



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH


IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Special Issue 2, December 2021


**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 7.569**

 9940 572 462

 6381 907 438

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# A Novel Machine Learning Based Brain Tumor Detection and Classification System

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**ABSTRACT:** A brain tumor is one of the most serious cancers among children and adults. Initial recognition, classification, and analyzation of brain tumors are particularly significant to treat the tumor adequately. Brain is a complicated structure consisting of millions of millions cells so that, it's difficult to identify any diseases without using any computerized technology. Detection of primary brain tumors is inspired by the necessity of high accuracy as it deals with human life. Detecting brain tumors in their early stages is crucial. The early identification of brain tumors and the subsequent appropriate treatment may lower the death rate. Magnetic resonance imaging stands as the gold standard for brain tumor diagnosis using machine vision, surpassing computed tomography, ultrasound, and X-ray imaging in its effectiveness. Despite this, brain tumor diagnosis remains a challenging endeavour due to the intricate structure of the brain. Recent advances in machine learning have led to the identification and classification of medical imaging patterns. In this work, a novel machine learning based brain tumor detection and classification system is presented. In this work, Decision Tree algorithm is used to detect the brain tumor. The performance of this system is evaluated in terms of Accuracy, Precision and F1-score.

**KEYWORDS:** Brain Tumor, Brain, detection, Magnetic Resonance Imaging (MRI) and Machine Learning.

## I. INTRODUCTION

Cancer is one of the major cause of death among children and adults around the world. Among of all types of cancers, Brain cancer is one of the most fatal neurological brain disorder caused by malignant tumors inside the brain [1]. The brain is the most complicated and key part of the human anatomy that contains tissues and nerve cells to regulate the key actions of the whole body like breathing, the operation of our senses and muscles. A cell has its capabilities; with its functionality, some cells are developed normally, some decrease their capabilities, stop their growth, and then become abnormal [2]. Such a bulk group of irregular cells produces the tissue which is described as a tumor. So, brain tumors are independent and irregular propagation of brain cells [3].

The brain tumor analyzation, classification, and identification are critical issues for a neurologist who is using CAD (computer-aided diagnosis) as a supportive tool for a medical operation. There are three noticeable kinds of brain tumors: meningioma, pituitary, and glioma. Precise and timely analyzation of brain cancer is imperative for the satisfactory treatment of this ailment. The decision of a treatment depends upon the pathological type, the phase at the moment of examination, and the grade of the tumor [4].

Medical imaging can be defined as a technique used to create images for clinical research, diagnosis, and treatment. Microwave imaging which is a new area of research that has become an emerging issue for detecting brain tumor due to its many advantages over currently available imaging systems like X-ray, magnetic resonance imaging (MRI), computed tomography (CT scan) and ultrasound technique [5]. Magnetic resonance imaging (MRI) is an imaging technique that uses magnetic fields to capture images. It can provide reproducible, non-invasive, and quantitative measurements of tissue, including structural, anatomical, and functional information. Because of its outstanding soft tissue contrast and detailed resolution, MRI is the most commonly utilized modality for brain tumour growth imaging and location detection [6].

Brain tumor detection has gained research interest due to complexity involved in tumor detection and mortality ratio over the few decades. Categorization of brain tumor uses grade I to grade IV to classify benign and malignant brain tumors. Grade I and II (benign tumors) have slow growth rate and if left untreated, is likely to develop into grade III

and IV (malignant brain tumor). There is a very small intensity variation in tissues of grade I/II tumor and healthy tissues [7].

The manual classification of brain MRI image is not always gives careful results and a time consuming. Therefore, there is an important for automatic classification using different techniques [8]. Brain tumors can lead to death if left untreated. The complexity of brain tumors poses challenges for healthcare providers in diagnosing and caring for affected patients. Early detection of brain tumors and initiation of treatment play vital roles in the survival rate of these patients. Brain tumor biopsy is not as easy as biopsy of other parts of the body, as it must be performed with surgery. Therefore, the need for another method for accurate diagnosis without surgery is crucial. Magnetic Resonance Imaging (MRI) is the best and most commonly used option for diagnosing brain tumors [9].

