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Brain Tumor Detection from MRI Images Using Machine Learning and an Enhanced Image Processing Pipeline

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Abstract: The brain is responsible for regulating vital functions, including memory, vision, cognition, and decision-making. Brain tumors, which result from the uncontrolled growth of abnormal cells within the brain, are among the major causes of mortality worldwide and require early detection to improve treatment outcomes. Conventional diagnosis through manual examination of MRI scans is labor-intensive, time-consuming, and susceptible to errors due to the large volume of imaging data and the diverse characteristics of tumors. Consequently, automated brain tumor detection has become an important area of research for enhancing the accuracy and efficiency of medical diagnosis. This study presents a machine learning–based framework for brain tumor detection using MRI image processing techniques. The proposed approach combines effective feature extraction with classification algorithms to accurately identify abnormal tumor regions, thereby reducing the workload of radiologists and improving diagnostic consistency. Experimental findings indicate that the proposed method achieves superior detection performance compared with conventional classification techniques, demonstrating its potential as a reliable clinical decision support tool.

Index Terms - Brain Tumor, Machine Learning Techniques, Image Processing.

I. Introduction

A brain tumor is characterized by the abnormal growth of cells within the brain or its surrounding structures, including the cranial nerves, pituitary gland, pineal gland, and meninges. Brain tumors are broadly classified into primary and secondary (metastatic) tumors. Primary brain tumors originate within the brain and may be either benign or malignant. Benign tumors generally exhibit slow growth and do not invade adjacent tissues; however, they can still cause significant neurological complications by compressing healthy brain structures. In contrast, malignant tumors grow rapidly, infiltrate surrounding tissues, and often result in severe neurological impairment. Secondary brain tumors arise when cancer cells spread to the brain from other parts of the body.

The diagnosis of brain tumors is often challenging because of their variability in size, shape, location, and growth patterns. Clinical symptoms also differ depending on the affected brain region, and tumors located in less functionally active areas may remain undetected until they reach an advanced stage. Since the central nervous system (CNS), comprising the brain and spinal cord, governs essential functions such as cognition, speech, sensation, and motor control, the presence of a brain tumor can significantly impair neurological function and overall quality of life.

The brain is a highly complex organ composed of neurons and neuroglial cells and is anatomically divided into the forebrain, midbrain, and hindbrain. Owing to its intricate structure and critical functions, accurate diagnosis requires advanced medical imaging techniques. Among the available imaging modalities, Magnetic Resonance Imaging (MRI) is the most widely used for brain tumor diagnosis because it provides superior soft-tissue contrast and high-resolution images, enabling detailed visualization of gray matter, white matter, and tumor boundaries. Electroencephalography (EEG), which records the brain's electrical activity within the frequency range of approximately 0.2–30 Hz, is also employed for neurological assessment and the evaluation of functional brain disorders.

Despite the effectiveness of MRI in identifying brain abnormalities, manual interpretation of MRI scans is time-consuming and subject to inter-observer variability, particularly when analyzing large volumes of imaging data. Consequently, automated image processing and machine learning techniques have emerged as effective solutions for improving the speed, accuracy, and consistency of brain tumor detection. These intelligent approaches assist clinicians in identifying tumor regions more efficiently, reducing diagnostic workload, facilitating early diagnosis, and supporting informed clinical decision-making.

Table 1: Different types of MRI Images Literature

MRI Image	**Description**
FLAIR	• Standard Sequences • Used for Lesion Detection Particularly in White Matter In the Posterior Fossa it's Less Sensitive • Applied in Axial or Coronal Imaging Plane
FLAIR + Gd	Detection of Leptomeningeal Diseases
PD/T2	• Alternative of FLAIR • More Sensitive in the Posterior Fossa Lesion Detection Uses Proton Density • Uses First Echo Concept
T2-W1	Uses Second Echo Concept Staple Sequence for T2 Lesions Detection of Microbleeds
SW1	• Combines Magnitude and Phase Information and Forms a Sequence Detection of Intracranial Calcifications • Used in Detecting Microbleeds
T1+Gd	• Uses All the 3 Imaging Planes • To Highlight contrast in the Images it Uses Gadolinium-Chelate Injection
SPGR	Isotropic 3D T1-W Sequences Used Differentiate Gray and white Matter Detect Migration Disorders

