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Machine learning for brain tumor classification: evaluating feature extraction and algorithm efficiency

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Abstract
Uncontrolled fast cell growth causes brain tumors, posing a significant threat to global health and leading to millions of deaths annually. Early cancer detection is crucial to save lives. The purpose of this study is to investigates the capability of machine learning algorithms and feature extraction methods to detection and classification of brain tumors. We implemented six machine learning algorithms and three features extraction methods, including Image Loading, HOG, and LBP. The objective of this study is to identify best combination of machine learning and features extraction method for brain tumor detection and classification. This study utilized two Brain Tumor MRI Datasets downloaded from Kaggle. Our analysis revealed that Random Forest emerged as the most effective classifier by achieving an accuracy of 99% with image loading feature extraction method based on different metrics, closely followed by SVM and Logistic Regression. However, 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. A case study with interpretable machine learning is also presented in the paper.

Keywords Machine learning · Brain tumors · Feature extraction · Magnetic resonance imaging · Comparative analysis

1 Introduction

Brain cancer, a highly destructive and potentially fatal 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 tumors [1].

In 2023, approximately 24,810 adults (14,280 men and 10,530 women) in the USA are expected to be diagnosed with primary cancerous tumors affecting the brain and spinal cord. Brain tumors comprise 85% to 90% of all primary central nervous system (CNS) tumors. Additionally, it is estimated that 5230 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 where cells within the brain tissue grow uncontrollably, causing the brain to malfunction [3]. Tumors can be benign (grades 1 and 2) or malignant (grades 3 and 4), with malignant tumors rated according to their aggression levels. The

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least aggressive tumors are minimally invasive, while the most aggressive are highly invasive. Among the histological criteria that define the tumor grade are vascularity, invasiveness, and growth rate. As a tumor progresses to a higher stage, the patient's survival and treatment prognosis decrease drastically. Therefore, early diagnosis and treatment of brain tumors are crucial for improving patient survival chances.

In clinical practice, the most widespread primary brain tumors include meningioma, glioma, and pituitary tumors, as illustrated in Fig. 1 and detailed in [4]. Meningiomas usually begin in the meninges tissues comprising the brain or spinal cord, expressing as benign growths in the protective membranes. Conversely, gliomas, which are fatal, originate from glial cells that support neurons, comprising about one-third of all brain tumor cases [5]. Pituitary tumors, typically benign, form within the pituitary gland [6]. Accurate diagnosis is pivotal for prognosis and treatment decisions, yet traditional biopsy approaches have drawbacks such as pain, time consumption, and sampling inaccuracies [7, 8]. Additionally, histopathological grading faces challenges like intra-tumor heterogeneity and variations in expert assessments [9], complicating the diagnostic process further. These characteristics pose significant challenges in the diagnosis and management of brain tumors.

So, magnetic resonance imaging (MRI) plays an important role in this method, offering higher soft tissue contrast and multi-planar imaging capabilities. MRI allows for accurate visualization of tumor location, size, and characteristics, aiding in surgical planning, radiation therapy, and treatment monitoring [10]. 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 gain comprehensive information about internal brain tissues. During the process of brain tumor investigation, detecting the tumor core location is a key task in determining the size and shape of the brain tumor [11].

However, despite MRI's capabilities, challenges persist in brain tumor detection. Because tumors can have a variety of morphological and textural features, it can be difficult to distinguish them from normal brain tissue or other diseases. Furthermore, small or subtle tumors may evade detection on conventional MRI scans, leading to delayed diagnosis and potentially poorer outcomes for patients [12, 13]. Therefore, there is a pressing need for more accurate and efficient methods for brain tumor detection using MRI.

Machine learning techniques offer promising opportunities to enhance the accuracy and efficiency of brain tumor detection in MRI scans [14]. By leveraging computational algorithms, machine learning can extract complex patterns and relationships from large volumes of imaging data, facilitating the automated detection of subtle abnormalities [15, 16]. 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 aid in early detection and diagnosis by identifying regions of interest that may indicate the presence of a tumor through the analysis of these features [17, 18].

