

Exploring the Effectiveness of Machine Learning Methods for Brain Tumor Detection in MRI and Comparative analysis

Krishan Kumar ¹ , Research Scholar, Guru Nanak Dev Engineering College, Ludhiana IKG Punjab Technical University	Dr. Kiran Jyoti ² Associate Professor Guru Nanak Dev Engineering College, Ludhiana	Krishan Kumar ³ Assistant Professor Hindu College, Amritsar
---	--	--

Correspondence

Krishan Kumar, Research Scholar,
Department of Computer Science, Guru Nanak Dev Engineering College, Ludhiana
Punjab Technical University, Kapurthala, India

Abstract

Uncontrolled, fast cell growth is the cause of brain tumors and has a significant threat to global health, leading to millions of deaths annually. So, early cancer detection is extremely important to save many lives. This study investigates the capability of machine learning algorithms in advancing the classification of brain tumors, leveraging advanced imaging techniques like Magnetic Resonance Imaging (MRI). We have implemented six machine learning algorithms for classifying the brain tumor using various feature extraction methods like Image loading, HOG, and LBP. After analyzing the performance of different machine learning algorithms and feature extraction methods, we found that Random Forest emerged as the most effective classifier based on different metrics, closely followed by SVM and Logistic Regression. However, the performance varied with KNN, Naive Bayes, and Decision Tree, highlighting the importance of tailored approaches for optimal classification accuracy. Further optimization and experimentation are crucial for improving algorithm performance in real-world applications of brain tumor classification.

1.Introduction:

Brain cancer, a highly destructive and potentially disease, continues to pose significant challenges to the global healthcare community. Brain tumors are distinguished by their high morbidity and mortality rates due to their specific location and tendency to grow invasively in the surrounding area. Most neoplastic brain lesions are metastases arising from cancers outside the central nervous system (which are 5–10-times more common than primary brain tumours) [1].

In 2023, it is expected that approximately 24,810 adults (14,280 men and 10,530 women) in the USA will be detected with primary cancerous tumors affecting the brain and spinal cord. Brain tumors include 85% to 90% of all primary central nervous system (CNS) tumors. It is estimated that 5,230 children under the age of 20 will also be diagnosed with a CNS tumor in the United States in 2023[2].

A tumor is an abnormal and uncontrollable growth of cells in an organ. A brain tumor is an abnormal mass of tissue, which growth the cells within the brain tissue and start causing problems to allow the brain to continue functioning normally. Benign tumors, grades 1 and 2, or malignant, grades 3 and 4. Malignant tumors are also rated according to scaling aggression. Thus, the least aggressive tumors are minimally aggressive and the most aggressive high. Among the histological criteria that can give an exact definition of the grade of the tumor include not only vascularity and invasiveness but also the rate of tumor growth. When a tumor progresses into a higher stage, the patient's survival and treatment prognosis decreases drastically. Therefore, brain tumor diagnosis and early treatment will certainly improve the patient's survival chances[2][3].

In clinical practice, the most widespread primary brain tumors include meningioma, glioma, and pituitary tumors, as illustrated in Figure 1 and detailed in [4]. Meningioma normally begins from the meninges tissues comprising the brain or spinal cord, expressing as a benign growth in the protective membranes. Conversely, glioma, the fatal brain tumor, come from glial cells that support neurons, comprising about one-third of all brain tumor cases [6]. Pituitary tumors, which are benign, form within the pituitary gland [7]. Accurate diagnosis is pivotal for prognosis and treatment decisions, yet traditional biopsy approaches are oppressed with drawbacks such as pain, time consumption, and sampling inaccuracies [8,9]. Additionally, histopathological grading faces encounters like intra-tumor heterogeneity and variations in expert assessments [10], complicating the diagnostic process further. These characteristics pose significant challenges in the diagnosis and management of brain tumors.

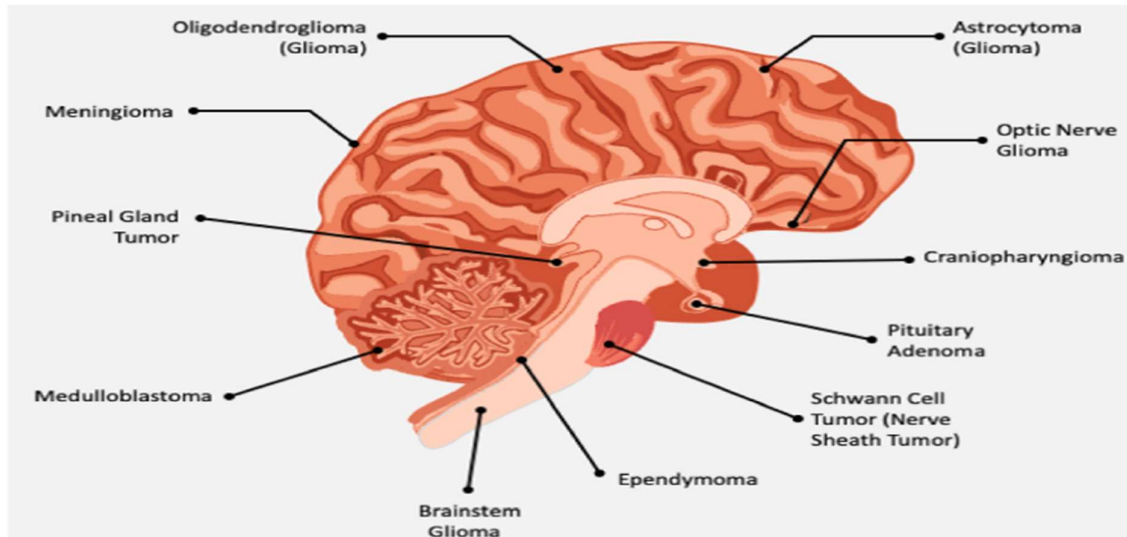


Fig. 1. Structure of Brain with various types of Brain Tumor

So, magnetic resonance imaging (MRI) plays a crucial role in this method, offering higher soft tissue contrast and multi-planar imaging capabilities. MRI allows accurate visualization of tumor location, size, and characteristics, aiding in surgical planning, radiation therapy, and treatment monitoring [11]. Moreover, MRI can distinguish between various tumor types based on their distinct imaging features, guiding treatment selection and predicting patient outcomes. Images obtained from MRI are employed to obtain comprehensive information about internal brain tissues. During the process of brain tumor investigation, detection of the tumor core location is the key task to determine the size and shape of the brain tumor [12].

However, despite MRI's capabilities, challenges persist in brain tumor detection. Tumors can display diverse morphological and textural characteristics, making it challenging to differentiate them from healthy brain tissue or other pathologies. Furthermore, small or subtle tumors may avoid detection on conventional MRI scans, leading to delayed diagnosis and potentially minor outcomes for patients. Therefore, there is a pressing need for more accurate and efficient methods for brain tumor detection using MRI [13] and [14].

Machine learning techniques offer promising opportunities to enhance the accuracy and efficiency of brain tumor detection in MRI scans [15]. By leveraging computational algorithms, machine learning can extract complex patterns and relationships from large volumes of imaging data, facilitating the automated explanation and detection of subtle abnormalities [16][17]. These techniques can be trained on annotated MRI datasets to identify characteristic features revealing brain tumors, such as shape, intensity, texture, and spatial location. Machine learning models can help with early detection and diagnosis by identifying regions of interest that may indicate the presence of a tumor through the analysis of these features [18] and [19].

Moreover, machine learning techniques can be integrated with a variety of imaging modalities, such as T1-weighted, T2-weighted, and contrast-enhanced MRI sequences. By compiling information from multiple imaging modalities, these models can improve diagnostic accuracy and provide more comprehensive insights into the morphology and biology of tumors [20–22]. Additionally, radiologists can read MRI images more

quickly by using machine learning-based techniques that rank suspicious regions for review. In the end, this can enhance patient outcomes by cutting down on diagnostic errors and interpreting times [23].

Overall, the integration of machine learning techniques into brain tumor detection workflows holds immense potential to revolutionize clinical practice by enhancing diagnostic accuracy, enabling early tumor detection, and ultimately improving patient care [24, 25].

The major contributions of this study are as follows:

- To extract the features from images, three feature extraction methods are implemented.
- To classify the brain tumor, six machine learning techniques (Support Vector Machines (SVM), Logistic Regression, k-Nearest Neighbors (KNN), Naive Bayes, Decision Trees, and Random Forests) are implemented.
- The comparison of implemented machine learning techniques is performed using accuracy, sensitivity, specificity, and precision.
- The impact of different feature extraction methods on different metrics was also studied.

The study is structured in such a manner that Section 2 provides related work and a problem statement, Section 3 outlines the proposed research methodology, Section 4 depicts the modeling, Section 5 shows experimental results and discussion, and Section 6 provides a conclusion to the research along with the future work that will be done.