Table 2: Architecture & Efficiency

S.No	Author	Datasets	Filters	Architecture	Training	Effectiveness / Efficiency
1.	Havaei, M, 2017	(BRATS) 2013 dataset	Convolution of kernels	Two-pathway and Cascaded	Stochastic gradient descent	Change in accuracy & speed
2.	Dou, Q, 2017	Abdomen 3D CT scans	3D kernels	3D Deeply Supervised Network	Gaussian distribution	The high-quality score obtained from 3D DSN
3.	Zhao, X, 2018	BRATS (2013, 2015 &2016)	3D kernels	Fully CNN	Gaussian distribution	Achieved efficiency
4.	Karimagh aloo, Z, 2016	Multi - center clinical trials	Kernel-based classifier: Relevance Vector Machine	Hybrid CNN	Kappa	fast and accurate
5.	Mohsen, H, 2017	Fuzzy C-means	Cascaded and Convolution filters	Deep Neural Network classifier	Discrete wavelet transform	Performance measures were quite good
6.	Xie, Y, 2018	Four microscopy image datasets	Convolution kernels	Fully CNN	Hungarian algorithm	accuracy and time
7.	Kamnitsas, K, 2017	Traumatic Brain Injury	Small kernels	3D CNN	Stochastic Gradient Descent	Efficient
8.	Wan, S, 2017	A LOT and Outex	Gabor Filters	K-nearest neighbors (KNN) and Neural network	Histogram of Oriented Gradients (HOG)	Able to achieve moe accurate image
9.	Hor, S, 2016	Alzheimer's Disease Neuroimaging Initiative	Multi-kernel with support vector machine	Single modal tree	Scandent tree	Efficiently transfer the discriminative power of imaging
10.	Drozdzal, M, 2018	Electron Microscope	Median filter	Fully Convolu-tional Networks and ResNets	Watershed algorithm	Potential and versatility of the framework achieved accurate segmentations
11.	Arabi, H and Zaidi, H, 2016	Co-registered atlas dataset	Gradient anisotropic diffusion filtering	Sorted atlas pseudo-CT	Gaussian kernel	Resulted in better PET 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	Automated DCE-MRI	Perfusion-super voxel	Dice similarity coefficient (DSC) of 0.63and 0.71 achieved

Table 3 CNN - Algorithm, Accuracy and Future scope

S. No	Author	Algorithm	Accuracy	Future Scope
1	Havaei M, 2016	Deep learning algorithm	It improved the Dice measure on all tumor regions and Input Cascade CNN is better	Future scope not defined 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 both databases.	Future scope not defined by the author

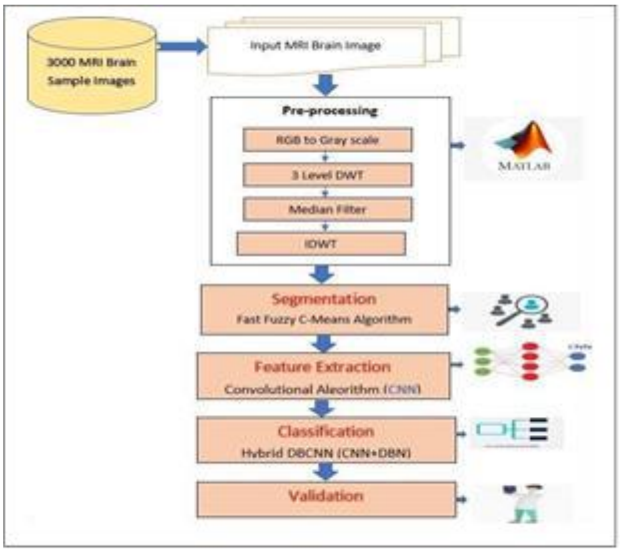
Table 4: SVM - Algorithm, Measurement, Accuracy and Future scope

S. No	Author & Algorithm	Measurement	Accuracy	Future Scope
1.	Soltaninejad, M, 2017 Fixed 3D super voxel patches	Their dataset has average of 0.81	With Dice scores of 0.80 and 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) and Grey Wolf Optimization (GWO)	Pixel values (0 to 255)	The value thus obtained by 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 al 2017	Measurement not provided in the research work.	Obtained an accuracy of 99.69%	Future scope not defined by the

III. Proposed Methodology

Many researchers have proposed various methods for analyzing and detecting brain tumors in MRI scans. The proposed methodology typically comprises two primary stages: preprocessing and segmentation. Preprocessing is essential for enhancing image quality, reducing noise, and improving the visibility of anatomical structures to facilitate accurate tumor localization. Subsequently, segmentation algorithms are applied to extract regions of interest and delineate tumor boundaries, enabling precise identification of affected areas. Brain tumors are generally classified into four stages: stages I and II are considered benign, whereas stages III and IV are malignant. This staged classification aids in determining prognosis and treatment planning.