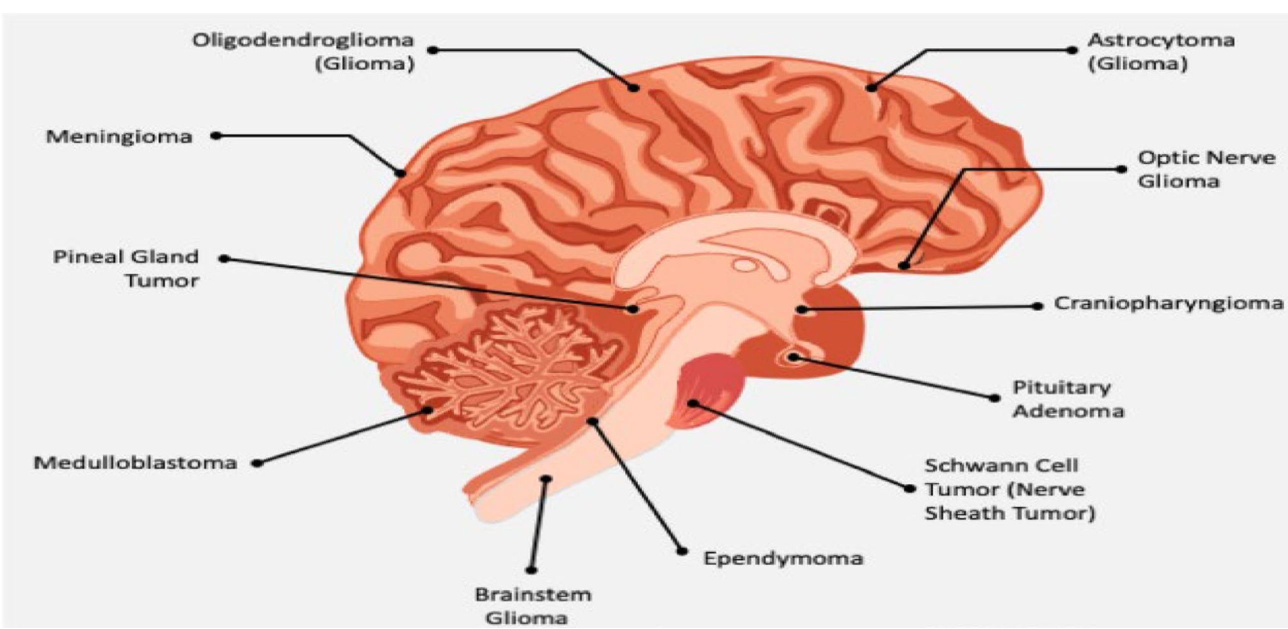


Fig. 1 Structure of brain with various types of brain tumor

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 broader insights into the morphology and biology of tumors [19–21]. 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 reducing diagnostic errors and interpretation times [22].

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 [23, 24]. The Novelty of this study.

The primary contributions of this paper are as follows:

- Features are extracted using Histograms of Oriented Gradients (HOGs), Local Binary Patterns (LBPs), and the Image Loading method.
- 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.
- A case study with Interpretable Machine learning using LIME is presented.

The paper is organized as follows: Sect. 2 covers the related work and problem statement. Section 3 outlines the research methodology and the proposed computational approach. Section 4 describes the modeling process; Sect. 5 describes the experimental results; Sect. 6 includes a discussion of findings; and Sect. 7 draws conclusions and outlines potential future work.

2 Related work

Sheela et al. [25] present a method designed to classify between brain tumors (BT) and standard brain conditions. This study investigates abnormalities in several brain malignancies using magnetic resonance imaging (MRI). SVMs, together with various wavelet transformations, are used to detect and classify MRI-detected brain cancers. The study [26] employed a hybrid K-means Galactic Swarm Optimization (GSO) technique to address the image segmentation problem, treating it as a classification model. To extract brain tumors from 2D MRI images, the researchers developed a fuzzy C-means clustering method. This method was then utilized by Convolutional Neural Networks (CNN) and traditional detectors for further processing. The study [27] conducted a comprehensive review of the literature on current techniques for segmenting brain tumors (BT) from MRI data.

An automated method to differentiate between malignant and non-cancerous brain MRI scans was developed in the study [28]. The method was tested in three benchmark datasets using a support vector machine classifier coupled with different cross-validation techniques to compute its accuracy. From this, the average results showed 97.1% accuracy, an area under the curve (AUC) of 0.98, a sensitivity of 91.9%, and a specificity of 98.0%. In the study [29], a two-step Dragonfly algorithm (DA) clustering method was introduced for accurately extracting starting contour points. Initially, during the preprocessing stage, the brain was separated from the skull. Following this, the tumor edges were identified using the two-step DA. These extracted edges then served as the starting contour for the MRI sequence.

