International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Brain Tumor Detection Through Image Processing and Machine Learning Techniques

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**Submitted:** 06/12/2023 **Revised:** 15/01/2024 **Accepted:** 27/01/2024

***Abstract:*** Mind was an administrative unit in human body. It controls the capabilities, for example, memory, vision, hearing, information, character, critical thinking, and so on. Presently a day's growth is second driving reason for disease. Because of malignant growth huge no of patients are in harm's way. The clinical field needs quick, robotized, productive and dependable strategy to recognize growth like cerebrum cancer. Discovery assumes vital part in treatment. In the event that legitimate recognition of growth is potential, specialists keep a patient out of risk. Different picture handling procedures are utilized in this application. Utilizing this application specialists give legitimate treatment and save various growth patients. A growth is only overabundance cells filling in an uncontrolled way. Cerebrum cancer cells fill such that they in the long run take up every one of the supplements implied for the sound cells and tissues, which brings about mind disappointment. At present, specialists find the position and the area of cerebrum growth by taking a gander at the MR Pictures of the mind of the patient physically. This outcomes in off base location of the cancer and is considered very tedious.

Mechanized imperfection recognition in clinical imaging has turned into the new field in a few clinical demonstrative applications. Computerized discovery of growth in X-ray is exceptionally critical as it gives data about strange tissues which is important for arranging treatment. The regular technique for deformity location in attractive reverberation cerebrum pictures is human examination. This technique is unfeasible because of enormous measure of information. Thus, trusted and programmed arrangement plans are fundamental to forestall the demise pace of human. Thus, mechanized cancer recognition techniques are created as it would save radiologist time and get a tried exactness. The X-ray cerebrum growth recognition is convoluted assignment because of intricacy and change of cancers. In this venture, we propose the AI calculations to defeat the downsides of customary classifiers where cancer is identified in mind X-ray utilizing AI calculations. AI and picture classifier can be utilized to recognize disease cells in mind through X-ray effectively.

***Keywords:*** *Brain Tumor, Machine Learning Techniques, Image Processing etc.*

## 1. Introduction

A cerebrum cancer alludes to an unusual development of cells either inside the mind or in its area such as nerves, pituitary organ, pineal organ, layers covering an mind's area. Essential cerebrum growths start in the mind, while optional growths, otherwise called metastatic mind cancers, result from the spread of disease from other body parts.

There are different kinds of essential mind growths, with some being noncancerous or harmless, and others named dangerous or destructive. Noncancerous cancers, however not carcinogenic, can develop after some time, applying strain on the cerebrum tissue. Threatening cancers, then again, may develop quickly, attacking and obliterating encompassing mind tissue.

Cerebrum cancers differ in size, going from little ones that make prompt side effects enormous growths that might stay undetected for quite a while. Recognition might be deferred on the off chance that the growth creates in a less dynamic piece of the mind, where side effects may not show right away.

Treatment choices for cerebrum cancers rely upon variables, for example, the growth type, size, and area. Normal methodologies incorporate a medical procedure and radiation treatment. The focal sensory system (CNS), including the cerebrum and spinal segment, oversees essential capabilities like idea, discourse, and body developments. Subsequently, growths in the CNS can affect mental cycles, discourse, and engine capabilities.Human brain is a very complex structure and

it is tightly packed within the skull, and viewed as a kernel (core) section of the body. Study of the brain and its structure, and analysis of diseases are very difficult. The structure of the brain is that, it is a soft spongy mass of tissues and is very delicate. Human brain systemizes and controls all activities and functions of the human body. Anatomy of brain is shown in Figure 1.3. Anatomically, brain can be divide into 3 main regions, namely, Forebrain, Midbrain and Hindbrain [2]. Prosencephalon is the biological name of mid brain which is alsocalled as the center of the brain, and composes the Brainstem. Rhombencephalon is the biological name [3] of the hind brain and having other brainstem,

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and the Cerebellum along Pons. Brain cells were classified to 2 groups: Neurons as well as Neuroglia. Neurons carry an communication process in between the brain cells. Neuroglia supports and acts as a shield for neurons, and are also called as Glial Cells. Researchers and medical experts are putting tremendous efforts to study [4] on the structure and complexity of the brain, so as to study its disease and the function of various diseases. There are numerous methods, procedures and techniques used to capture images of the human brain for clinical analysis.