Figure 1: Architecture of Proposed Methodology



The dataset used in this study comprises real-time medical records from **3,000 patients** collected between **2010 and 2019**. The data were obtained from multiple sources, including the Gemini Scan Center and SRM Medical College and Hospital in southern India, as well as publicly available repositories such as GitHub. The dataset includes MRI brain images along with corresponding clinical information, enabling comprehensive analysis and validation of the proposed tumor detection methodology.

IV. Proposed Algorithm

Algorithm 1: Procedure: Using AHCN-LNQ, image features are learned and preprocessed.
Input: α_z *and* β_y
Output: δ_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 δ_b 9. End process.

V. 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

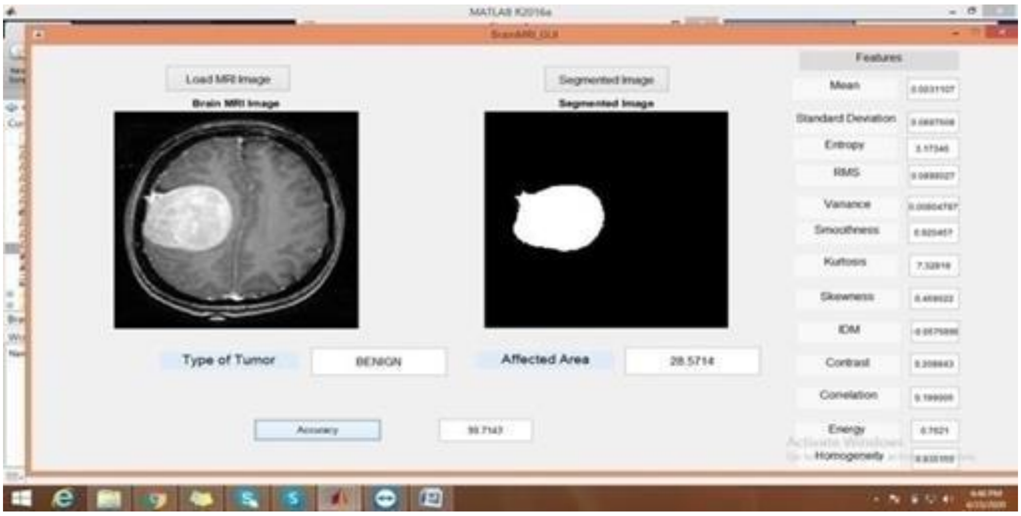
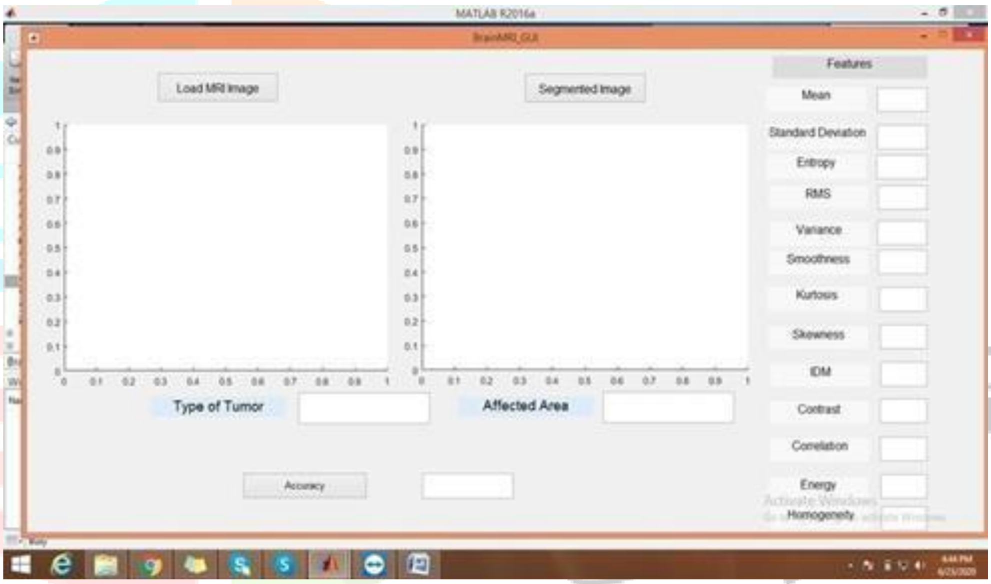