Currently, different techniques have been developed to help achieve this goal, but none have succeeded in reliable real-time and non-invasive tissue differentiation. Brain abnormalities, such as injuries, damage, tumor-related causes, affects, and symptoms, have been analyzed for tumor recognition by using image processing, data mining, and machine learning techniques [10]. The integration of Machine Learning and AI has significantly improved medical image analysis, leading to significant advancements in the detection, diagnosis, and characterization of various medical conditions. This has enabled healthcare professionals to make more informed decisions, particularly in the accurate classification of cancer types, such as lung and breast cancer [11].

This integration has resulted in earlier diagnoses, improved treatment decisions, and improved patient outcomes. Artificial intelligence plays a crucial role in surgical planning, enabling precise segmentation of lesion boundaries and brain structures, balancing intervention with quality-of-life preservation. It predicts complications, recurrence rates, and therapeutic responses, guiding optimal follow-up strategies and enabling personalized patient guidance through tailored screening protocols [12].

In this work, a novel Machine Learning based brain tumor detection and classification system is presented. The remaining work is arranged as follows: The section II describes the literature survey. The section III presents a novel Machine Learning based brain tumor detection system. The section IV evaluates the result analysis. The section V ends with conclusion.

## II. LITERATURE SURVEY

A. Islam, S. M. S. Reza and K. M. Iftekharuddin et. al., [13] describes Multifractal Texture Estimation for Detection and Segmentation of Brain Tumors. A multifractal feature-based brain tumor segmentation method is developed next. To evaluate efficacy, tumor segmentation performance using proposed multifractal feature is compared with that using Gabor-like multi-scale texton feature. Furthermore, novel patient-independent tumor segmentation scheme is proposed by extending the well-known AdaBoost algorithm. The modification of AdaBoost algorithm involves assigning weights to component classifiers based on their ability to classify difficult samples and confidence in such classification. Experimental results for 14 patients with over 300 MRIs show the efficacy of the proposed technique in automatic segmentation of tumors in brain MRIs.

A. Demirhan, M. Törü and İ. Güler et. al., [14] describes Segmentation of Tumor and Edema Along With Healthy Tissues of Brain Using Wavelets and Neural Networks. An algorithm was designed for stripping the skull before the segmentation process. The segmentation is performed using self-organizing map (SOM) that is trained with unsupervised learning algorithm and fine-tuned with learning vector quantization (LVQ). Unlike other studies, we developed an algorithm for clustering the SOM instead of using an additional network. Input feature vector is constructed with the features obtained from stationary wavelet transform (SWT) coefficients.

P. Mohamed Shakeel, T. E. E. Tobely, H. Al-Feel, G. Manogaran and S. Baskar et. al., [15] describes Neural Network Based Brain Tumor Detection Using Wireless Infrared Imaging Sensor. MLBPNN (Machine Learning based Back Propagation Neural Network) is analyzed with the help of infra-red sensor imaging technology. Then, the computational multifaceted nature of neural distinguishing proof incredibly diminished when the entire framework is deteriorated into a few subsystems. The features are extracted using fractal dimension algorithm and then the most significant features are selected using multi fractal detection technique to reduce the complexity. This imaging sensor is integrated via wireless infrared imaging sensor which is produced to transmit the tumor warm data to a specialist

clinician to screen the wellbeing condition and for helpful control of ultrasound measurements level, especially if there should arise an occurrence of elderly patients living in remote zones.

Samah Abdelaziz, Songfeng Lu et. al., [16] describes K-means algorithm with level set for brain tumor segmentation. An approach was described to segment brain tumor MRI images into three parts (WM (white matter), GM (gray matter), and background). The first algorithm is for applying median filtering on brain MRI image for removing the noise from the image for achieving accurate results. The second algorithm is for applying K-means algorithm for accuracy in time consuming and for clustering into regions and the third algorithm indicate the detecting the boundary of the image with the use of level set. By comparison, our proposed method, its efficiency to segment perfectly more than other previous used algorithms especially on time consuming.