Various methodologies are available to classify brain images. Brain Tumor, Paralysis, Alzheimer and Stroke are some of the different types of diseases of the human brain. Study of the brain play a vital role in medical imaging. Brain tissue can be divided to 2 groups, namely, Gray Matter & White Matter.

The Electroencephalogram or EEG [5] signal is the process of recording the human brainactivity by means of electrical change in the signal. The frequency of the EEG signal s 0.2 Hz – 30 Hz. Brain waveforms are divided into bandwidths, which are called as Alpha, [6] Beta and Theta. The magnificent organs of our body is the brain, and it is the center of command for the entire nervous system of the human body. [7] Many researchers have carried out their work in multi- disciplinary approach and gained understanding of Machine Learning, Deep Leering and other technologies related to brain tumor. Since brain imaging analysis is complicated, it can be analyzed only by medical experts, physicians and radiologists with the help of medical image and is related techniques.

**Types of Brain Tumors**

The tumor is termed in various techniques depends on kind of tumor. All tumors aren't cancerous tumors some tumors were cancer tumors and some were non – cancerous tumors. Tumors were called as benign tumor which are slow growing tumors and some tumors were called as malignant brain tumors which were fast growing tumors.

**Description of MRI**

MRI is used take images of Brain, Leg and hands, stomach, lungs and various human body parts. Lung cancer is one amount the dangerous disease-causing death to humans [14]. Similarly, MRI helps to classify the types, stages of diseases like beginning stage, middle stage and final stage. MRI contrast shows the images in deeper and explores the minute particles or tissue growth in detail. Images can be portable in film format or CD format with detail report from the physician with findings.

| MRI Image | Description |
|---|---|
| FLAIR | Standard Sequences<br><br>Used for Lesion Detection Particularly in White MatterIn the Posterior Fossa it's Less Sensitive<br>Applied in Axial or Coronal Imaging Plane |
| FLAIR + Gd | Detection of Leptomeningeal Diseases |
| PD/T2 | Alternative of FLAIR<br><br>More Sensitive in the Posterior Fossa Lesion Detection UsesProton Density<br>Uses First Echo Concept |
| T2-W1 | Uses Second Echo ConceptStaple Sequence for T2 Lesions Detection of Microbleeds |
| SW1 | Combines Magnitude and Phase Information and Forms a SequenceDetection of Intracranial Calcifications<br>Used in Detecting Microbleeds |
| T1±Gd | Uses All the 3 Imaging Planes<br>To Highlight contrast in the Images it Uses Gadolinium-ChelateInjection |
| SPGR | Isotropic 3D T1-W Sequences UsedDifferentiate Gray and white MatterDetect Migration Disorders |

**Table 1:** Different types of MRI Images

## 2. Literature Work

| S.No | Author | Datasets | Filters | Architecture | Training | fectiveness /Efficiency |
|---|---|---|---|---|---|---|
| 1. | Havaei, M, 2017 | (BRATS)2013 dataset | Convolu-tion of kernels | Two-pathwayand Cascaded | Stochasticgradient descent | Change in accuracy & speed |
| 2. | Dou, Q,2017 | Abdomen3D CT scans | 3D kernels | 3D Deeply SupervisedNetwork | Gaussian distribution | The high-quality score obtained from 3DDSN |
| 3. | Zhao, X,2018 | BRATS(2013, 2015 and 2016) | 3D kernels | Fully CNN | Gaussian distribution | Achieved efficiency |
| 4. | Karimagh aloo, Z,2016 | Multi- center clinicaltrials | Kernel- based classifier: Relevance Vector Machine | Hybrid CNN | Kappa | fast and accurate |