Figure 3: Implementation using SVM classifier



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

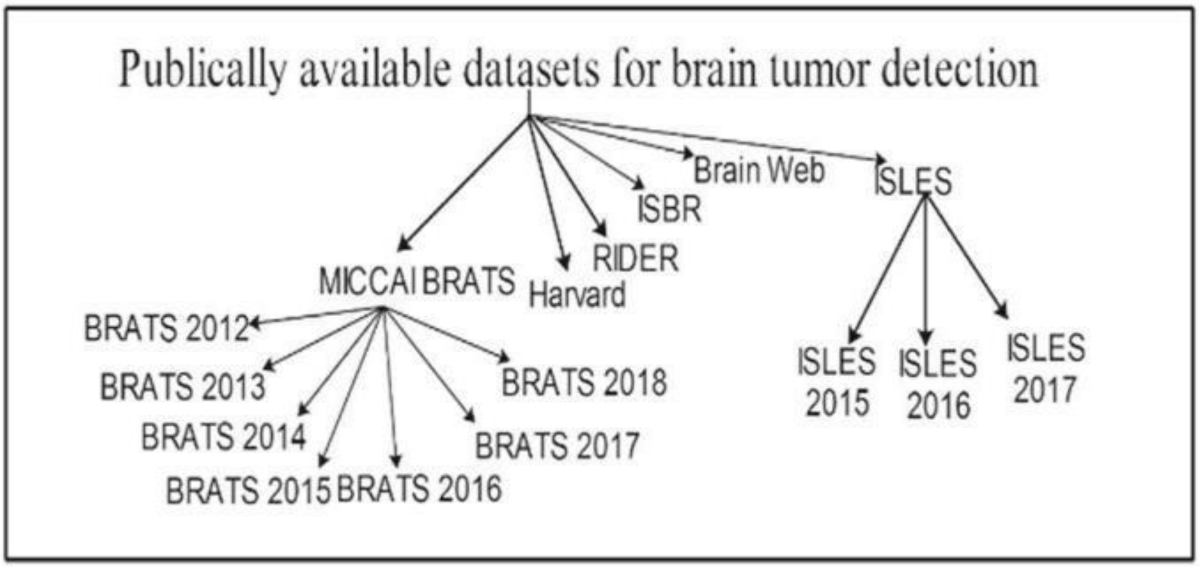


Figure 4 illustrates the default connection for the brain tumor detection. The interface has various fields like segmentation, features, segmentation, affected area and accuracy