2.Related Work

The research [26] suggested an approach that tries to distinguish between BT and normal brain tumors. Brain magnetic resonance imaging is used to research various forms of brain malignancies. Support vector machines and various wavelet transformations are used to identify and categorize MRI brain cancers. A hybrid K-means Galatic Swarm Optimization (GSO) technique was used in the study [27] as a workable solution to the image segmentation problem, which was regarded as a classification model. In order to extract brain tumors from 2D MRI, the study created a fuzzy C-means clustering technique that was subsequently used by CNN and conventional detectors. The authors of [28] presented a comprehensive assessment of the literature on current approaches to segmenting BT from brain MRI data. According to the study [29], an automated approach was offered to distinguish between malignant and non-cancerous brain MRI scans. Three benchmark datasets were used, and a support vector machine classifier was employed with different cross-validations to assess the accuracy of the proposed framework. The average results showed 97.1% accuracy, 0.98 area under the curve, 91.9% sensitivity, and 98.0% specificity. The study [30] proposed a two-step Dragonfly algorithm (DA) clustering method to precisely extract starting contour points. At the preprocessing stage, the brain was removed from the skull. Then, tumor edges were extracted using the two-step DA, and these extracted edges were utilized as a starting contour for the MRI sequence. To assess the system's performance, the study [31] used a variety of machine learning classifiers, such as Support Vector Machine (SVM), Gradient Boost, K Nearest Neighbor (KNN), XG Boost, and Logistic Regression. The results showed how different classifiers performed in terms of accuracy, with Extreme Gradient Boosting (XG Boost) coming out on top with an accuracy of 92.02%. The goal of the study [32] was to use a random forest classifier to extract texture and demographic features from MRI Apparent Diffusion Coefficient (ADC) images of human brain tumors in order to distinguish between malignant and benign tumors. Following hyperparameter tuning, the Random Forest Classifier achieved an accuracy score of 90.41% and an accuracy level of 85% for both benign and malignant tumor types. The F1, recall, and precision scores for malignant tumor prediction were 92.02%, 92.64%, and 92.33%, respectively. An intelligent classification method based on Support Vector Machines (SVM) was presented in this study [33] to differentiate between abnormal and normal MRI brain images. The study focuses on extracting features from MRI images and uses texture, symmetrical, and grayscale features to describe tumor patterns. Paper [34] proposed an MRI image classification system for distinguishing between malignant and benign brain tumors. It utilized image processing and Support Vector Machine (SVM) classification with various kernels. The system demonstrated robustness in accurately identifying tumor types. The linear kernel achieved maximum sensitivity, specificity, and accuracy at 80%, 90%, and 80%, respectively. In a study [35], researchers used discriminative properties taken from 3D patches to propose an automated classification approach that uses random forests to distinguish between WHO Grade III and Grade IV gliomas. The framework's efficacy in correctly classifying high-grade

gliomas was evaluated in a cohort of 96 patients with malignant brain tumors, including Grade III and Grade IV gliomas.

A technique for categorizing and segmenting brain tumors using multi-modal MRI data was presented in the study [36]. In order to preprocess the images, the researchers used the MICCAI BraTS 2013 dataset, which contains co-registered and skull-stripped MRI data. They did this by performing histogram matching on a high-contrast reference volume. With Dice overlap scores of 88% for the entire tumor region, 75% for the core tumor region, and 95% for the augmenting tumor region, the study showed better segmentation results than the MICCAI BraTS challenge.

The study [37] suggested a methodology that involves several key steps, including image acquisition, pre-processing, segmentation using threshold segmentation and the watershed algorithm, and feature extraction using techniques such as MSER, FAST, and Harlick features. The results of the study demonstrate that the proposed approach improves brain tumor detection compared to existing techniques, achieving an accuracy of more than 90%. A novel multiclass brain tumor classification method based on deep feature fusion was proposed in the paper [38]. SVM and KNN were used to predict the outcome after deep CNN features from transfer-learned architectures like AlexNet, GoogLeNet, and ResNet18 were fused to create a single feature vector. After 15,320 magnetic resonance images (MRIs) were used for training and evaluation, the framework outperformed other systems with a 99.7% accuracy rate. The paper [39] introduced a novel approach for differentiating MRI brain images using a hybrid naive-Bayes classifier. The proposed model included image pre-processing, feature extraction, and noise reduction to enhance classification accuracy. The paper [40] introduced a novel approach to predicting the development of brain tumors using MRIs, employing SVM in conjunction with ant colony optimization. The SVM-ACO classifier is used to enhance tumor segmentation in images, aiming for greater reliability and precision. The study [41] aimed to analyze and compare the performance of three main classification models: random forest classifiers, support vector machines, and artificial neural networks, in classifying multiclass brain tumors based on MRI images. The performance of the classification models was evaluated based on accuracy, precision, recall, and F1 score. The study [42] utilized 7022 MR images sourced from the Kaggle library, dividing them into 40% for testing and 60% for training. Various architectures like VGG, ResNet, DenseNet, and SqueezeNet were trained for feature extraction from brain MRI images. Initially, machine learning methods were applied to classify extracted features, followed by an ensemble learning approach where ResNet achieved 100% accuracy.

The study [43] focused on automatic brain abnormality detection using the logistic regression machine learning technique from MRI brain images collected for training and testing. Training utilized the ADNI-1 and ADNI-2 datasets. Disease classification was achieved through logistic regression and threshold segmentation, with performance measures including 97% accuracy, 97.9% precision, and 97% recall, surpassing existing models' capabilities. In the study [44], computational examination of MRI results was conducted using the K-Nearest Neighbor method. A tumor classification system was developed to identify tumors and edema in T1 and T2 image sequences and classify tumor types based solely on the axial section of MRI results. Tumor area detection employed basic image processing techniques such as image enhancement, binarization, morphological operations, and watershed segmentation, achieving an accuracy of 89.5 percent in tumor classification. The study [45] introduced a machine learning technique (MLT) to recognize and classify tumor and non-tumor regions based on brain MRI datasets. Initially, manual skull removal reduced time complexity, followed by median filtering to eliminate noise. The Chan-Vese (C-V) technique was then employed for tumor segmentation, selecting an accurate initial point. The paper [46] applied a multilevel thresholding algorithm for region of interest (ROI) delineation and extracted intensity and texture attributes from the ROI. It utilized a combined Fisher+ Parameter-Free BAT optimization approach for feature subset selection and introduced a novel learning approach, PFree BAT enhanced fuzzy K-nearest neighbor (FKNN), for MR image classification into high- and low-grade categories. Experimental results demonstrated the efficacy of the proposed system, achieving high accuracy in tumor-grade classification. The research [47] tackled the issue of absent values in the k-NN algorithm, particularly in 4D frequency analysis. Its objective was to enhance image precision and effectiveness by deploying a composite k-NN approach. The study aimed to differentiate cancer-damaged regions from non-tumor areas in 4D MRI images, introducing a new technique that amalgamated hybrid k-NN, Fast Fourier transform, and Laplace transform methods for early detection of brain tumors or cerebrospinal fluid (CSF) emergence. The investigation [48] initially utilized a range of classifiers, including logistic regression, random forest, decision tree, and Naïve Bayes, but their accuracy was deemed inadequate. To boost tumor prediction accuracy, a convolutional neural network (CNN) was selected, employing Keras and TensorFlow. CNN, a deep learning method for image classification, attained 90% accuracy, utilizing 20–30 networks to detect patterns in raw images without preprocessing. The investigation [49] advocated deploying multiple pre-trained CNNs on T1-weighted MR brain scans to extract features, which were then fed into a stacking algorithm to consolidate

predictions from base classifiers. Evaluation on two publicly available brain MRI datasets showcased superior lesion detection accuracy compared to alternative methods. Utilizing pre-trained CNNs facilitated transfer learning, drawing on previously acquired knowledge from a vast image database for tumor classification.

In the investigation [50], the proposed framework consisted of several stages, including preprocessing, feature extraction, classification, and segmentation. Initially, T1-weighted MRI brain images served as input, with a median filter optimized for skull stripping. Abnormal brain tissues were isolated, and the edges of the affected tissue were meticulously identified. Feature extraction utilized techniques such as the discrete wavelet transform (DWT) and the histogram of oriented gradients (HOG) for texture and shape extraction. Classification employed machine learning techniques such as random forest classifiers (RFC), support vector machines (SVM), and decision trees (DT), evaluating performance through parameters like sensitivity, specificity, and accuracy.