| | | | | | | |
|---|---|---|---|---|---|---|
| 5. | Mohsen,H, 2017 | Fuzzy C-means | Cascaded and Convolu- tion filters | Deep NeuralNetwork classifier | Discrete wavelet transform | Performance measures were quite good |
| 6. | Xie, Y,2018 | Four microscopy image datasets | Convolu- tion kernels | Fully CNN | Hungarian algorithm | accuracy andtime |
| 7. | Kamnitsas , K, 2017 | TraumaticBrain Injury | Small kernels | 3D CNN | Stochastic Gradient Descent | Efficient |
| 8. | Wan, S,2017 | A LOT andOutex | GaborFilters | K-nearest neighbors (KNN) andNeural network | Histogram of OrientedGradients (HOG) | Able to achieve moe accurate image |
| 9. | Hor, S,2016 | Alzheimer's Disease Neuroimaging Initiative | Multi-kernelwith supportvector machine | Single modaltree | Scandenttree | Efficiently transferthe discriminative power of imaging |
| 10. | Drozdzal,M, 2018 | Electron Microscope | Medianfilter | Fully Convolu- tional Networks and ResNets | Watershed algorithm | Potential and versatility of the framework achieved accurate segmentations |
| 11. | Arabi, Hand Zaidi, H,2016 | Co-registered atlas dataset | Gradient anisotropic diffusion filtering | Sorted atlas pseudo-CT | Gaussiankernel | Resulted in betterPET quantification accuracy |
| 12. | Wenzel,F, 2018 | Model-based segmentation | Conjugate gradient | CNN | Gauss- Newton optimization | High accuracy, test-retest consistency |
| 13. | Irving, B,2016 | Rectal DCE-MRI dataset | 1D Gaussian filter | AutomatedDCE-MRI | Perfusion- super voxel | Dice similarity coefficient (DSC)of 0.63and 0.71 achieved |

**Table 2:** Architecture & Efficiency

| S. No | Author | Algorithm | Accuracy | Future Scope |
|---|---|---|---|---|
| 1 | Havaei M, 2016 | Deep learningalgorithm | It improved the Dice measure on all tumor regions and Input Cascade CNN is better | Future scope notdefined by the author |
| 2. | Chen et al., 2016 | Auto-context algorithm | The proposed work is increased from(80.45–84.91%) | Future work to investigate the performance in the techniques |
| 3. | Dhungel et al., 2015 | SSVM based in loss minimization parameter learning algorithms | Their outcome with values (0.91 v 0.89 & 0.90 v 0.81) for bothdatabases. | Future scope not defined by theauthor |

**Table 3** CNN - Algorithm, Accuracy and Future scope

| S. No | Author &Algorithm | Measurement | Accuracy | Future Scope |
|---|---|---|---|---|
| 1. | Soltaninejad, M,2017<br><br>Fixed 3D supervoxel patches | Their dataset has average of 0.81 | With Dice scores of 0.80and 0.89 obtained. An improvement was found for tumor core by 9.8%, 4.95%, 0.02, and for the whole tumor by 2.68%, 2.59% and 0.02. | Future work will be working on DTT mechanisms |
| 2. | Ramakrishnan T,2017 Evolutionary Programming (EP), Harmony Search (HS) andGrey Wolf Optimization(GWO) | Pixel values (0 to255) | The value thus obtainedby using GWO is 99.96% whereas the value attained by using the other two Techniques HS and EP is 98%. | Future scope not defined by the author |
| 3. | Nayak D. R et al2017 | Measurement notprovided in the research work. | Obtained an accuracy of99.69% | Future scope not defined by the author |