figure 5: Input Image

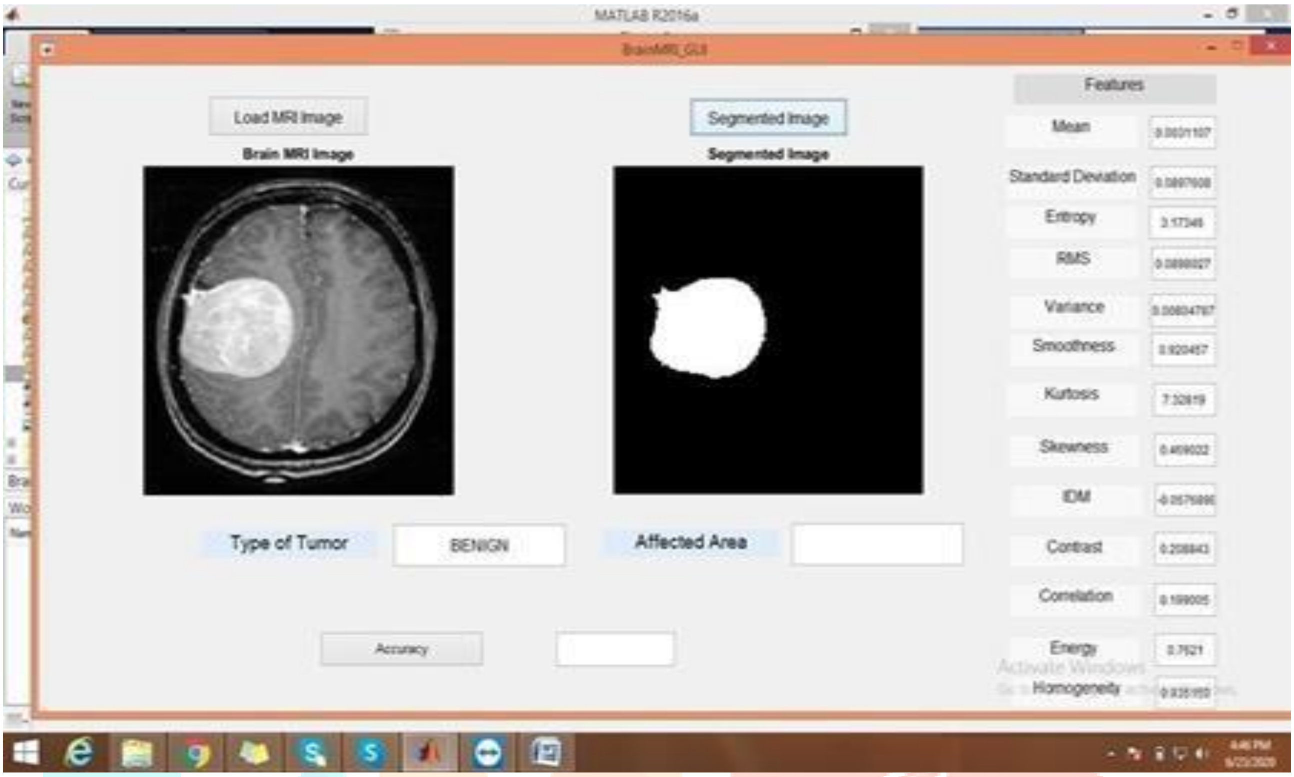
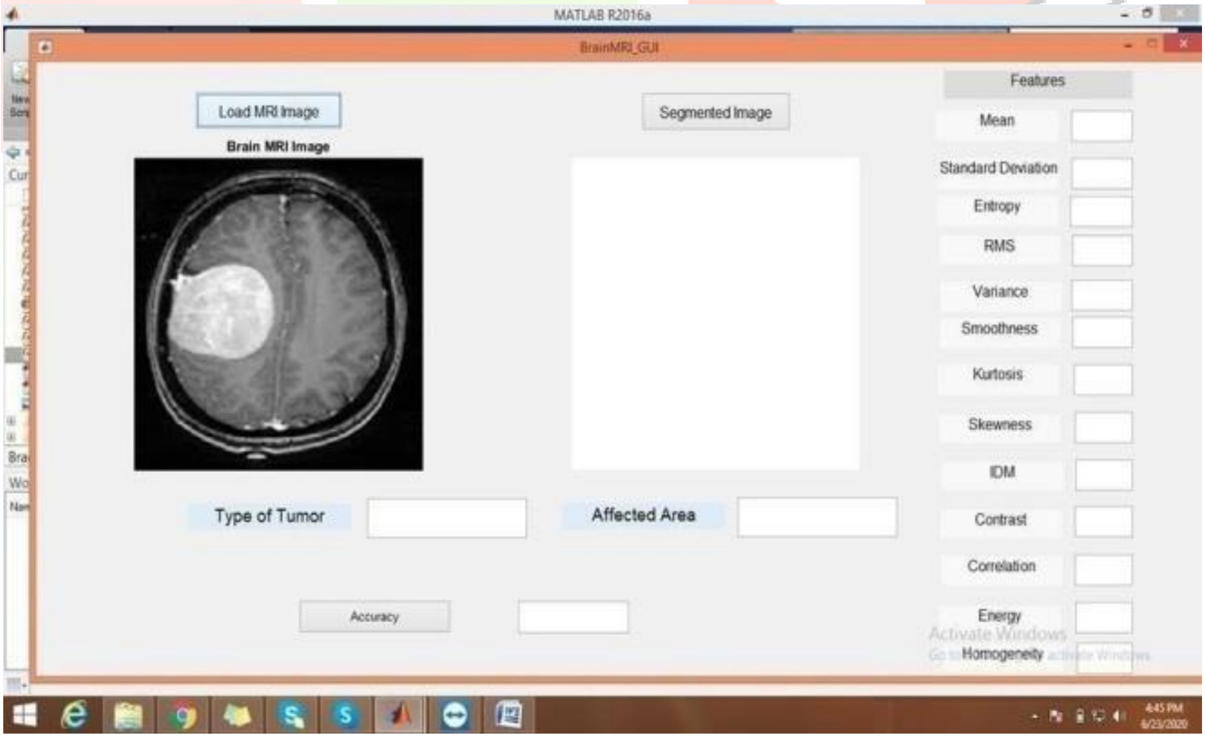
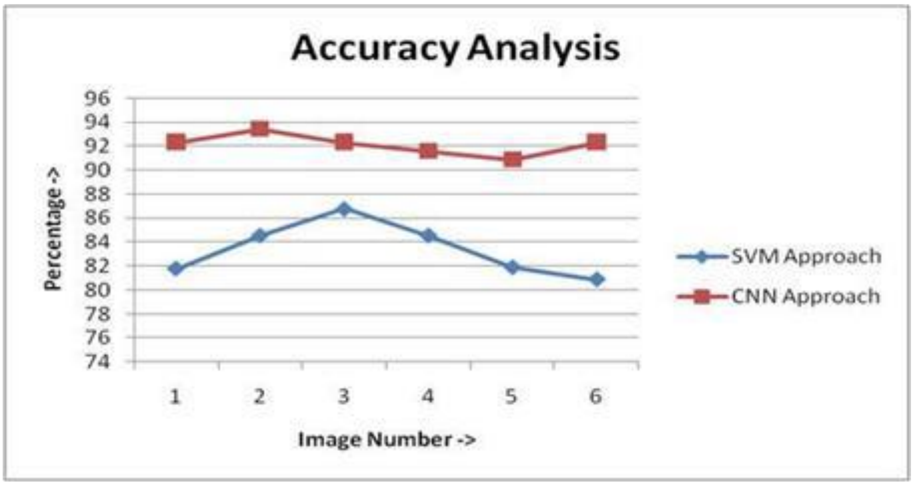