The paper [51] addressed the detection and segmentation of glioma brain tumors using a random forest classifier and feature optimization technique. Texture features were initially extracted from brain MRI images, then optimized through an ant colony optimization algorithm. The optimized feature set was subsequently used for training and classification, employing the random forest classification method. This approach effectively categorized brain MRI images into glioma or non-glioma groups based on the optimized features, achieving a sensitivity of 97.7%, a specificity of 96.5%, and an accuracy of 98.01%. In [52], the author integrated the traditional k-means algorithm with SGHO for segmentation. The SURF algorithm was applied to extract features from brain tumor images, while an SGHO-based method was utilized for feature selection. Lastly, an SVM classifier was employed for tumor image classification, achieving accuracy, precision, and recall values of 99.24%, 95.83%, and 95.30%, respectively. In the paper [53], brain tumor detection was proposed using modified particle swarm optimization (MPSO) segmentation with ensemble classification. Following this, Haralick features were utilized for feature extraction. A comparison was conducted between the SVM classifier with improved fuzzy segmentation and the proposed method, where the new model surpassed the previous one with an accuracy of 98.2 percent. This paper [54] utilized the identification and extraction of brain tumors from MRI scans based on MWT and image processing techniques. The MWT was applied in the preprocessing stage to enhance the input image and remove noise. Segmentation methods based on thresholding were employed, and statistical classification Methods were used to categorize brain MRI images as normal or abnormal. The paper [55] utilized MRI brain images to locate tumor regions using deep learning and optimization methods. The Convolutional Neural Network (CNN) algorithm was then employed to classify the segmented images. Experimental results revealed that, compared to alternative optimization algorithms, the CNN-MSO algorithm exhibited superior performance in accuracy, sensitivity, and specificity. The investigation [56] employed modified fuzzy C mean clustering (MFCM) and artificial neural networks (ANN) to segment and categorize brain tumor MR images. The proposed approach extracted shape, intensity, and texture features from the input image, which were optimally chosen using Hybrid Fruit Fly and Artificial Bee Colony (HFFABC). The classification performance exhibited sensitivity, specificity, and efficiency rates of 98.1%, 99.8%, and 99.59%, respectively.

The investigation [57] employed an innovative approach to categorize brain MRI images using segmentation and a KNN classifier. Initially, brain MRI images from databases underwent preprocessing with a Gaussian filter, followed by normalization. Subsequently, the normalized images were segmented using the texture and intensity-oriented region-growing technique (TIORGW). Texture features were then extracted from the segmented images. Later, the Genetic Algorithm (GA) was utilized to select optimal texture features, and these features were inputted into KNN to categorize whether the brain MRI image was normal. The proposed technique was implemented in MATLAB, and its performance was analyzed using a larger number of brain MRI images.

2.1 Problem Statement

Brain tumors had the ability to stimulate repercussions such as physical limitations, compelling patients to undergo rigorous therapy, often supplemented by considerable discomfort, to alleviate or mitigate resultant disabilities. Also, the antagonistic effects on brain function varied depending on tumor dimensions, location, and type. Pressure from tumors on regions governing bodily movement could result in immobility for patients. Earlier diagnosis had the potential to forestall the onset of disability. However, challenges existed in accurately classifying brain tumors due to their diverse sizes, shapes, and intensities, alongside similarities in outward appearance among various pathological types.

3. Proposed Methodology

This section offers a comprehensive discussion on the detection of MRI brain tumors using various ML approaches. The progression of the proposed method is illustrated in Fig. 2. Initially, MRI brain tumor data are acquired and undergo pre-processing. Following this, features are extracted using three different methods, and all the extracted features are stored in a NumPy array. The data is then split into training and testing sets using the `train_test_split` method from the sklearn library. Various ML techniques, including Support Vector Machines (SVM), Logistic Regression, k-Nearest Neighbors (KNN), Naive Bayes, Decision Trees, and Random Forests, are employed to classify images into tumor and non-tumor categories.

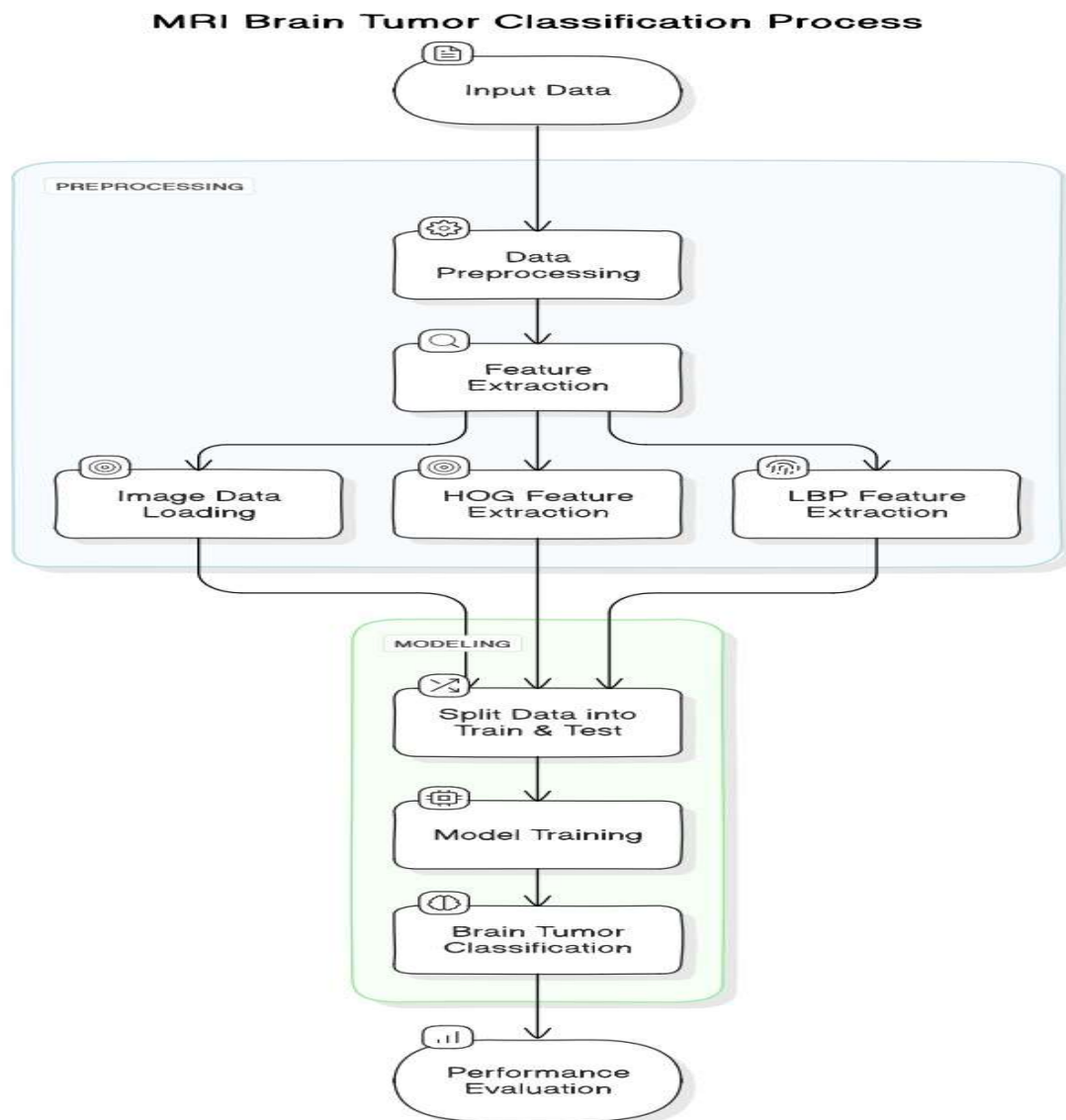
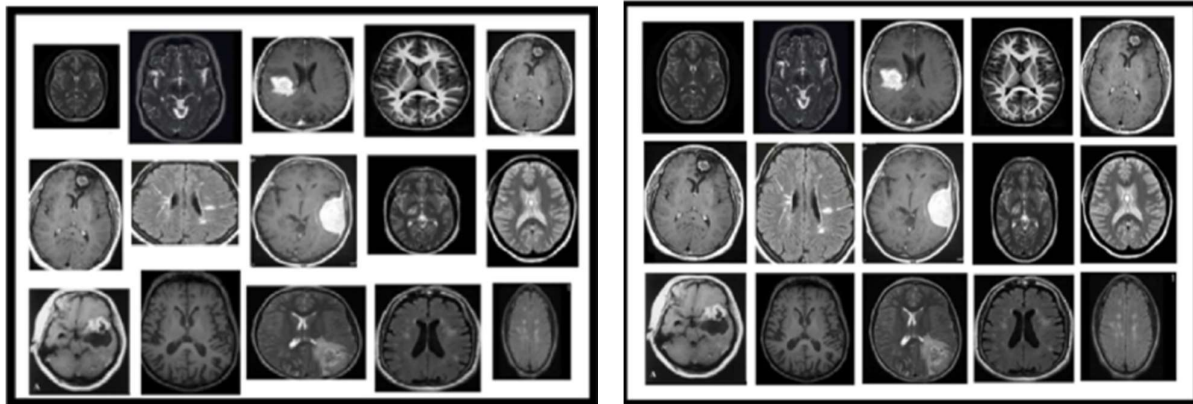


Figure 2: Workflow of Research work.