**Table 4:** SVM - Algorithm, Measurement, Accuracy and Future scope

## 3. Proposed Methodology

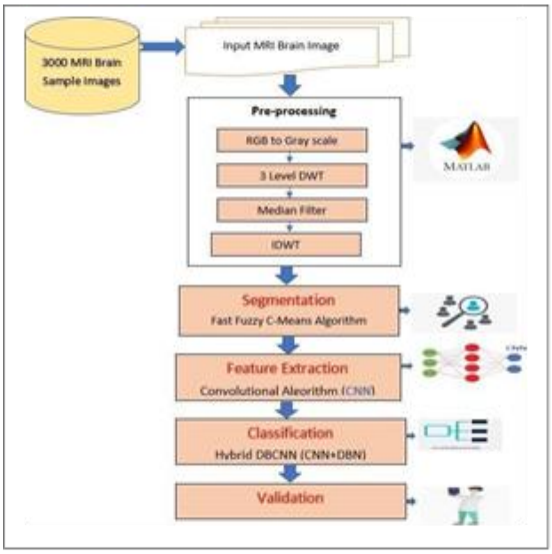


**Figure 1:** Architecture of Proposed Methodology

Many methods have been used by various researchers for analyzing and finding of brain tumor in MRI brain images. The proposed methodology has two stages; pre-processing and Segmentation. Image processing techniques are necessary, for identifying location in MRI brain image, for removing noises as well as to improve the quality for images. [18] All images is extracted using segmentation algorithms to find the tumor area and affected locations over photos accurately. Generally, tumor was classified to 4 stages like stage 1, stage 2, stage 3 and stage 4. Here stage 1 and 2 are beginun tumor and stage 3 and 4 were malignant tumor. [19]

The real time data taken in this research work comprises 3000 patients medical record from the year 2010 to 2019. [20] It as collected from various sources Gemini Scan center, SRM Medical College and Hospital located in the southern region of India and from Internet site like github. [21]

## 4. Proposed Algorithm

**Algorithm 1: Procedure**: Using AHCN-LNQ, image features are learned and preprocessed.

**Input**: $\alpha_x$ *and* $\beta_y$

**Output**: $\delta_b$

1. In array image, calculating histogram of every contextual region about neighboring gray levels.
2. Using CL value $N_{avg} = \frac{NrX \times NrY}{N_{gray}}$ to calculate contextual region contrast limited histogram. Where the average number of pixels is denoted as *N avg*, the number of gray levels is denoted as *N gray*, X and Y dimension number of pixels is denoted as *NrX* and *NrY*.
3. $N_{CL} = N_{clip} \times N_{avg}$ is actual CL, then *clip N* has normalized CL with range [0, 1]. Pixels are clipped when *N CL* is less than the number of pixels.
4. $N_{\sum clip}$ isatotal number of concise pixels, $N_{avggray} = N_{\sum clip}/N\,gray$ is the gray level of standard pixels.
5. Until the outstanding pixels are scattered, enduring pixels do reallocate.
6. *P (i) input* probability of Clipped histogram, which is provided to create transfer process by enhancing intensity values.
7. Within a sub-matrix contextual area, evaluating new gray level assignment of pixels.
8. Find $\delta_b$
9. End process.

## 5. Results

The below were the datasets were used for testing various performance metrices for the project such as accuracy, precision and specificity. Overall, we have taken 3000 datasets which contain normal images and abnormal images.