Figure 6: Segmentation and Feature Extraction



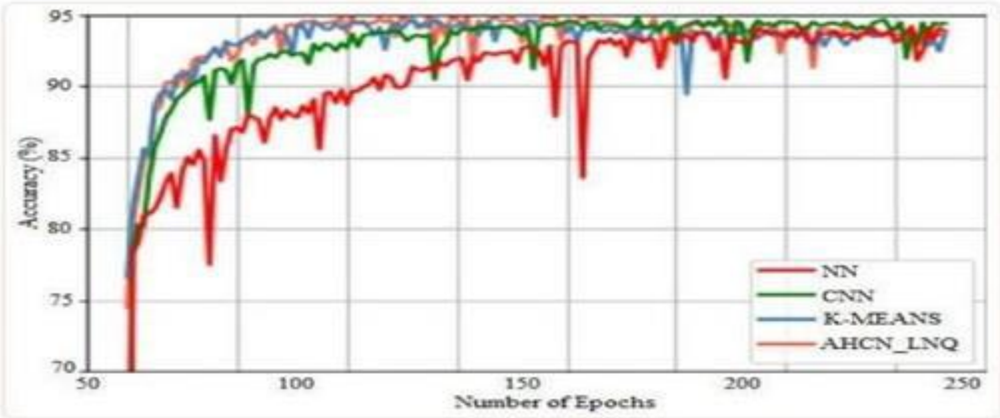
As demonstrated in figure 6, the MRI picture is taken as input which is processed to feature extraction. The GLCM technique is applied for the extrication of 13 characteristics for the tumor type detection.

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%.