3.1 Dataset Collection

We have utilized a dataset that may be found on the Kaggle open data website in order to evaluate the performance of the suggested architectural design. This Dataset comprises of 2328 brain MRI images of

patients with tumors and 1595 images with no tumors. Thus, a total of 3923 images are present. Because each of these images had a unique dimension, we needed to adjust it so that it would fit inside the parameters of our image requirements. A portion of the dataset that we used for our investigation is shown in Fig. 2(A). It depicts that the width and height of the images vary from one another. When looking at MRI brain scans with various heights and widths, it might be difficult to appropriately classify healthy brain tissue and tumorous brain tissue. As a consequence of this, we resize the images using `cv2.resize()` into 200*200. The scaled versions of the images from the dataset are shown in Fig. 2(B)



(A) (B)
Figure 2. Sample dataset images of (A) varying size (B) same size.

3.2 Data Pre-processing

Data pre-processing is super important in machine learning because it helps make sure that the input data is ready for the models to work their magic. Preprocessing is a very important stage in the medical field. Normally, noise enhancement or reduction in images occurs during preprocessing. Medical noise significantly reduces image quality, making them diagnostically inefficient. One key part of this is scaling the features so they're all on the same playing field. This procedure is carried out using a variety of approaches, including cropping, image scaling, histogram equalization, filtering using a median filter, and image adjusting. We have used StandardScaler for this job. It takes care of making sure all the features are standardized, so no one feature overpowers the others. This helps prevent problems related to overfitting [58].

Data labelling

The images of brain tumor have been labeled as 1 and the images with no brain tumor as 0.

Image pre-processing. The images have been read in the gray scale (2D). To build a classifier using ML algorithms all the images have been converted into the same dimension. So, each image has been resized into 200*200 pixels.

3.3 Feature extraction

The process of converting images into features based on several image characteristics in the medical field is known as feature extraction. These features carry the same information as the original images but are entirely different. This technique has the advantages of enhancing classifier accuracy, decreasing overfitting risk, allowing users to analyse data, and speeding up training. Feature extraction is a fundamental process in machine learning where we transform raw data (Images, text, numerical etc.) into a set of meaningful features that are more suitable for modelling. The primary objective of feature extraction is to convert raw data, which may be high-dimensional or unstructured, into a structured and compact representation that captures essential patterns and relationships. By extracting relevant features, researchers can enhance model performance, reduce computational complexity, and improve interpretability [59]. In this paper we have implemented three methods for feature extraction from images

3.3.1 Image Data Loading and Pre-processing

In this method OpenCV library (cv2) is used load and pre-process images for subsequent model training. For each image encountered in the directory, it employs the cv2.imread() function to load the image in grayscale mode (0) and subsequently resizes it to a standardized dimension of 200x200 pixels using cv2.resize(). These pre-processing steps ensure uniformity and consistency in the image data, facilitating seamless integration into the machine learning pipeline. The resized images are then appended to a feature array (X), while the corresponding class labels are appended to a target array (Y). Here each element represents an image represented as a 2D NumPy array form[60].

3.3.2 HOG Feature extraction

Histogram of Oriented Gradients (HOG) can identify the local structure and shape of an image. It functions by measuring the gradient orientation distribution in specific areas of the picture. HOG feature extraction entails several key steps: first, the computation of image gradients to capture edge and texture information; then, the division of the image into small, overlapping cells, followed by the quantization of gradient orientations into predefined bins within each cell. Subsequently, histograms of gradient orientations are constructed for each cell, and normalization techniques are applied to enhance the descriptor's robustness to illumination and contrast variations. Finally, the histogram values from all cells are concatenated to form the HOG feature descriptor for the entire image[61][62].

3.3.3 LBP Feature extraction

One effective method for examining texture patterns in photos is to extract features using Local Binary Patterns (LBP) analysis. This approach is useful for many different applications because it provides a reliable way to describe local texture variations. LBP feature extraction operates by comparing each pixel in the image with its surrounding neighbourhood, generating binary patterns that encode local texture information. These binary patterns are then used to construct a histogram, capturing the frequency of occurrence of different texture patterns within the image. The resulting histogram serves as the LBP feature vector, representing the distribution of texture patterns[63][64]. After extracting the feature through above methods, all the extracted data is stored in two NumPy array X and Y.

4. Modelling

4.1 Data Splitting: Partitioning the Dataset for Model training and test

Dividing the dataset into training and testing subsets is a crucial step for the model evaluation. The machine learning model is trained on observed patterns and relationships within the data using the training set, which typically consists of the majority of the data. The testing set, which is a smaller portion of the data, is kept secret during the training phase to serve as a separate benchmark for assessing the performance of the model[65]. For training and testing purposes, we have split the dataset in this study into two groups: 80% and 20%.

4.2 Training Models

Brain tumor classification requires model training, and the right machine learning algorithms are chosen with great care to maximize diagnostic accuracy and clinical decision-making. In this research, we present a comparative analysis of several popular algorithms for brain tumor classification tasks, including Support Vector Machines (SVM)[52], Logistic Regression[43], k-Nearest Neighbors (KNN)[44], Naive Bayes[39], Decision Trees[54], and Random Forests [50].

4.3 Brain Tumor Classification

Brain tumor classification is a crucial process in medical imaging analysis, helping clinicians in correctly diagnosis, treatment planning, and patient management. Through the application of machine learning techniques and sophisticated imaging modalities, scientists have achieved notable advancements in automating and enhancing the precision of brain tumor classification procedures. In this study, we classified images as having tumors or not using Support Vector Machines (SVM), Logistic Regression, k-Nearest Neighbors (KNN), Naive Bayes, Decision Trees, and Random Forests.

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this part, we will explore the classification of brain tumors by MRI utilizing machine learning techniques. Here we used the Python 3.10.12 version for implementation in google colab. The four basic matrices that are used in performance prediction are referred to as “True Positive (tp)”, “True Negative (tn)”, “False Positive (fp)”, and “False Negative (fn).” These measures are calculated by applying the model to a dataset of 3923 MRIs and counting the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). In this context, cases are said to be true positives if the tumour can be accurately anticipated. Instances that may have been fairly anticipated to be negative, known as true negatives, are examined. Instances of cases that were meant to be successfully predicted but turned out to be inaccurate are examples of false positives. False negatives are situations that are meant to be mistakenly detected but are, in reality, it is properly predicted one. Following equations are used to determine each model’s accuracy, precision, sensitivity, specificity, and elapsed time in order to evaluate their overall performance:

$$\text{Accuracy:} (TP+TN)/(TP+TN+FN+FP) \dots\dots\dots (I)$$

$$\text{Sensitivity:} (TP/(TP+FN)) \dots\dots\dots (II)$$

$$\text{Specificity:} (TN/(TN+FP)) \dots\dots\dots (III)$$

$$\text{Precision:} (TP/(TP+FP)) \dots\dots\dots (IV)$$

$$\text{Elapsed Time: end_time - start_time} \dots\dots\dots (V)$$

The attributes for determining the performance metrics for each of the 6 ML algorithms has been demonstrated in Table I

	Image Data Loading				Hog Feature Extraction				LBP Feature Extraction			
ML Algorithm	TP	TN	FP	FN	TP	TN	FP	FN	TP	TN	FP	FN
SVM	319	18	3	445	331	6	0	448	333	4	2	446
LR	319	18	3	445	331	6	0	448	333	4	2	446
KNN	320	17	9	439	324	12	1	447	337	0	430	18
NB	330	7	2	450	276	61	72	376	255	82	113	335
DT	306	31	10	438	295	42	37	411	303	34	27	421
RF	333	4	1	447	319	18	0	448	325	12	2	446

5.1 Accuracy

The percentage of healthy and tumorous brain tissue that can be accurately predicted is determined by comparing the total number of MRI brain images to the total number of images. This is how accuracy is measured. In this study, we used three different feature extraction methods—image loading, Histogram of Oriented Gradients (HOG) feature extraction, and Local Binary Patterns (LBP) feature extraction—to assess how well different machine learning algorithms performed on tasks related to brain tumor classification. The Accuracy Chart below provides an overview of the accuracy scores attained for every combination of algorithm and feature extraction technique:

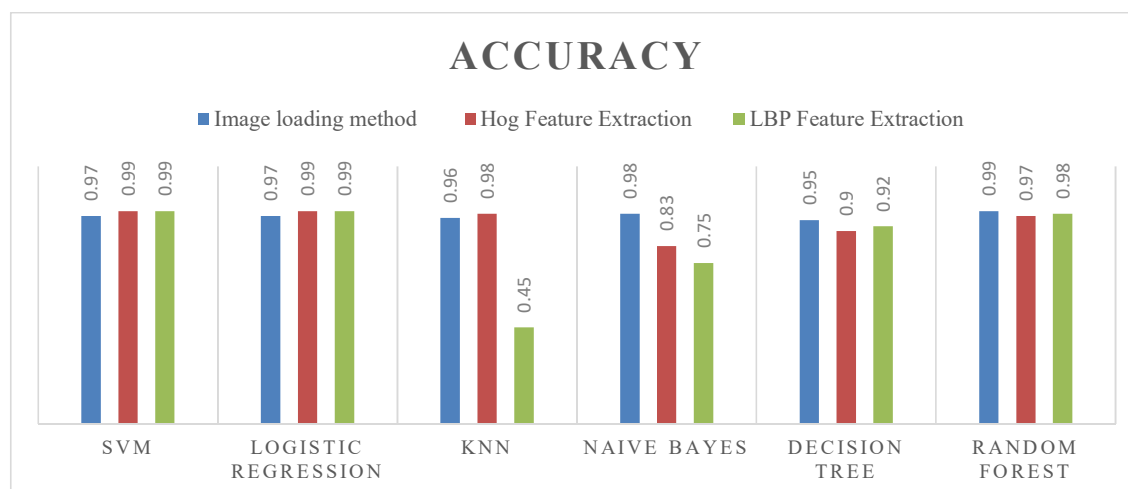


Fig. 3. Comparative analysis of ML Techniques on the basis of Accuracy

Key observation

- With accuracy scores ranging from 0.97 to 0.99, SVM (Support Vector Machine) and Logistic Regression consistently achieve high accuracy across all feature extraction methods. This suggests that regardless of the feature representation employed, both algorithms are reliable and efficient in correctly classifying the brain tumor.
- KNN (K-Nearest Neighbors) achieves accuracies of 0.96 and 0.98, respectively, and shows good performance with the Image loading method and HOG Feature Extraction. However, if LBP Feature Extraction is used, its performance drastically drops to 0.45. This implies that KNN might have trouble using LBP features for classification in an efficient manner.
- When using the Image loading method, Naive Bayes achieves high accuracy (0.98); however, when using the HOG (0.83) and LBP (0.75) Feature Extraction methods, accuracy noticeably decreases. This suggests that when utilizing these feature extraction techniques, Naive Bayes might not be as successful in identifying the underlying patterns in the data.
- Decision Tree achieves slightly lower accuracy with LBP Feature Extraction (0.92) but performs reasonably well with the Image loading method (0.95) and HOG Feature Extraction (0.9). Decision Tree exhibits consistent performance across various feature extraction techniques, notwithstanding this minor decline.
- Among all feature extraction techniques, Random Forest consistently achieves the highest accuracy scores: 0.99 for Image loading, 0.97 for HOG feature extraction, and 0.98 for LBP feature extraction. Random Forest is clearly the best performer. This suggests that, independent of the feature representation employed, Random Forest is very successful at accurately classifying data.

5.2 Sensitivity

The probability of a positive test under the presumption that it is positive is referred to as "sensitivity." This is also known as the "true positive rate." In this work, we examined the sensitivity scores of several machine learning algorithms applied to tasks related to brain tumor classification using three distinct feature extraction techniques: local binary patterns (LBP), Histogram of Oriented Gradients (HOG) feature extraction, and image loading method. Recall, another name for sensitivity, is the measurement of the percentage of real positive cases that the model correctly identified out of all true positive cases. The sensitivity chart below provides an overview of the scores obtained for each combination of algorithm and feature extraction method:

Key Observations

- With sensitivity scores of 0.99 or 1, SVM (Support Vector Machine) and Logistic Regression consistently show outstanding sensitivity across all feature extraction techniques. According to this,

both algorithms—regardless of the feature representation—are very good at accurately identifying positive instances.

- KNN (K-Nearest Neighbors) shows good sensitivity when using HOG Feature Extraction (0.99) and the Image loading method (0.97). Its sensitivity drops to 0.43 with LBP Feature Extraction, though, a considerable reduction. This implies that KNN might have trouble using LBP features to identify positive instances.
- When using the Image loading method, Naive Bayes achieves high sensitivity (0.99); however, when using the HOG (0.79) and LBP (0.69) Feature Extraction methods, sensitivity noticeably decreases. This suggests that when utilizing these feature extraction techniques, Naive Bayes might not be as successful in identifying the positive instances in the data.
- Decision Tree achieves slightly lower sensitivity with LBP Feature Extraction (0.918) but performs reasonably well with the Image loading method (0.97) and HOG Feature Extraction (0.88). Decision Tree exhibits consistent performance across various feature extraction techniques, notwithstanding this minor decline.
- With all feature extraction techniques, Random Forest consistently achieves the highest sensitivity scores: 0.99 for Image loading, 1 for HOG feature extraction, and 0.99 for LBP feature extraction. Random Forest is clearly the best performer. This suggests that Random Forest, irrespective of the feature representation employed, is very good at accurately identifying positive instances.

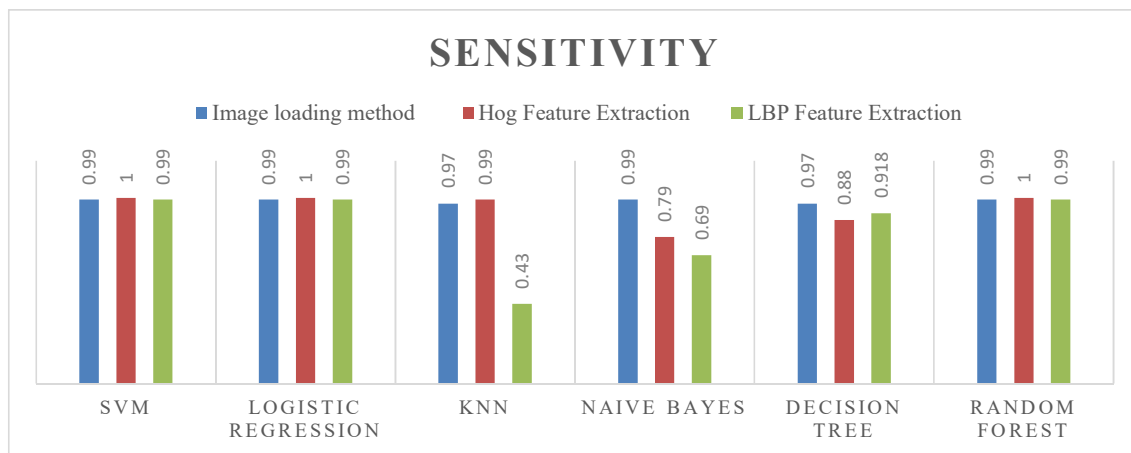


Fig.4. Comparative analysis of ML Techniques on the basis of sensitivity

5.3 Specificity

Specificity, also known as the true negative rate, is the possibility of a negative test result under the supposition that the result is in fact negative. We examined at the specificity scores of several machine learning algorithms across a range of feature extraction techniques in our analysis of the performance of brain tumor classification, including the image loading method, Histogram of Oriented Gradients (HOG) feature extraction, and Local Binary Patterns (LBP) feature extraction. Out of all actual negative cases, specificity quantifies the percentage of true negative cases that the model correctly identified. The specificity chart below provides an overview of the specificity scores for each combination of algorithm and feature extraction technique.

Key Observations

- With specificity scores ranging from 0.96 to 0.99, SVM (Support Vector Machine) and Logistic Regression consistently show high specificity across all feature extraction techniques. This suggests that, irrespective of the feature representation employed, both algorithms are very good at accurately identifying negative cases.
- KNN (K-Nearest Neighbors) shows good specificity when using HOG Feature Extraction (0.97) and the Image loading method (0.96). However, when LBP Feature Extraction is used, its specificity rises to 1. This implies that when using LBP features, KNN might be especially useful for accurately identifying negative instances. When using the Image loading method, Naive Bayes achieves high specificity (0.98); however, when using the HOG (0.86) and LBP (0.8) Feature Extraction methods,

specificity slightly decreases. This suggests that when utilizing these feature extraction techniques, Naive Bayes might not be as successful as the Image loading method in accurately identifying negative instances.

- With the Image loading method (0.93) and HOG Feature Extraction (0.9), Decision Tree performs reasonably well; however, with LBP Feature Extraction (0.92), it achieves slightly lower specificity. Decision Tree exhibits consistent performance across various feature extraction techniques, notwithstanding this minor decline.
- Among all feature extraction techniques, Random Forest is the best performer, consistently attaining high specificity scores of 0.99 with Image loading method, 0.97 with HOG feature extraction, and 0.97 with LBP feature extraction. This suggests that, independent of the feature representation employed, Random Forest is very good at accurately identifying negative instances.

