the

suggested approach is then assessed in terms of accuracy, precision, and sensitivity before brain tumours are found. The evaluation is based on the following definitions for the TP, TN, FP, and FN confusion matrix parameters:
False Positive (FP) stands for incorrectly classified positive cases; False Negative (FN) for the cases, that were classified incorrectly as negative; and True Negative (TN) for the cases, that were classified incorrectly as negative. Positive cases should be classified using the letters TP (true positive), FP (false positive), and FN (false negative). The following definitions apply to the metrics obtained from the confusion matrix:

Accuracy: The fraction of accurately detected outcomes is used to define accuracy. It's represented as.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (4)$$

Sensitivity: This metric assesses a model's ability to predict the true positives for each class of available data. It is also referred to as True Positive Rate (TPR) or Recall.

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (5)$$

Precision: The metric used to measure the accuracy of positive predictions is called precision. It is defined as the ratio of all cases that were correctly classified to all instances that were positive (i.e., FP+TP).

$$Precision = \frac{TP}{TP + FP} \times 100 \quad (6)$$

Performance evaluation is presented in Table 1.

Table 1: Performance Evaluation

Metrics/Methods	Brain Tumour Segmentation using Machine Learning Classifiers	Automatic brain tumor identification using novel self organizing maps
Sensitivity (%)	89.23	95.36
Precision (%)	91.23	96.54
Accuracy (%)	89.34	96.23

From the table 1, it is clear that, presented approach has better accuracy, precision and sensitivity than brain tumor segmentation using ML classifiers. The Fig. 2 shows the precision comparison. In fig. 2, the x-axis indicates different approaches and y-axis indicates the precision in terms of percentage.

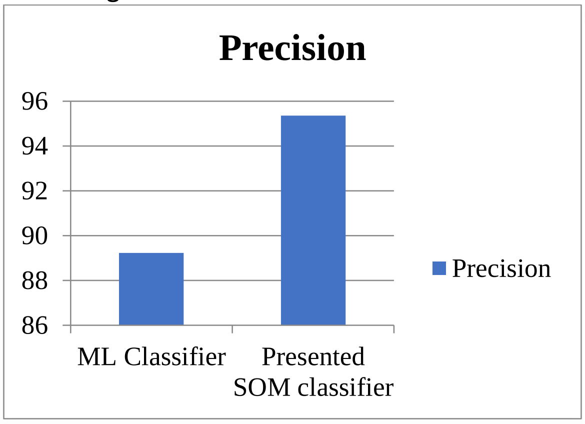

Fig. 2: Precision Comparison

Presented novel SOM has high precision value than ML classifiers. Fig. 3 illustrates the comparison of sensitivity.

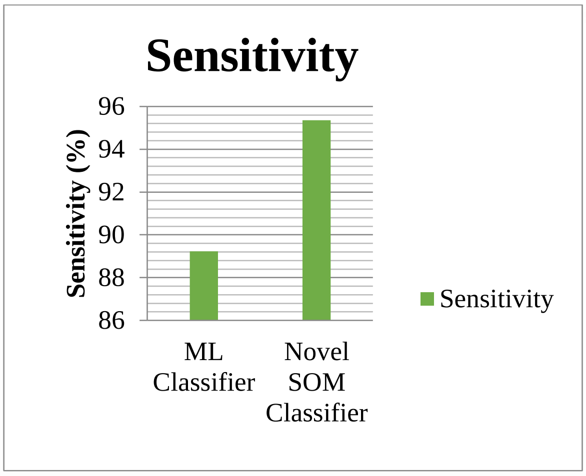

Fig. 3: Sensitivity Comparison

In fig. 3, the x-axis indicates different approaches and y-axis indicates the sensitivity in terms of percentage. Compared to ML classifier, presented novel SOM has high sensitivity for brain tumor identification. The Fig. 4 shows the accuracy comparison.

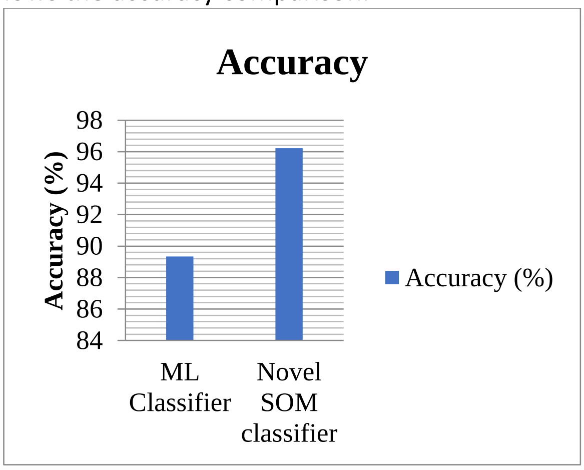

Fig. 4: Accuracy Comparison

Compared to, ML classifier, presented novel SOM classifier has obtained high accuracy for identifying brain tumor. Hence presented approach has achieved better results for identifying the brain tumors. If brain tumors are identified then proper treatment will be provided and as a result, deaths due to brain tumor will be decreased and patient's lives will be saved.

V. CONCLUSION

In this section, automatic brain tumor identification using novel self organizing maps is presented. Anisotropic Diffusion involves reading the brain images, followed by the skull stripping before pre-processing to eliminate non-cerebral regions inside the brain. Preprocessing is then performed to eliminate unwanted data and enhance classifier accuracy. ADF is utilized to reduce noise in brain MRIs. The medical images are obtained from publicly available datasets. A novel Self-Organizing Map (SOM) is employed, which is a data visualization model that reduces data dimensions through self-organizing neural networks. Watershed segmentation is a region-based method that justifies segmentation outcomes on picture morphology, which is used to identify brain tumors. The accuracy, precision, and sensitivity of the algorithm's performance are then evaluated. Novel SOM has demonstrated greater performance in terms of sensitivity, accuracy, and precision when compared to ML classifier. This approach identified the brain tumor patients very accurately and effectively. Hence, this approach will be a better solution for accurate brain tumor detection.

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