Table 8: Accuracy Analysis

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

Figure 9: Sensitivity Analysis

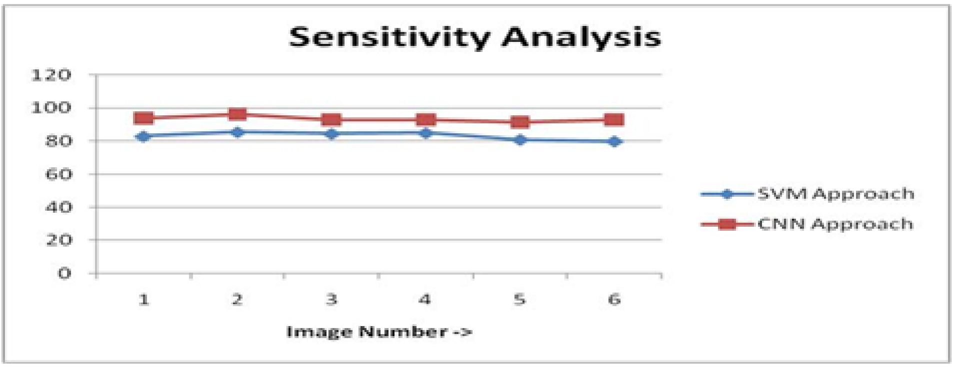
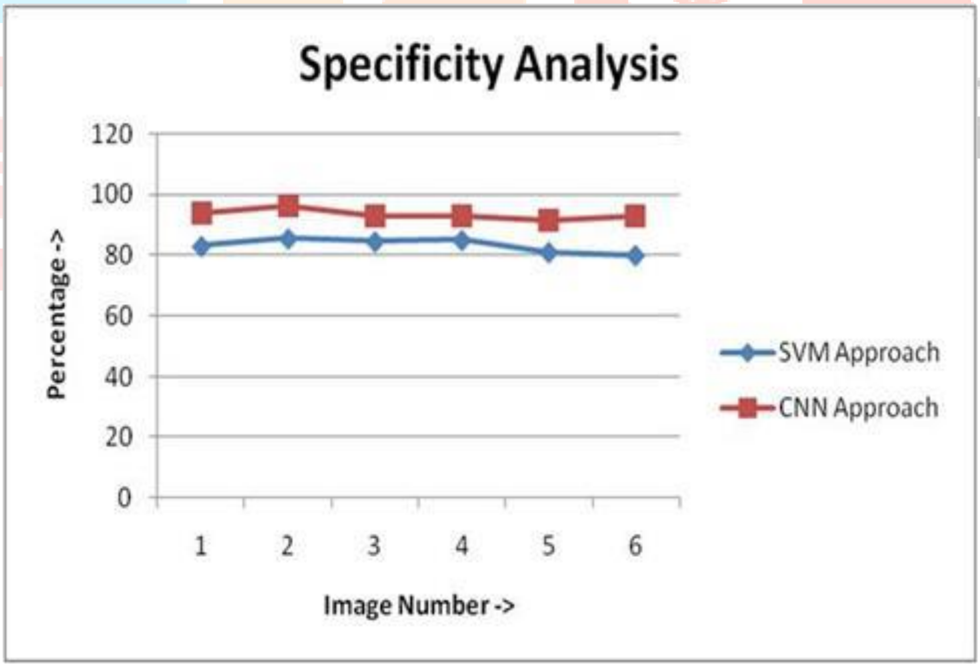


Figure 9 compares the sensitivity of the current SVM method with the proposed CNN approach. The SVM technique yields a sensitivity of 81%, while the proposed method achieves a notable accuracy of 96%.

Table 9: Sensitivity Analysis

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

Figure 10: Specificity Analysis



Illustrated in Figure 10 is a comparison of the specificitybetween 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%.

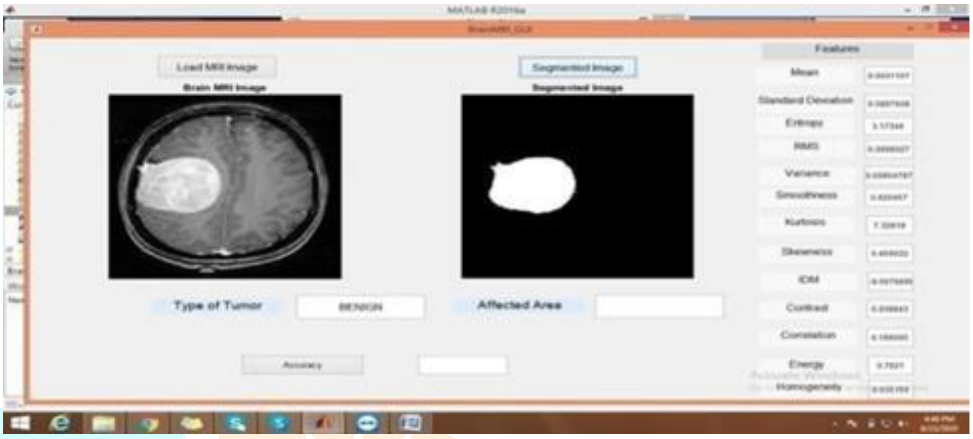
Table 10: Specificity Analysis

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 11: Comparative analysis for tumor detection in brain

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

Figure 11 Comparison of accuracy



Performance Analysis

1. Accuracy

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

$$Accuracy = TP+TNTP+TN+FP+FN \text{ -1}$$

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.