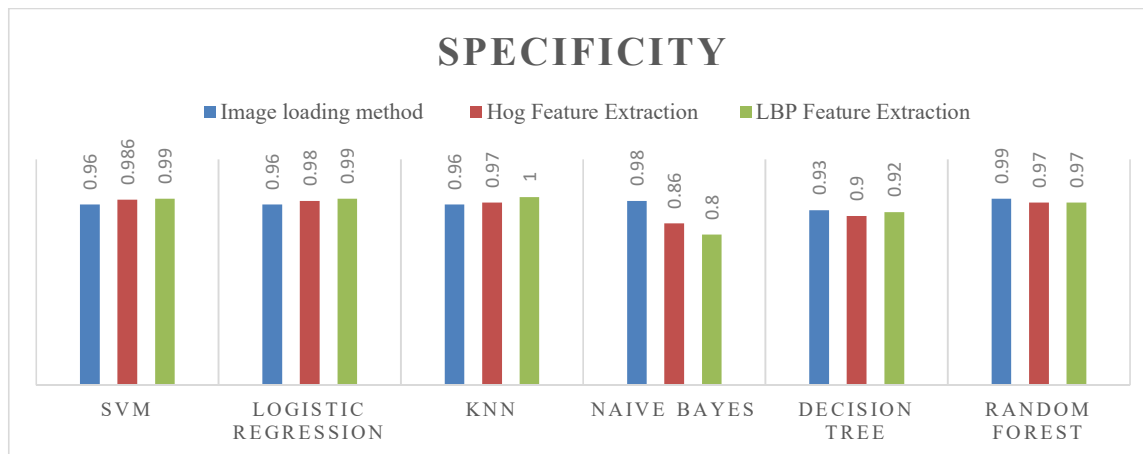


Fig.5. Comparative analysis of ML Techniques on the basis of Specificity

5.4 Precision

In our analysis of brain tumor classification performance, we examined the precision scores of various machine learning algorithms across different feature extraction methods: Image loading method, Histogram of Oriented Gradients (HOG) feature extraction, and Local Binary Patterns (LBP) feature extraction. Precision measures the proportion of true positive cases correctly identified by the model out of all cases predicted as positive.

Key Observations:

- With precision scores ranging from 0.94 to 0.988, SVM (Support Vector Machine) and Logistic Regression consistently demonstrate high precision across all feature extraction techniques. This suggests that, regardless of the feature representation employed, both algorithms are very good at correctly identifying positive instances while minimizing false positives.
- KNN (K-Nearest Neighbors) shows good precision when using HOG Feature Extraction (0.96) and the Image loading method (0.95). However, when LBP Feature Extraction is used, its precision rises to 1. This implies that when using LBP features, KNN might be especially useful in reducing false positives. With the Image loading method, Naive Bayes achieves high precision (0.97), but when using the HOG (0.81) and LBP (0.75) Feature Extraction methods, its precision noticeably decreases. This suggests that when employing these feature extraction techniques, Naive Bayes might not be as successful in reducing false positives as the Image loading method.
- When using the Image loading method (0.91) and HOG feature extraction (0.88), Decision Tree performs reasonably well; however, when using LBP feature extraction (0.899), it achieves slightly lower precision. Decision Tree exhibits consistent performance across various feature extraction techniques, notwithstanding this minor decline.
- Random Forest is the best performer among all feature extraction methods with high precision score of 0.99 with the image loading method, 0.94 with HOG feature extraction and 0.96 with LBP feature extraction. This suggests that, irrespective of the feature representation employed, Random Forest is

very good at correctly identifying positive instances while minimizing false positives.

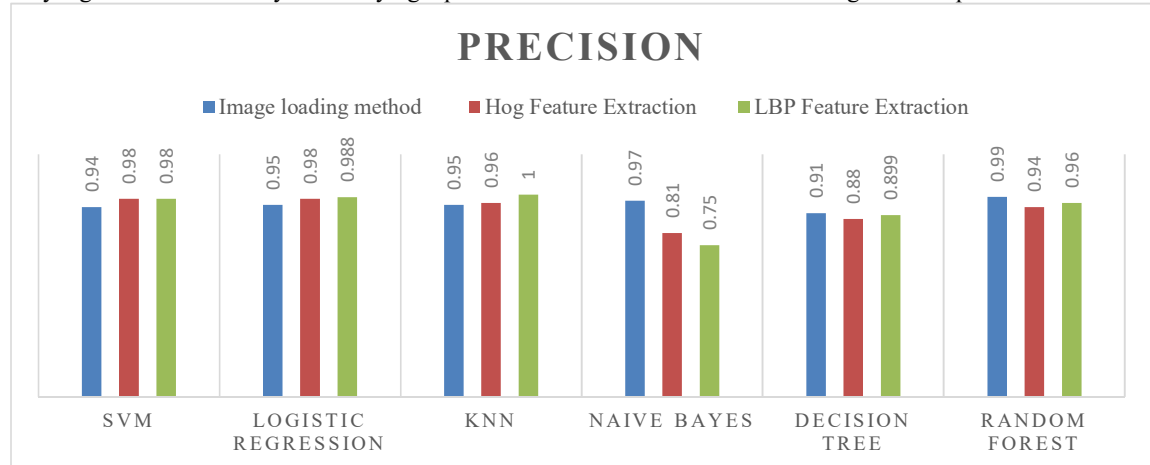


Fig.6. Comparative analysis of ML Techniques on the basis of Precision

5.5 Elapsed Time

The elapsed time table represents the time taken by different machine learning algorithms for processing data using three different feature extraction methods: Image loading, HOG (Histogram of Oriented Gradients) Feature Extraction, and LBP (Local Binary Patterns) Feature Extraction. The values are presented in seconds.

- The duration required for the SVM classifier differs greatly depending on the feature extraction technique, with LBP feature extraction taking the longest (1021.28 seconds), followed by HOG feature extraction (166.97 seconds) and image loading method (320.9 seconds).
- The elapsed time for each feature extraction method varies when using Logistic Regression; the Image loading method takes the longest (666.74 seconds), followed by HOG Feature Extraction (186.93 seconds) and LBP Feature Extraction (251.85 seconds).
- For all feature extraction techniques, CNN shows incredibly short elapsed times; for example, the image loading method (0.09 seconds), HOG feature extraction (0.05 seconds), and LBP feature extraction (0.09 seconds) all show negligible values.
- When it comes to image loading method, HOG feature extraction, and LBP feature extraction, Naive Bayes exhibits slightly longer elapsed times (1.69 seconds, 1.38 seconds, and 1.67 seconds, respectively) than KNN.
- The elapsed times for the Random Forest and Decision Tree algorithms are relatively moderate when compared to SVM and Logistic Regression. For example, Random Forest takes 85.03 seconds to extract features from load images method, 136.55 seconds to extract HOG features, and 62.5 seconds to extract LBP features. Decision Tree takes 33.93 seconds to load images, 44 seconds to extract HOG features, and 24.9 seconds to extract LBP features.

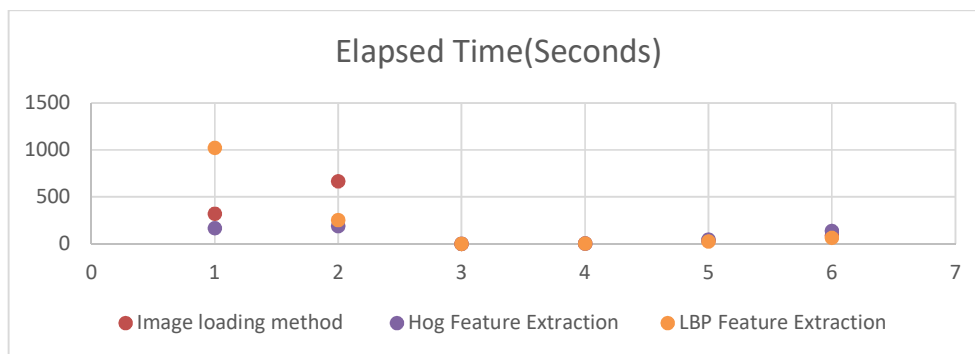


Fig.7. Comparative analysis of ML Techniques on the basis of Elapsed Time

6.Conclusion:

In summary, the analysis evaluated the performance of machine learning algorithms in classifying brain tumors using different feature extraction methods: Image loading, HOG, and LBP.

Overall, Random Forest consistently outperformed other algorithms across all feature extraction methods, demonstrating high accuracy, sensitivity, specificity, and precision. SVM and Logistic Regression also showed strong performance, while KNN exhibited some variability in its effectiveness depending on the feature extraction method. Naive Bayes demonstrated decent performance with simple features but struggled with more complex ones, and Decision Tree performed reasonably well but showed slight variations in performance metrics. The choice of feature extraction method significantly influenced algorithm performance, highlighting the importance of selecting appropriate methods tailored to the dataset characteristics and algorithm requirements. Further optimization and experimentation are crucial for improving algorithm performance in real-world applications of brain tumor classification.

In the future, we will investigate better ways to understand brain tumor images by improving the features extraction method. We could also try techniques to generate more diverse data and optimize our models for better performance. By combining predictions from multiple models and integrating medical expertise into our methods, we can make our classification systems more accurate and easier to understand for doctors. This could lead to better diagnoses and treatments for patients with brain tumors.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not for profit sectors.

Ethical compliance

No

Declaration of competing interest

All authors declare that there is no conflict of interest in this work.

Data availability

Data can be shared as and when required by contacting the author.

Acknowledgments

The authors would like to acknowledge Dr. Jit Sarkar, Computational Biologist, King's College, London for his guidance in conceptualisation and in writing the review paper. Additionally, author is thankful to the anonymous reviewers for their constructive comments and apologize to those researchers whom work is overlooked in this research

References

[1] Al-Galal, S.A.Y.; Alshaikhli, I.F.T.; Abdulrazzaq, M.M. MRI brain tumor medical images analysis using deep learning techniques:A systematic review. *Health Technol.* 2021, *11*, 267–282.