The study [30] employed a range of machine learning classifiers, including Support Vector Machine (SVM), Gradient Boost, K-Nearest Neighbor (KNN), XGBoost, and Logistic Regression, to evaluate the system's performance. The results showed how different classifiers performed in terms of accuracy, with Extreme Gradient Boosting (XGBoost) coming out on top with an accuracy of 92.02%. The goal of the study [31] 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.

Paper [32] 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 [33], 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.

The study [34] suggested a methodology that involves several key steps, including image acquisition, preprocessing, segmentation using threshold segmentation and the watershed algorithm, and feature extraction using techniques such as MSER, FAST, and Haralick features. The results 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 [35]. 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 [36] introduced a novel approach for differentiating MRI brain images using a hybrid Naive Bayes classifier. The proposed model included image preprocessing, feature extraction, and noise reduction to enhance classification accuracy. The paper [37] 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. To classify multiclass brain tumors based on MRI images, the study [38] compared and analyzed the performance of three main classification models: artificial neural networks, support vector machines, and random forest classifiers.

The performance of the classification models was evaluated based on accuracy, precision, recall, and F1 score. The author [39] utilized 7,022 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 [40] 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 [41], a 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% in tumor classification.

The study [42] 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 [43] 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 [44] 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 [45] 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 [46] 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 [47], 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 [48] addressed the detection and segmentation of glioma brain tumors using a random forest classifier and a 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 [49], 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 [50], 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%.

This paper [51] 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 [52] 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 [53] employed modified fuzzy C-means 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 [54] 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 large number of brain MRI images.

The study [55] presents an efficient model for brain tumor detection in MRI scans, designed to assist radiologists with fast, reliable diagnoses. Using InceptionV3 with SVM, it achieves high accuracy (98.31%) and precision (99.09%) while remaining computationally light. These promising results suggest it could be a valuable tool for early diagnosis, though further testing in diverse clinical settings would strengthen its real-world applicability.

The study [56] addresses key challenges in brain tumor classification by developing a deep learning model with evolutionary optimization, capable of distinguishing four tumor types. Using enhanced CNN and Encoder-Decoder networks with optimized hyperparameters, the model achieved strong results—98% average accuracy and 99% for single classifiers—on BraTS2020 and BraTS2021 datasets. While promising, further testing across varied clinical settings would help confirm its practical applicability. Summary of related work is shown in Table 1.

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

Research Gaps identified through literature review are described below:

Lack of Explainability: Most of the existing AI models focus primarily on accuracy but don't explain how predictions are made, which is crucial for building trust in medical field.

Limited Multimodal Data Use: Most of the existing studies solely relies on MRI data, So they are missing opportunities to improve accuracy by integrating multi omics data.

Computational Challenges: Many optimization techniques are resource-consuming, making them unsuitable for real-time use in clinical environments.

Generalizability Issues: Most of the existing studies utilized the single dataset that work well on specific datasets but struggle to generalize across diverse clinical settings.

Inconsistent Performance Metrics: High accuracy is often reported, but other critical metrics like sensitivity and specificity are inconsistently compared, complicating the evaluation of model reliability.

Non Availability of Source Code: Most of the existing studies don't provide source code that hinders reproducibility, transparency, and comparison of AI models. Without access to the code, researchers cannot verify results, build upon existing work, or improve upon models, slowing progress.

3 Proposed methodology

This section offers a comprehensive discussion on the detection of MRI brain tumors using various machine learning (ML) approaches. The progression of the proposed method is illustrated in Fig. 2. Initially, MRI brain tumor data are acquired and pre-processed. 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.

3.1 Dataset collection

The dataset used to evaluate the performance of our proposed work is collected from the Kaggle [57] open data website. This dataset comprises 4117 brain MRI images of patients with tumors and 1,595 images without tumors, totalling 5712 images. Another dataset Brain Tumor MRI Dataset [58] is used for validation. This dataset is a combination of the three datasets: figshare, SARTAJ dataset, Br35H contains 7023 images of human brain MRI images which are classified into two classes notumor(class:0) and tumor(class: 1). As all of these images had unique dimensions, they were resized using cv2.resize() to a standardized dimension of 200×200 pixels. Figure 3A illustrates a portion of the dataset, highlighting the varying widths and heights of the images. Therefore, we resized the images. Figure 3B displays the scaled versions of the dataset's images.