S. Ahdi Rezaeieh, A. Zamani and A. M. Abbosh et. al., [17] describes 3-D Wideband Antenna for Head-Imaging System with Performance Verification in Brain Tumor Detection. A 3-D slot-rotated antenna for a microwave head-imaging system is presented. The antenna is designed to have a wideband and unidirectional performance at the low microwave frequency band that are the requirements of the specified imaging system. It has a measured VSWR fractional bandwidth of 87% (1.41-3.57 GHz) and a peak front-to-back ratio of 9 dB. To verify the suitability of the antenna in head imaging, it is connected to a wideband microwave transceiver and used to circularly scan an artificial head phantom in 20° angle steps in a monostatic mode. The collected backscattered data are then processed and used to generate an image that successfully shows brain tumors. The compact size, wide operating bandwidth, unidirectional radiation, and detection viability are merits of the presented antenna and the subsequent system.

H. Su, F. Xing and L. Yang et. al., [18] describes Robust Cell Detection of Histopathological Brain Tumor Images Using Sparse Reconstruction and Adaptive Dictionary Selection. An automatic cell detection framework was used using sparse reconstruction and adaptive dictionary learning. The main contributions of our method are: 1) A sparse reconstruction based approach to split touching cells; 2) An adaptive dictionary learning method used to handle cell appearance variations. The proposed method has been extensively tested on a data set with more than 2000 cells extracted from 32 whole slide scanned images. The automatic cell detection results are compared with the manually annotated ground truth and other state-of-the-art cell detection algorithms.

D. Ravi, H. Fabelo, G. M. Callic and G. -Z. Yang et. al., [19] describes Manifold Embedding and Semantic Segmentation for Intraoperative Guidance With Hyperspectral Brain Imaging. The proposed framework aims to overcome the problems through a process divided into two steps: dimensionality reduction based on an extension of the T-distributed stochastic neighbor approach is first performed and then a semantic segmentation technique is applied to the embedded results by using a Semantic Texton Forest for tissue classification. Detailed in vivo validation of the proposed method has been performed to demonstrate the potential clinical value of the system.

Z. Nie *et al.*, [20] describes Integrated Time-Resolved Fluorescence and Diffuse Reflectance Spectroscopy Instrument for Intraoperative Detection of Brain Tumor Margin. An integrated TRF-DR spectroscopy instrument was developed to acquire TRF spectra as well as spatially resolved diffuse reflectance spectra in sequence for intraoperative detection of brain tumor margin. The performance of TRF-DR spectroscopy instrumentation was calibrated and evaluated using endogenous biomolecules, tissue phantoms, and ex vivo brain tumor specimens. The results demonstrated that the TRF-DR system is capable to retrieve the fluorescence and optical properties accurately.

N. A. Al-Azzawi and M. K. Sabir et. al., [21] describes An superior achievement of brain tumor detection using segmentation based on F-transform. This paper describes the proposed approach for detection and extraction brain tumor from MRI scan images of brain. Asymmetry of brain is used for detection of abnormality, after detect of the tumor. The segmentation based on F-transform (Fuzzy-Transform) and morphological operations are performed to delineating brain tumor boundaries and calculate the area of the tumor. The F-transform is a professional intelligent method to handle uncertain information and to extract the salient edges. Accuracy and precision are co-dependent.

M. Kadkhodaei *et al.*, [22] describes Automatic segmentation of multimodal brain tumor images based on classification of super-voxels. In this analysis, images are enhanced and normalized to same scale in a preprocessing step. The enhanced images are then segmented based on their intensities using 3D super-voxels. Usually in images a tumor region can be regarded as a salient object. Inspired by this observation, we propose a new feature which uses a saliency detection algorithm. An edge-aware filtering technique is employed to align edges of the original image to the saliency

map which enhances the boundaries of the tumor. Then, for classification of tumors in brain images, a set of robust texture features are extracted from super-voxels. Experimental results indicate that our proposed method outperforms a comparable state-of-the-art algorithm in term of dice score

### III. MACHINE LEARNING BASED BRAIN TUMOR DETECTION SYSTEM

In this section, a novel machine learning based brain tumor detection and classification system is presented. The Figure 1 shows the block diagram of presented machine learning based brain tumor detection system.

Here, in this analysis, Brain tumor dataset is used from Kaggle. This dataset encompasses MRI images of the brains of 7,023 individuals, including those with brain tumors and those without. It comprises cases of meningioma, glioma, pituitary gland tumors, and non-tumor. Each category within this collection contains high-quality images. Pre-processing is an essential stage, where the data are processed to make them usable for training purposes. Since the MR images are obtained from a patient database, they are not clear and low-quality. In order to prepare the images for further processing, the images are normalized. Laplacian and Gaussian filters are used to smooth the images and remove the blurred images from the original images.