[2] <https://www.cancer.net/cancer-types/brain-tumor/statistics>

- [3] Louis, D.N.; Perry, A.; Wesseling, P.; Brat, D.J.; Cree, I.A.; Figarella-Branger, D.; Hawkins, C.; Ng, H.K.; Pfister, S.M.; Reifenberger, G. The 2021 WHO classification of tumors of the central nervous system: A summary. *Neuro-Oncology* 2021, **23**, 1231–1251.
- [4] Nodirov, J.; Abdusalomov, A.B.; Whangbo, T.K. Attention 3D U-Net with Multiple Skip Connections for Segmentation of Brain Tumor Images. *Sensors* 2022, **22**, 6501.
- [5] Shafi, A.S.M.; Rahman, M.B.; Anwar, T.; Halder, R.S.; Kays, H.E. Classification of brain tumors and autoimmune disease using ensemble learning. *Inform. Med. Unlocked* 2021, **24**, 100608.
- [6] Pereira, S.; Pinto, A.; Alves, V.; Silva, C.A. Brain tumor segmentation using convolutional neural networks in MRI images. *IEEE Trans. Med. Imaging* 2016, **35**, 1240–1251.
- [7] Ahuja, S.; Panigrahi, B.K.; Gandhi, T.K. Enhanced performance of Dark-Nets for brain tumor classification and segmentation using colormap-based superpixel techniques. *Mach. Learn Appl.* 2022, **7**, 100212.
- [8] Pereira, S.; Meier, R.; Alves, V.; Reyes, M.; Silva, C.A. Automatic Brain Tumor Grading from MRI Data Using Convolutional Neural Networks and Quality Assessment. In *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*; Springer: Cham, Switzerland, 2018; Volume 11038, pp. 106–114.
- [9] Tandel, G.S.; Tiwari, A.; Kakde, O.G. Performance optimisation of deep learning models using majority voting algorithm for brain tumour classification. *Comput. Biol. Med.* 2021, **135**, 104564.
- [10] Komaki, K.; Sano, N.; Tangoku, A. Problems in histological grading of malignancy and its clinical significance in patients with operable breast cancer. *Breast Cancer* 2006, **13**, 249–253.
- [11] Alejandro F. Frangi, Sotirios A. Tsafaris and Jerry L. Prince, Simulation and Synthesis in Medical Imaging, *IEEE Transactions on Medical Imaging*, vol.37, issue.3, pp. 673 – 679, 2018.
- [12] P.B. Kanade, and P. Gumaste, Brain tumor detection using MRI images. vol. Vol. 3. Brain, 2015.
- [13] Amin, J.; Sharif, M.; Haldorai, A.; Yasmin, M.; Nayak, R.S. Brain tumor detection and classification using machine learning: A comprehensive survey. *Complex Intell. Syst.* 2021, **8**, 3161–3183.
- [14] Abdel Razek, A.A.K.; Alksas, A.; Shehata, M.; AbdelKhalek, A.; Abdel Baky, K.; El-Baz, A.; Helmy, E. Clinical Applications of Artificial Intelligence and Radiomics in Neuro-Oncology Imaging. *Insights Imaging* 2021, **12**, 152.
- [15] Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. *Radiology*. 2016 Feb;278(2):563-77. doi: 10.1148/radiol.2015151169.
- [16] Saad NM, Bakar SARSA, Muda AS, Mokji MM (2015) Review of brain lesion detection and classification using neuroimaging analysis techniques. *J Teknol* 74:1–13
- [17] Huang M, Yang W, Wu Y, Jiang J, Chen W, Feng Q (2014) Brain tumor segmentation based on local independent projection-based classification. *IEEE Trans Biomed Eng* 61:2633–2645
- [18] Khan MA, Arshad H, Nisar W, Javed MY, Sharif M (2021) An integrated design of Fuzzy C-means and NCA-based multiproperties feature reduction for brain tumor recognition. *Signal and image processing techniques for the development of intelligent healthcare systems*. Springer, New York, pp 1–28
- [19] Tandel GS, Biswas M, Kakde OG, Tiwari A, Suri HS, Turk M et al (2019) a review on a deep learning perspective in brain cancer classification. *Cancers* 11:1–32
- [20] El-Dahshan E-SA, Mohsen HM, Revett K, Salem A-BM (2014) Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. *Expert Syst Appl* 41:5526–5545
- [21] Gordillo N, Montseny E, Sobrevilla P (2013) State of the art survey on MRI brain tumor segmentation. *Magn Reson Imaging* 31:1426–1438

- [22] Mohan G, Subashini MM (2018) MRI based medical image analysis: Survey on brain tumor grade classification. *Biomed Signal Process Control* 39:139–161
- [23] Amreen Batool, Yung-Cheol Byun, Brain tumor detection with integrating traditional and computational intelligence approaches across diverse imaging modalities - Challenges and future directions, *Computers in Biology and Medicine*, Volume 175, 2024, 108412, ISSN 0010-4825, <https://doi.org/10.1016/j.compbiomed.2024.108412>.
- [24] Stijn Bonte, Ingeborg Goethals, Roel Van Holen, Machine learning based brain tumour segmentation on limited data using local texture and abnormality, *Computers in Biology and Medicine*, Volume 98, 2018, Pages 39–47, ISSN 0010-4825, <https://doi.org/10.1016/j.compbiomed.2018.05.005>.
- [25] Fusun Citak-Er, Zeynep Firat, İlhami Kovanlıkaya, Ugur Ture, Esin Ozturk-Isik, Machine-learning in grading of gliomas based on multi-parametric magnetic resonance imaging at 3T, *Computers in Biology and Medicine*, Volume 99, 2018, Pages 154–160, ISSN 0010-4825, <https://doi.org/10.1016/j.compbiomed.2018.06.009>
- [26] C. Sheela, G. Suganthi, Brain tumor segmentation with radius contraction and expansion based initial contour detection for active contour model, *Multimed. Tool. Appl.* 79 (33) (2020) 23793–23819
- [27] S.J. Nanda, I. Gulati, R. Chauhan, R. Modi, U. Dhaked, A K-means-galactic swarm optimization-based clustering algorithm with Otsu's entropy for brain tumor detection, *Appl. Artif. Intell.* 33 (2) (2019) 152–170
- [28] A. Wadhwa, A. Bhardwaj, V.S. Verma, A review on brain tumor segmentation of MRI images, *Magn. Reson. Imag.* 61 (2019) 247–259
- [29] J. Amin, M. Sharif, M. Yasmin, S.L. Fernandes, A distinctive approach in brain tumor detection and classification using MRI, *Pattern Recogn. Lett.* 139 (2020) 118–127.
- [30] H.A. Khalil, S. Darwish, Y.M. Ibrahim, O.F. Hassan, 3D-MRI brain tumor detection model using modified version of level set segmentation based on dragonfly algorithm, *Symmetry* 12 (8) (2020) 1256.
- [31] S. Shilaskar, T. Mahajan, S. Bhatlawande, S. Chaudhari, R. Mahajan and K. Junnare, "Machine Learning based Brain Tumor Detection and Classification using HOG Feature Descriptor," *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, Coimbatore, India, 2023, pp. 67-75, doi: 10.1109/ICSCSS57650.2023.10169700.
- [32] Vijithananda, S. M., Jayatilake, M. L., Hewavithana, B., Gonçalves, T., Rato, L. M., Weerakoon, B. S., Kalupahana, T. D., Silva, A. D., & Dissanayake, K. D. (2022). Feature extraction from MRI ADC images for brain tumor classification using machine learning techniques. <https://doi.org/10.21203/rs.3.rs-1186157/v2>
- [33] Nandpuru, H.B., Salankar, S.S. and Bora, V.R., 2014, March. MRI brain cancer classification using support vector machine. In 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science (pp. 1-6). IEEE.
- [34] Giraddi, S. and Vaishnavi, S.V., 2017, September. Detection of brain tumor using image classification. In 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC) (pp. 640-644). IEEE.
- [35] Zhang, L., Zhang, H., Rekik, I., Gao, Y., Wang, Q. and Shen, D., 2018. Malignant brain tumor classification using the random forest method. In *Structural, Syntactic, and Statistical Pattern Recognition: Joint IAPR International Workshop, S+ SSPR 2018, Beijing, China, August 17–19, 2018, Proceedings 9* (pp. 14-21). Springer International Publishing.
- [36] Usman, K. and Rajpoot, K., 2017. Brain tumor classification from multi-modality MRI using wavelets and machine learning. *Pattern Analysis and Applications*, 20, pp.871-881.
- [38] Habib, H., Amin, R., Ahmed, B. and Hannan, A., 2022. Hybrid algorithms for brain tumor segmentation, classification and feature extraction. *Journal of Ambient Intelligence and Humanized Computing*, pp.1-22.
- [39] Nayak, M.M. and Kengeri Anjanappa, S.D., 2023. An Efficient Hybrid Classifier for MRI Brain Images Classification Using Machine Learning Based Naive Bayes Algorithm. *SN Computer Science*, 4(3), p.223.)
- [40] Warjurkar, S. V. ., & Ridhorkar, S. . (2024). Maximizing Precision in Early Prognosis using SVM-ACO Classifier and Hybrid Optimization Techniques in MRI Brain Tumor Segmentation with Integration of Multi-Modal Imaging Data. *International Journal of Intelligent Systems and Applications in Engineering*, 12(10s), 389–401. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/4388>