3.2 Data pre-processing

Data pre-processing is crucial in machine learning because it ensures that the input data is ready for the models to work effectively. In the medical field, image pre-processing is an extremely important step. Normally, during pre-processing, noise reduction or enhancement is performed. This process is carried out using a variety of methods, including image scaling, cropping, median filtering, histogram equalization, and image adjustment. We have used StandardScaler for this

Table 1 Summary of related work

Study No	Methodology	Algorithms used	Merits	Demerits
[25]	Classifies between BT and standard brain conditions	SVM + Wavelet Transformations	Effective in identifying tumor patterns	Limited by dependence on SVM and wavelet-only feature extraction
[26]	Hybrid segmentation for MRI brain cancer	K-means + GSO, Fuzzy C-means, CNN	Combines clustering with CNN for segmentation	Lacks generalizability due to complex hybrid models
[28]	Automated malignant vs. benign classification	SVM with cross-validation	High performance in classification tasks	Limited generalizability to multiclass tumors
[29]	Tumor edge extraction using Dragonfly Algorithm	Dragonfly Algorithm	Two-step process for precise contour extraction	Edge detection method sensitive to noise
[30]	Performance comparison of ML classifiers	SVM, Gradient Boost, KNN, XGBoost, Logistic Regression	Comparative analysis of classifier accuracy	Only binary tumor types addressed
[31]	Texture + demographic features for MRI analysis	Random Forest	Texture feature based enhanced differentiation	limited model adaptability
[32]	MRI image classification	SVM with different kernels	Robust tumor identification using linear kernel	Sensitivity lower than some methods
[33]	3D patch-based glioma classification	Random Forest	Differentiates WHO Grade III and IV gliomas	Study cohort limits broader applicability
[34]	Multistep image processing for BT detection	MSER, FAST, Haralick features	Effective feature extraction in tumor detection	High computational complexity
[35]	Multiclass tumor classification with deep CNN fusion	CNN (AlexNet, GoogLeNet, ResNet18)	High accuracy with CNN feature fusion	Requires significant computing resources
[36]	MRI differentiation using Naive Bayes	Naive Bayes	Enhanced accuracy through preprocessing	Limited flexibility due to naive Bayes assumptions
[37]	SVM with ant colony optimization	SVM + ACO	High precision with ACO enhancement	Complex to train with ACO methodology
[38]	Multiclass classification model comparison	ANN, SVM, Random Forest	Useful in model comparison	Relies on specific classifiers for comparison
[39]	Transfer learning with ensemble methods	VGG, ResNet, DenseNet, SqueezeNet	Leverages pre-trained networks for high accuracy	Requires extensive pre-trained data for transfer learning
[40]	Logistic regression on ADNI dataset	Logistic Regression	High precision and recall	Limited to ADNI dataset insights
[41]	Tumor and edema detection in MRI sequences	KNN, watershed segmentation	Specificity in T1 and T2 analysis	KNN performance can degrade with large data
[42]	Tumor recognition with MLT + Chan-Vese	MLT, Chan-Vese	Reduces time complexity with manual skull removal	Requires user interaction for skull removal
[43]	Multilevel thresholding for tumor grade	PFree BAT + FKNN	Efficacy in high-grade tumor classification	Complex multi-step optimization process
[44]	4D MRI tumor differentiation with k-NN	Hybrid k-NN + FFT + Laplace	Accurate differentiation in 4D MRI	High processing requirement with 4D data
[45]	CNN for tumor prediction accuracy	CNN with TensorFlow/Keras	High accuracy without preprocessing	Requires substantial training data
[46]	Feature extraction using pre-trained CNN	Stacking algorithm with CNN	Efficient transfer learning	High reliance on pre-trained networks
[47]	Feature extraction and classification	SVM, Random Forest, DT	Robust to noise with median filtering	Complex multistage process
[48]	Glioma detection with Random Forest	Random Forest + ACO	Enhanced accuracy with ACO optimization	Feature optimization can increase complexity
[49]	Tumor classification with SGHO and SVM	k-means + SGHO + SURF + SVM	Precision in segmentation	Complex segmentation process
[50]	Brain tumor detection with MPSO	MPSO + SVM	Robust fuzzy segmentation	Complexity in ensemble processing

Table 1 (continued)