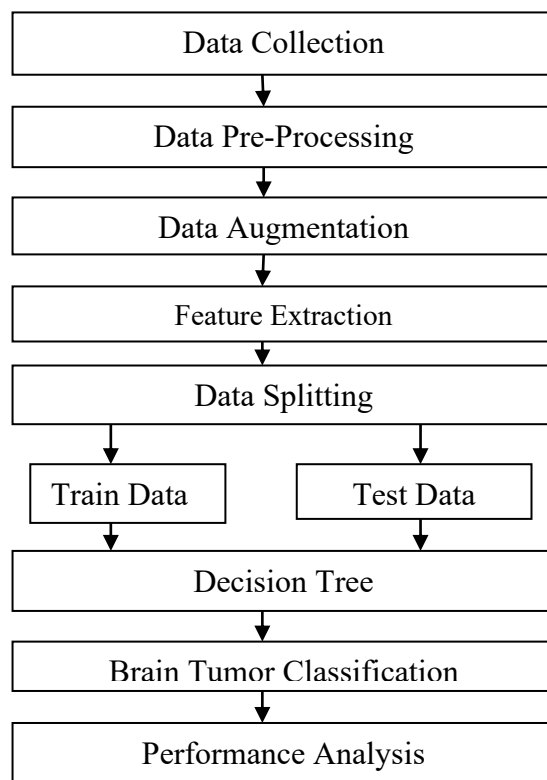


Figure 1: Block Diagram of machine learning based brain tumor detection system

Data augmentation is the process of artificially generating the new data from existing data to train the Machine Learning (ML) model. The data augmentation is done to reduce the overfitting. Image augmentation, a key technique using Keras' ImageDataGenerator is done to expand the dataset for training a ML model in brain tumor diagnosis. By creating modified copies of images with rotations, zooming, and flipping, the model gets exposed to a wider range of variations, improving its ability to handle new data. This is vital for simulating the variability in medical imaging, making the model more robust to noise and variations. The ultimate goal is to build a reliable and strong ML model, especially in the medical field where data is limited, and adapting to diverse and unseen cases is crucial. It introduces variations like rotations, flips, shifts, and zooms, contributing to balanced classes during model training. Feature extraction is the process of extracting the important details from segmented image such as texture, shape, contrast, and



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color features. The feature extraction process is carried out through two phases: Feature Extraction is performed using Discrete Wavelet Transform (DWT) & Principle Component Analysis (PCA).

In this method, 3 level of (DWT) is used for extracting wavelet coefficients, followed by (PCA) to reduce the feature vector dimensions and increase the discriminative ability. The extracted statistical features include mean, standard deviation, mean of variance, entropy, skewness, Kurtosis, Inverse Difference Moment, Root mean square and smoothness. The textural features are extracted using GLCM (Gray Level Co-occurrence Matrix) which include Contrast, Energt, Homogeneity and Correlation. Next the data is divided in to training and test data. The training is applied to train the DT classifier and test data is used to test the DT classifier.

Decision Tree is a supervised learning techniques that can be used for both classification and regression problems. It is a tree-structured classifier where internal nodes represent the features of dataset, branches represents the decision rules and each leaf node represents the outcome. In a decision tree, there are two nodes which are the decision node and leaf node. Decision nodes are used to make any decision and have multiple branches whereas leaf nodes are the output of those decisions and do not contain any further branches. The decision or the test are performed on the basis of features of the dataset. The Decision tree is used to detect and classify the brain tumor as No Tumor, Galimos, Meningioma, Pituitary. The effectiveness of this model is measured in terms of Accuracy, Precision and F1-score and are expressed as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \quad (3)$$

Where TP (True Positive), TN (True Negative), False Negative (FN) and False Positive (FP) are confusion matrix parameters.

#### IV. RESULT ANALYSIS

In this section, result analysis of a novel machine learning based brain tumor detection and classification system is presented. The performance of presented system is evaluated in terms of Accuracy, Precision and F1-score. The table 1 shows the performance metrics comparison.