- [41] Amaliah Faradibah, Dewi Widyawati, A Ulfah Tenripada Syahar, & Sitti Rahmah Jabir. (2023). Comparison analysis of random forest classifier, support vector machine, and artificial neural network performance in Multiclass brain tumor classification. *Indonesian Journal of Data and Science*, 4(2), 54-63. <https://doi.org/10.56705/ijodas.v4i2.73>
- [42] Güler, M., & Namlı, E. (2024). Brain tumor detection with deep learning methods' classifier optimization using medical images. *Applied Sciences*, 14(2), 642. <https://doi.org/10.3390/app14020642>
- [43] Gajula, S., Rajesh, V. An MRI brain tumour detection using logistic regression-based machine learning model. *Int J Syst Assur Eng Manag* **15**, 124–134 (2024). <https://doi.org/10.1007/s13198-022-01680-8>
- [44] R. H. Ramdlon, E. Martiana Kusumaningtyas and T. Karlita, "Brain Tumor Classification Using MRI Images with K-Nearest Neighbor Method," *2019 International Electronics Symposium (IES)*, Surabaya, Indonesia, 2019, pp. 660-667, doi: 10.1109/ELECSYM.2019.8901560.
- [45] Budati, A. K., & Katta, R. B. (2021). An automated brain tumor detection and classification from MRI images using machine learning techniques with IoT. *Environment, Development and Sustainability*, 24(9), 10570-10584. <https://doi.org/10.1007/s10668-021-01861-8>
- [46] Kaur, T., Saini, B.S. & Gupta, S. An adaptive fuzzy K-nearest neighbor approach for MR brain tumor image classification using parameter free bat optimization algorithm. *Multimed Tools Appl* **78**, 21853–21890 (2019). <https://doi.org/10.1007/s11042-019-7498-3>
- [47] Saeed, S., Abdullah, A., Jhanjhi, N.Z. *et al.* New techniques for efficiently k-NN algorithm for brain tumor detection. *Multimed Tools Appl* **81**, 18595–18616 (2022). <https://doi.org/10.1007/s11042-022-12271-x>
- [48] Vikkurty, S., Hegde, N.P., Vinay Kumar, S., Recherla, A., Ganapa, M. (2024). Effective Prediction of Brain Tumor Using Machine Learning Algorithms. In: Kumar, A., Mozar, S. (eds) *Proceedings of the 6th International Conference on Communications and Cyber Physical Engineering . ICCCE 2024. Lecture Notes in Electrical Engineering*, vol 1096. Springer, Singapore. https://doi.org/10.1007/978-981-99-7137-4_48
- [49] Saqlain Raza, Nasim Gul, Haider Ali Khattak, Arisha Rehan, Muhammad Imran Farid, Anum Kamal, Dr Jai Singh Rajput, Sajid Mukhtiar, & Aziz Ullah. (2024). BRAIN TUMOR DETECTION AND CLASSIFICATION USING DEEP FEATURE FUSION AND STACKING CONCEPTS. *Journal of Population Therapeutics and Clinical Pharmacology*, 31(1), 1339–1356. <https://doi.org/10.53555/jptcp.v31i1.4179>
- [50] Thayumanavan M, Ramasamy A. An efficient approach for brain tumor detection and segmentation in MR brain images using random forest classifier. *Concurrent Engineering*. 2021;29(3):266-274. doi:[10.1177/1063293X211010542](https://doi.org/10.1177/1063293X211010542)
- [51] Rajagopal R. Glioma brain tumor detection and segmentation using weighting random forest classifier with optimized ant colony features. *Int J Imaging Syst Technol*. 2019; 29: 353–359. <https://doi.org/10.1002/ima.22331>
- [52] Neha Bhagat, Gurmanik Kaur, MRI brain tumor image classification with support vector machine, *Materials Today: Proceedings*, Volume 51, Part 8, 2022, Pages 2233-2244, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2021.11.368>.
- [53] G. Deepa, G. Leena Rosalind Mary, A. Karthikeyan, P. Rajalakshmi, K. Hemavathi, M. Dharanisri, Detection of brain tumor using modified particle swarm optimization (MPSO) segmentation via haralick features extraction and subsequent classification by KNN algorithm, *Materials Today: Proceedings*, Volume 56, Part 4, 2022, Pages 1820-1826, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2021.10.475>.
- [54] Waleed A. Mahmoud Al-Jawher, Sarah H. Awad, A proposed brain tumor detection algorithm using Multi wavelet Transform (MWT), *Materials Today: Proceedings*, Volume 65, Part 5, 2022, Pages 2731-2737, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2022.06.016>.
- [55] A. Srinivasa Reddy, Effective CNN-MSO method for brain tumor detection and segmentation, *Materials Today: Proceedings*, Volume 57, Part 5, 2022, Pages 1969-1974, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2021.10.145>.
- [56] Dhiraj Kapila, Neha Bhagat, Efficient feature selection technique for brain tumor classification utilizing hybrid fruit fly based abc and ann algorithm, *Materials Today: Proceedings*, Volume 51, Part 1, 2022, Pages 12-20, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2021.04.089>.
- [57] K.S. Angel Viji, D. Hevin Rajesh, An Efficient Technique to Segment the Tumor and Abnormality Detection in the Brain MRI Images Using KNN Classifier, *Materials Today: Proceedings*, Volume 24, Part 3, 2020, Pages 1944-1954, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2020.03.622>.
- [58] Raschka, S., Liu, Y., Mirjalili, V., & Dzhuļgakov, D. (2022). *Machine learning with PyTorch and scikit-learn: Develop machine learning and deep learning models with Python*. Packt Publishing.

- [59] Abraham, A., Pedregosa, F., Eickenberg, M., Gervais, P., Mueller, A., Kossaifi, J., Gramfort, A., Thirion, B., & Varoquaux, G. (2014). Machine learning for neuroimaging with scikit-learn. *Frontiers in Neuroinformatics*, 8. <https://doi.org/10.3389/fninf.2014.00014>
- [60] Raschka, S., Liu, Y., Mirjalili, V., & Dzhulgakov, D. (2022). *Machine learning with PyTorch and scikit-learn: Develop machine learning and deep learning models with Python*. Packt Publishing.
- [61] Dalal, N., & Triggs, B. (n.d.). Histograms of oriented gradients for human detection. *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*. <https://doi.org/10.1109/cvpr.2005.177>
- [62] OpenCV: Cv::HOGDescriptor Struct reference. (n.d.). OpenCV documentation index. https://docs.opencv.org/4.x/d5/d33/structcv_1_1HOGDescriptor.html
- [63] Ahonen, T., Hadid, A., & Pietikainen, M. (2006). Face description with local binary patterns: Application to face recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 28(12), 2037-2041. <https://doi.org/10.1109/tpami.2006.244>
- [64] OpenCV: Histograms - 1 : Find, plot, analyze !!! (n.d.). OpenCV documentation index. https://docs.opencv.org/4.x/d1/db7/tutorial_py_histogram_begins.html *Local binary pattern for texture classification — skimage 0.23.2 documentation*. (n.d.). scikit-image: Image processing in Python — scikit-image. Retrieved May 6, 2024, from https://scikitimage.org/docs/stable/auto_examples/features_detection/plot_local_binary_pattern.html
- [65] Sklearn.model_selection.train_test_split. (n.d.). scikit-learn. Retrieved May 6, 2024, from https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html.
- [66] Adair, J.; Brownlee, A.; Ochoa, G. Evolutionary Algorithms with Linkage Information for Feature Selection in Brain Computer Interfaces. In *Advances in Computational Intelligence Systems*; Springer Nature: Cham, Switzerland, 2016; pp. 287–307.
- [67] Arakeri, M.P.; Reddy, G.R.M. Computeraided diagnosis system for tissue characterization of brain tumor on magnetic resonance images. *Signal Image Video Process.* 2015, **9**, 409–425.
- [68] Wang, S.; Zhang, Y.; Dong, Z.; Du, S.; Ji, G.; Yan, J.; Phillips, P. Feed-forward neural network optimized by hybridization of PSO and ABC for abnormal brain detection. *Int. J. Imaging Syst. Technol.* 2015, **25**, 153–164.
- [69] Abbasi, S.; Tajeripour, F. Detection of brain tumor in 3D MRI images using local binary patterns and histogram orientation gradient. *Neurocomputing* **2017**, **219**, 526–535.
- [70] Kaplan, K.; Kaya, Y.; Kuncan, M.; Ertunç, H.M. Brain tumor classification using modified local binary patterns (LBP) feature extraction methods. *Med. Hypotheses* 2020, **139**, 109696.