Study No	Methodology	Algorithms used	Merits	Demerits
[51]	Tumor classification with MWT	MWT + statistical classifiers	Effective noise removal with MWT	Limited segmentation accuracy with MWT
[52]	CNN classification with MSO	CNN + MSO	High specificity in CNN-MSO results	CNN requires high computational power
[53]	MFCM for tumor categorization	MFCM + ANN	Accurate shape and intensity feature extraction	Computationally intensive with hybrid optimization
[54]	MRI segmentation with KNN and GA	KNN + GA + TIORGW	Effective feature selection with GA	High processing time with GA
[55]	Resource-efficient Inceptor model	InceptionV3, Transfer Learning, SVM	resource-efficient design tailored for healthcare applications; timely diagnosis	Limited to binary classification; specific to dataset used; requires testing on broader datasets
[56]	CAD system with evolutionary optimization	CNN, Grey Wolf optimizer, Jaya algorithm, Stack Encoder-Decode	High performance across multiple tumor types	Needs domain expertise for model assessment; potentially high computational demand

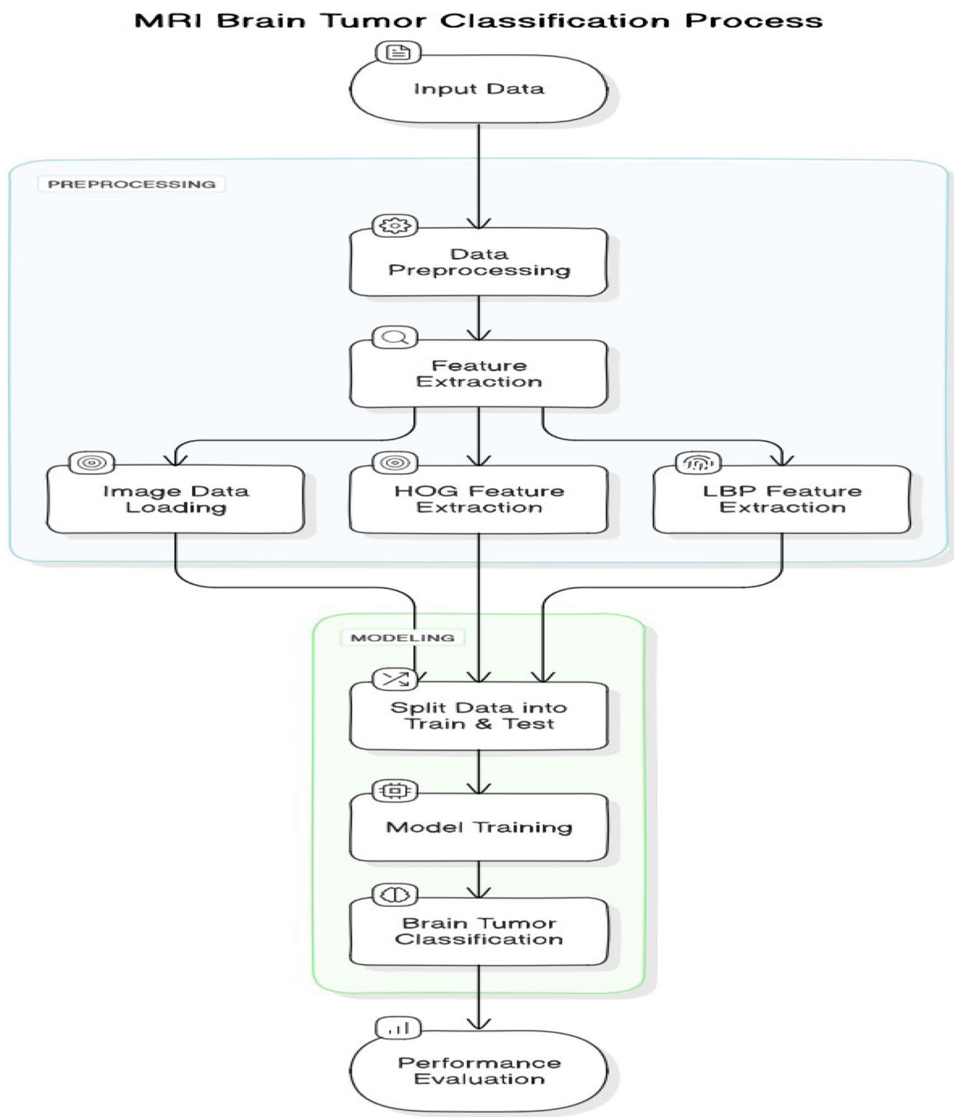


Fig. 2 Workflow of research work

task. It ensures that all the features are standardized so that no single feature overpowers the others. This helps prevent problems related to overfitting [59].