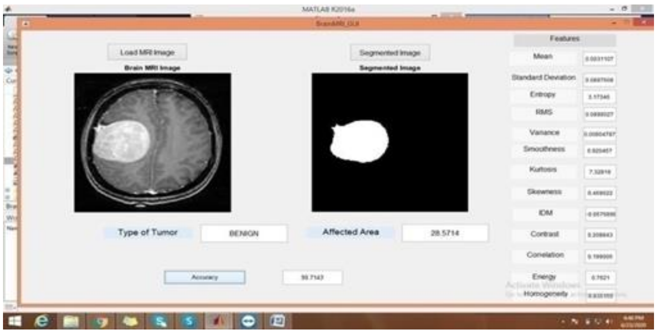

**Figure 2:** Names Of The Datasets

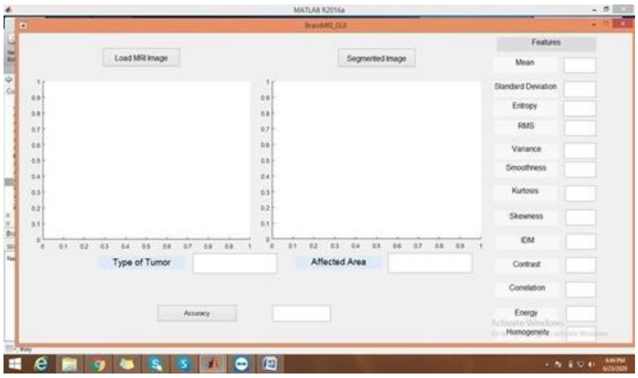

**Figure 3:** Implementation using SVM classifier

The MRI image is taken as input which can be further processed for the tumor detection. The image which is taken as input has the skull and tumor potion which can be detection. Implement of the suggested hybrid CNN model is illustrated bellow.

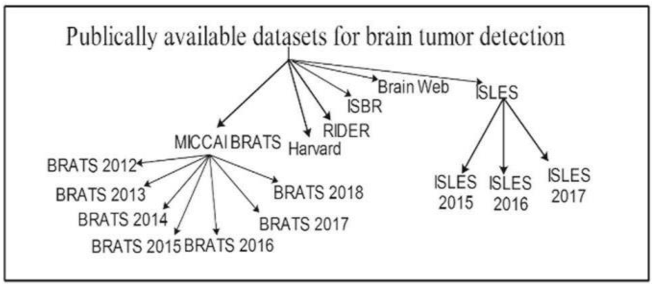


**Figure 4:** Default Interface

Figure 4 illustrates the default connection for the brain tumor detection. The interface has various fields like segmentation, features, segmentation, affected area and accuracy

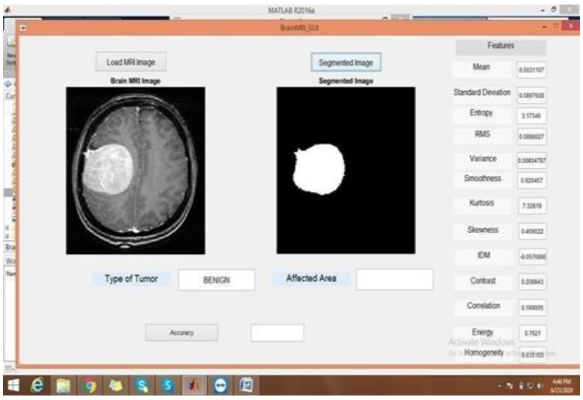


**figure 5:** Input Image

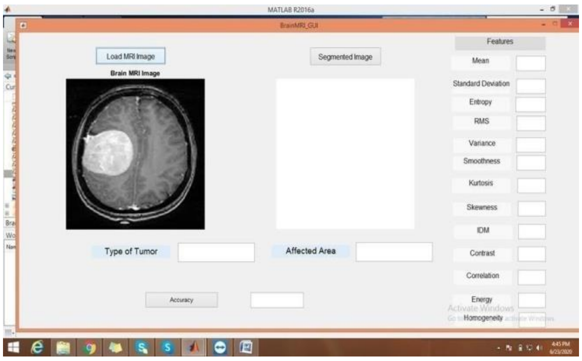


**Figure 6:** Segmentation and Feature Extraction

As demonstrated in figure 6, the MRI picture is taken as input which is processed to feature extraction. The GLCM technique is applied for the extrication of 13 characteristics for the tumor type detection.