2. Precision

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

$$\text{Precision} = TPTP+FP \text{ -2}$$

3. Specificity

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

$$\text{Specificity} = TN/ (TN + FP). \text{ -3}$$

VI. 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.

References

[1] Methil, Aryan. (2021). Brain Tumor Detection using Deep Learning and Image Processing. 100-108. 10.1109/ICAIS50930.2021.9395823.
[2] Amin, J., Sharif, M., Haldorai, A. et al. Brain tumor detection and classification using machine learning: a comprehensive survey. Complex Intell. Syst. (2021).
[3] Gurunathan, A., Krishnan, B. A Hybrid CNN-GLCM Classifier For Detection And Grade Classification Of Brain Tumor. Brain Imaging and Behavior (2022).
[4] Brain Tumor Detection using Convolutional Neural Network ByPoornimasre Jegannathan in Turkish Journal of Computer and Mathematics Education Vol.12 No.11 (2021), 686-692.
[5] Yadav, S.S., Jadhav, S.M. Deep convolutional neural network based medical image classification for disease diagnosis. J Big Data 6, 113 (2019).
[6] Ranjbarzadeh, R., Bagherian Kasgari, A., Jafarzadeh Ghoushchi, S. et al. Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Sci Rep 11, 10930 (2021). https://doi.org/10.1038/s41598-021-90428-8
[7] N Saranya et al 2021 J. Phys.: Conf. Ser. 1916 012206.
[8] Seetha J, Raja S. S. Brain Tumor Classification Using Convolutional Neural Networks. Biomed Pharmacol J 2018;11(3).
[9] Arabahmadi M, Farahbakhsh R, Rezazadeh J. Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging. Sensors. 2022; 22(5):1960.
[10] Arkapravo Chattopadhyay, Mausumi Maitra,MRI-based brain tumour image detection using CNN based deeplearningmethod,NeuroscienceInformatics,Volume 2, Issue 4,2022.
[11] Díaz-Pernas, F.J.; Martínez-Zarzuela, M.; Antón-Rodríguez, M.; González-Ortega, D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network. Healthcare 2021, 9, 153.
[12] Brain Tumor Classification in MRI Images Using En-CNN in international journal of intelligent engineering & systems Vol.14, No.4, 2021.
[13] Omar Adil Kamil, Shaymaa W. Al-Shammari, IoT Framework for Brain Tumor Classification Using Optimized CNN-MRFO Model, American Journal of Bioinformatics Research, Vol. 11 No. 1, 2021, pp. 32-37. doi: 10.5923/j.bioinformatics.20211101.02.
[14] A Survey On Brain Tumor Detection Based On Structural MRI Using Machine Learning And Deep Learning Techniques. Dhanashri Joshi, Hemlata Channe INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 9, ISSUE 04, APRIL 2020.
[15] DETECTION OF BRAIN TUMOR USING TRANSFER LEARNING Apoorva Ramaiah , Hemalatha J , Himanshu Raj, Samarth Mohapatra, Prof. Kavitha K VOLUME-8, ISSUE-7, 2021.
[16] PREDICTIVE MODELLING OF BRAIN TUMOR DETECTION USING DEEP LEARNING Suraj Patil , Dr D. K. Kirange , Varsha Nemade journal of critical reviews, VOL 7, ISSUE 04, 2020.
[17] S. K. Palvadi and K. S. Joseph, “An Improved Proposed Algorithm for Brain Tumor Detection Using Image Processing and Machine Learning,” *Gradiva Review Journal*, vol. 9, no. 6, 2023.
[18] S. K. Palvadi and K. S. Joseph, “An optimal comparison of brain tumor detection by various Enhanced Machine Learning and Deep Learning Algorithms,” *Journal of Cardiovascular Disease Research*, vol. 12, no. 7, pp. 1297, 2021.
[19] S. K. Palvadi and K. S. Joseph, “An Overall Survey of Brain Tumor Detection with Improved Machine Learning and Deep Learning Techniques,” *International Journal of Intelligent Systems and Applications in Engineering (IJISAE)*, vol. 12, no. 15s, pp. 425–436, 2024.
[20] S. K. Palvadi and K. S. Joseph, “An Overall Survey of Brain Tumor Detection with Improved Machine Learning and Deep Learning Techniques,” *International Journal of Intelligent Systems and Applications in Engineering (IJISAE)*, vol. 12, no. 15s, pp. 425–436, 2024.
[21] S. K. Palvadi and K. S. Joseph, “Brain Tumor Detection Through Image Processing and Machine Learning Techniques,” International Journal of Intelligent Systems and Applications in Engineering (IJISAE), vol. 12, no. 15s, pp. 382–388, 2024.