3.2.1 Data labelling

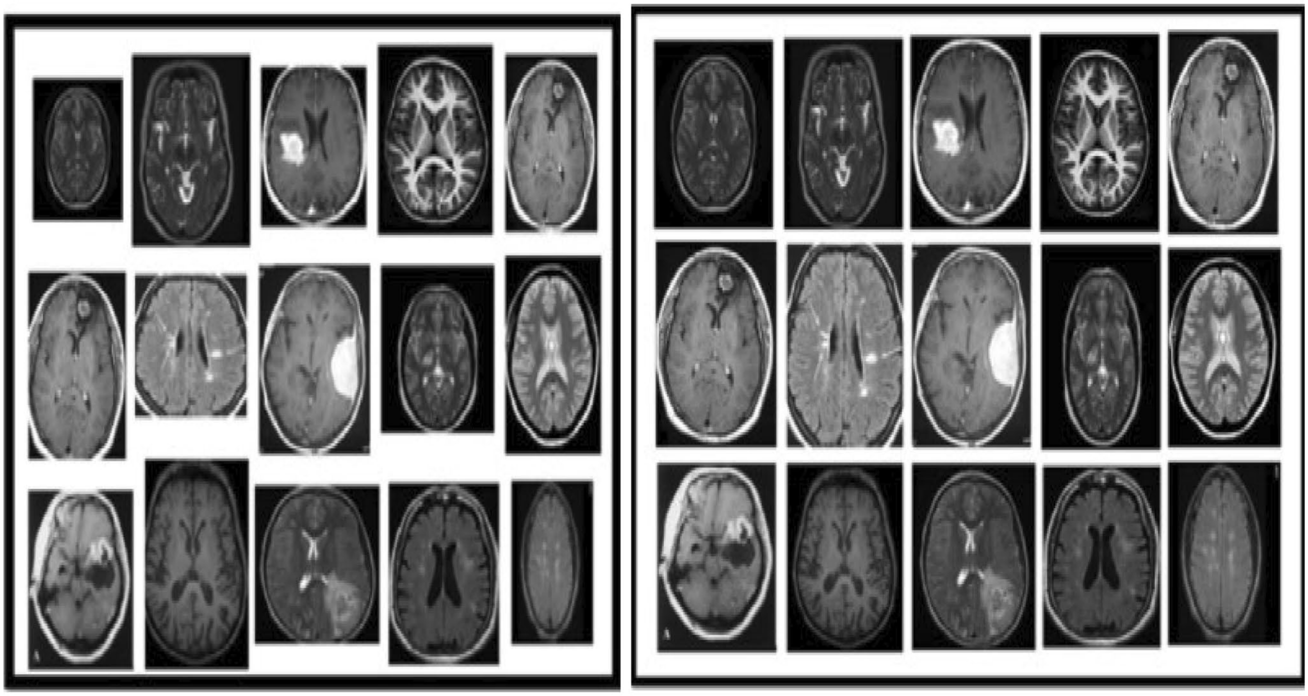
Images showing a brain tumor are labeled 1, and images showing no brain tumor are labeled 0.

3.2.2 Image pre-processing

The images have been read in grayscale (2D). In order to construct a classifier through machine learning algorithms, each image has been resized to have the same dimensions—200 × 200 pixels.

3.3 Feature extraction

In the medical field, the process of turning images into features based on several image characteristics is known as feature extraction. These features are similar to the original images, even though they are represented differently. This approach has the advantages of increasing classifier accuracy, reducing overfitting, facilitating data analysis, and accelerating training. Feature extraction is a fundamental process in machine learning where we transform raw data (images,



(a) (b)

Fig. 3 **a** Sample dataset before resizing **b** and after resizing

text, numerical data, etc.) into a set of meaningful features that are more suitable for modeling. 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 [60]. In this paper, we have implemented three methods for feature extraction from images:

3.3.1 Image data loading

In this method, the OpenCV library (cv2) is used to 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 200×200 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 in the form of a 2D NumPy array [59].

3.3.2 HOG feature extraction

The 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 neighborhood, 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 features through the above methods, all the extracted data is stored in two NumPy arrays, X and Y.