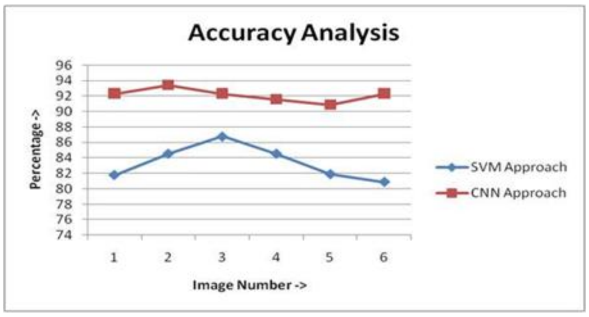


**Figure. 7:** Result of proposed Model

As illustrated in figure 7.6, the MRI picture is taken as input which is processed to feature extraction. The GLCM technique which is given to withdrawal of 13 attributes for the tumor type detection. The operation will fragment the tumor from the e. given MR picture. The affect area is28.57 percent and tumor type is benign type.

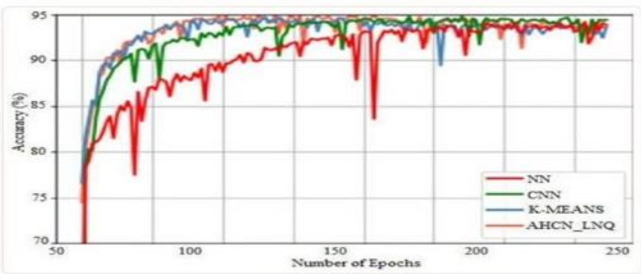


**Figure 8:** Accuracy Analysis

**Performance parameters**

As exposed in figure 7 accuracy for the present works which were already present was contrast with the proposed mechanism with CNN. The SVM technique generates accuracy with 82% and proposed mechanism has a better accuracy with 94%.

| Picture Digit | SVM Model | CNN Model |
|---|---|---|
| 1 | 82.2 | 92.25 |
| 2 | 85 | 94 |
| 3 | 86 | 93 |
| 4 | 84.1 | 92 |
| 5 | 82 | 91.56 |
| 6 | 81 | 92 |

**Table 8:** Accuracy Analysis

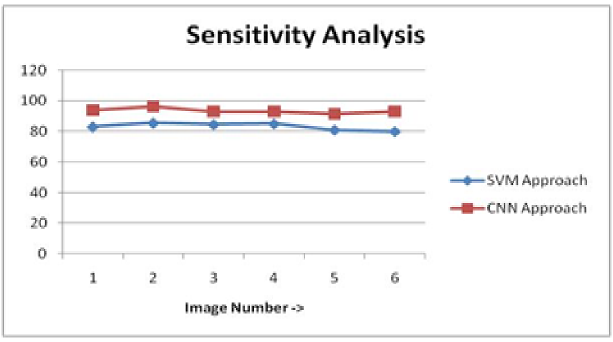


**Figure 9:** Sensitivity Analysis

Figure 9 compares the sensitivity of the current SVM method with the proposed CNN approach. The SVM technique yields a sensitivity of 81%, while the proposed method achieves a notable accuracy of 96%.

| Picture Digit | SVM Model | CNN Model |
|---|---|---|
| 1 | 80 | 92.3 |
| 2 | 81 | 96 |
| 3 | 81 | 93 |
| 4 | 81 | 94.79 |
| 5 | 80 | 90.5 |
| 6 | 79.5 | 93 |

**Table 9:** Sensitivity Analysis

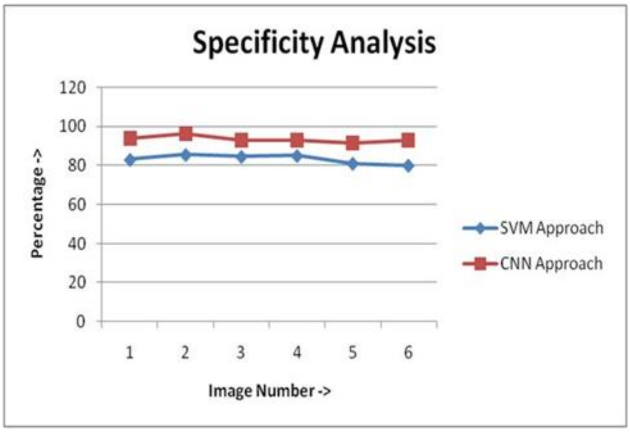


**Figure 10:** Specificity Analysis

Illustrated in Figure 10 is a comparison of the specificity between the current SVM method and the proposed CNN approach. The SVM technique demonstrates a specificity of 82%, while the proposed method attains a commendable accuracy of 95%.