Table 1: Performance Metrics Comparison

Metrics/ Classifiers	Linear Regression (LR)	DT (Decision Tree)
Precision (%)	87.54	92.23
Accuracy (%)	88.23	93.2
F1-score (%)	86.3	92.4

Compared to linear regression classifier, the DT classifier has obtained better performance. The Figure 2 demonstrates the precision performance comparison.

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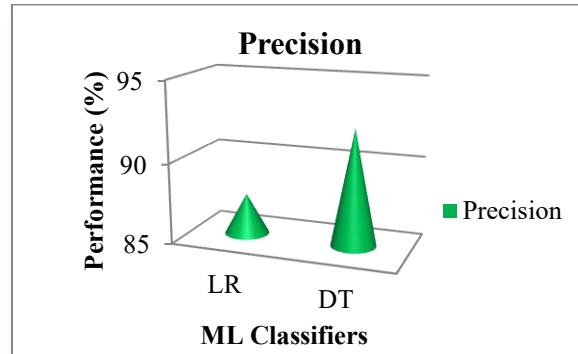


Figure 2: Precision Comparison

In figure 2, the x-axis indicates the ML classifiers and y-axis indicates the performance values. The DT classifier has achieved better precision than LR classifier. The Figure 3 shows the accuracy performance comparison.

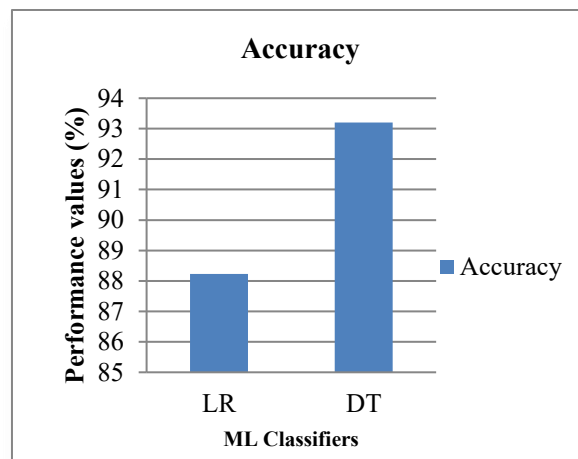


Figure 3: Accuracy Comparison

In figure 3, the x-axis represents the ML classifiers and y-axis indicates the accuracy values. The DT has achieved better accuracy for brain tumor detection and classification. The Figure 4 demonstrates the F1-score comparison.

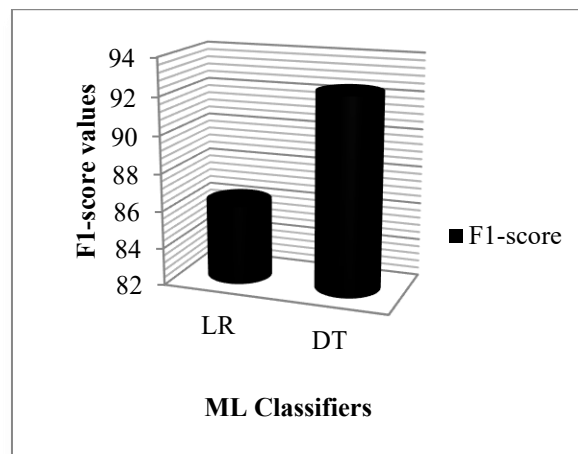


Figure 4: F1-score Comparison

Compared with LR, the DT has obtained better F1-score. Hence, presented classifier has achieved better performance for brain tumor detection and classification.

## V. CONCLUSION

In this work, result a novel machine learning based brain tumor detection and classification system is presented. In this analysis, the brain tumor dataset is collected from kaggle. The dataset contains MRI images of the individuals brains, including those with brain tumors and those without. The data is preprocessed is performed to improve the performance of classifier. Principle component analysis and discrete wavelet transform are used to extract the statistical features. The Gray level Co-occurrence matrix is used to extract the Textural features from the image. Then the data is splitted in to train and test data. The trained data is used to train the Decision Tree classifier and test data is used to test the DT classifier. The decision Tree classifier is used to detect and classify the brain tumor. The DT classifier classifies the brain tumor as No Tumor, Galimos, Meningioma, Pituitary. The performance of presented system is measured and compared in terms of Accuracy, Precision and F1-score. Compared to previous ML models, this system has achieved better performance for brain tumor detection and classification. This system can be used in real time to help the doctors for diagnosis of brain tumor.

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