4 Modeling

4.1 Data splitting: partitioning the dataset for model training and testing

Dividing the dataset into training and testing subsets is a crucial step for 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% for training and 20% for testing.

4.2 Training models

Brain tumor classification requires model training, and selecting the right machine learning algorithms is done 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) [51], Logistic Regression [42], k-Nearest Neighbors (KNN) [43], Naive Bayes [38], Decision Trees [53], and Random Forests [49]. Models are trained using the following parameters settings as shown in Table 2.

4.3 Brain tumor classification

Brain tumor classification is a crucial process in medical imaging analysis, aiding clinicians in accurate 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.

Table 2 Model training parameters

Algorithm	Parameters
SVM	C = 12,kernel = 'linear',probability = True
Logistic Regression	cv = 5,random_state = 2
KNN	n_neighbors = 3, metric = 'minkowski', p = 2
Naive Bayes	priors = None,var_smoothing = 1e-9
Decision Tree	max_depth = 5,criterion = 'entropy
Random Forest	n_estimators = 500,criterion = 'entropy',max_depth = 8,min_samples_split = 5

5 Experimental results

In this section, we study the classification of brain tumors using various ML techniques. Here, we implemented the Python 3.10.12 version in Google Colab. When predicting performance, the four fundamental matrices are known as "True Positive (TP)," "True Negative (TN)," "False Positive (FP)," and "False Negative (FN)." The model is applied to a dataset of 3,923 MRIs, and the numbers of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) [66–70] are counted to determine these metrics. The accuracy, precision, sensitivity, specificity, and elapsed time of each model are calculated using the following equations to assess their overall performance:

$$\mathrm{Accuracy:(TP+TN)/(TP+TN+FN+FP)} \tag{1}$$

$$\mathrm{Sensitivity:(TP/(TP+FN))} \tag{2}$$

$$\mathrm{Specificity:(TN/(TN+FP))} \tag{3}$$

$$\mathrm{Precision:(TP/(TP+FP))} \tag{4}$$

$$\text{Elapsed Time: end\_time} - \text{start\_time} \tag{5}$$

5.1 Accuracy

Accuracy is measured using different values of TP, TN, FP, and FN from Table 3. The Accuracy Chart in Fig. 4 provides an overview of the obtained accuracy scores for every combination of algorithm and feature extraction technique for dataset A and B. With testing and validation on datasets A and B, among all feature extraction techniques, Random Forest consistently achieved 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 with both the datasets. This suggests that, independent of the feature representation employed, Random Forest is very successful at accurately classifying data. Accuracy scores of SVM and LR varied from 0.97 to 0.99, across all feature extraction methods. This suggests that, regardless of the feature extraction method implemented, both algorithms are reliable and efficient in correctly classifying the brain tumors. KNN obtained accuracies ranging from 0.95 to 0.98 with dataset A and B, respectively.

However, with LBP feature extraction method, KNN performance sharply declined to 0.45. Naive Bayes achieved high accuracy (0.98) with dataset A and B. However, with the HOG and LBP methods, accuracy declined with dataset A. This suggests that when utilizing HOG and LBP, Naive Bayes might not be as successful in identifying the underlying patterns in the data. Whereas with dataset B Naive Bayes accuracy varied from (0.83) to (0.92). Accuracies of DT varied from (0.90)

Table 3 Provides the performance metrics determined through experimental work for each of the six machine learning algorithms using two datasets [57, 58]

Dataset	ML Model	Image data loading				Hog feature extraction				LBP feature extraction			
		Acc	Sen	Spe	Prec	Acc	Sen	Spe	Prec	Acc	Sen	Spe	Prec
Dataset A	SVM	0.97	0.99	0.96	0.94	0.99	1	0.98	0.98	0.99	0.99	0.99	0.98
	LR	0.97	0.99	0.96	0.95	0.99	1	0.98	0.98	0.99	0.99	0.99	0.988
	KNN	0.96	0.97	0.96	0.95	0.98	0.99	0.97	0.96	0.45	0.43	1	1
	NB	0.98	0.99	0.98	0.97	0.83	0.79	0.86	0.81	0.75	0.69	0.8	0.75
	DT	0.95	0.97	0.93	0.91	0.9	0.88	0.9	0.88	0.92	0.92	0.92	0.899
	RF	0.99	0.99	0.99	0.99	0.97	1	0.97	0.94	0.98	0.99	0.97	0.96
Dataset B	SVM	0.94	0.91	0.96	0.9	0.98	0.96	0.98	0.96	0.99	0.97	0.99	0.98
	LR	0.95	0.92	0.96	0.9	0.97	0.95	0.98	0.96	0.98	0.95	0.99	0.98
	KNN	0.95	0.93	0.96	0.9	0.97	0.94	0.97	0.94	0.8	0.58	0.97	0.94
	NB	0.85	0.8	0.87	0.68	0.92	0.85	0.95	0.87	0.86	0.67	0.98	0.95
	DT	0.95	0.9	0.97	0.93	0.91	0.87	0.93	0.83	0.92	0.86	0.94	0.88
	RF	0.96	0.92	0.98	0.95	0.95	0.64	0.95	0.89	0.97	0.94	0.98	0.97