| Picture Digit | SVM Model | CNN Model |
|---|---|---|
| 1 | 82 | 94 |
| 2 | 81.5 | 93.5 |
| 3 | 82.12 | 92 |
| 4 | 83.5 | 95 |
| 5 | 81 | 90.5 |
| 6 | 8.6 | 95 |

**Table 10:** Specificity Analysis

| Parameters | NN | CNN | K-MEANS | AHCN_LNQ |
|---|---|---|---|---|
| Accuracy | 92 | 93 | 94 | 95 |
| Precision | 85 | 86.5 | 89 | 89.5 |
| Specificity | 89 | 89.3 | 89.5 | 89.9 |

**Table 11**: Comparative analysis for tumor detection in brain

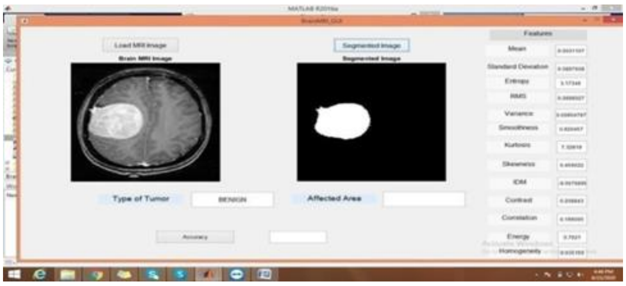

**Figure 11** Comparison of accuracy

**Performance Analysis**

**Accuracy**

It is defined as presages with positives as well as negetives for binary relegation which is defined as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad -1$$

Here true positive is defined by TP, false positive is defined by FP, true negative is defined by TN, and false negative is defined by FN.

**Precision**

Precision is termed as percentage of true positive, it is defined as

$$\text{Precision}=\frac{TP}{TP+FP} \qquad -2$$

**Specificity**

This concept gives the exact set of negative proportion which is also known as -ve rate which is defined as

Specificity = TN/ (TN + FP). -3

## 6. Conclusion

The popularity of medical image processing has grown significantly, driven by its applications in disease detection, prediction, and classification. The primary objective of medical image processing is the processing and evaluation of both normal and abnormal images, aiding in the diagnosis of tumor-affected regions in brain image datasets. This automation facilitates processing in challenging scenarios without requiring human intervention. The accuracy and effectiveness of tumor diagnosis depend on the techniques employed in various phases of cancer recognition.

This study focuses on detecting brain cancer from MRI pictures. The research paper's designed approach aims to localize and categorize tumor portions in MRI images with high execution speed but low accuracy. Due to its complexity, the methodology accurately performs its task. However, to overcome this bottleneck and achieve high accuracy with minimal execution time, an effective technique needs to be designed. To attain this objective, a median filter will be applied to denoise the MRI images.

The image segmentation process will involve applying threshold-based technique for remove an skull in MRI image. Textural feature extraction will be performed using the GLCM algorithm. In the final phase, machine learning algorithms will be applied in localization & categorization at tumor regions over MRI pictures. The proposed method, when implemented in the MATLAB simulator, utilizes computer vision and machine learning toolbox. To detect the tumor portion, the behavior of an proposed approach will be tallied with existing lesion localization as well as characterization methods. Various working concepts were checked with various parameters like precision, recall, and accuracy will be calculated for identifying the effective way of working in proposed mechanism.

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