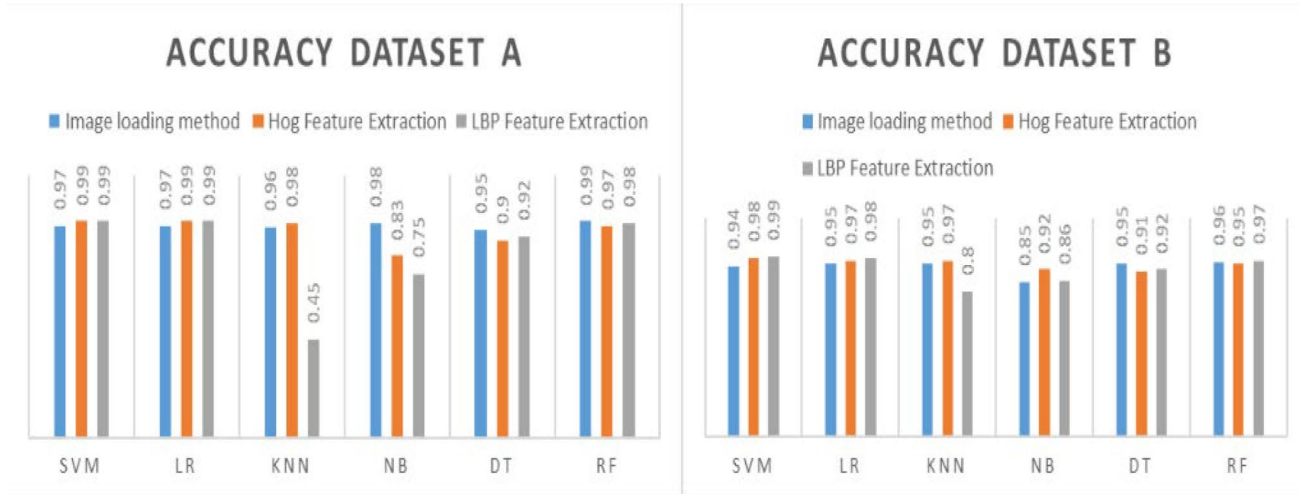


Fig. 4 Comparative analysis of ML techniques on the basis of accuracy of dataset A and B

to (0.95) with datasets A and B with all feature extraction techniques. Decision Tree exhibited consistent performance across various feature extraction techniques.

5.2 Sensitivity

In this study, we examined the sensitivity scores of several machine learning algorithms as shown in Table 3. The sensitivity chart in Fig. 5 provides an overview of the scores obtained for each combination of algorithm and feature extraction method with both the datasets [57, 58]. Random Forest consistently achieved the highest sensitivity scores: 0.99 for Image loading, 1 for HOG feature extraction, and 0.99 for LBP feature extraction with dataset [57]. However, sensitivity reduced to (0.64) with HOG feature in dataset [58]. SVM and Logistic Regression consistently show outstanding sensitivity across all feature extraction techniques with sensitivity scores varied from 0.91 to 1. This indicates that both algorithms—regardless of the feature representation—are very good at accurately identifying positive instances. KNN shows good sensitivity score varied from 0.97 to 0.99 With HOG and the Image loading method. However, with LBP Feature Extraction, it achieved a sensitivity of (0.43), a considerable reduction in both datasets. This implies that KNN might struggle to identify positive instances when using LBP features. Naive Bayes achieved sensitivity of (0.99) with image loading method; however, when using the HOG and LBP methods, sensitivity sharply declined. This suggests that when utilizing

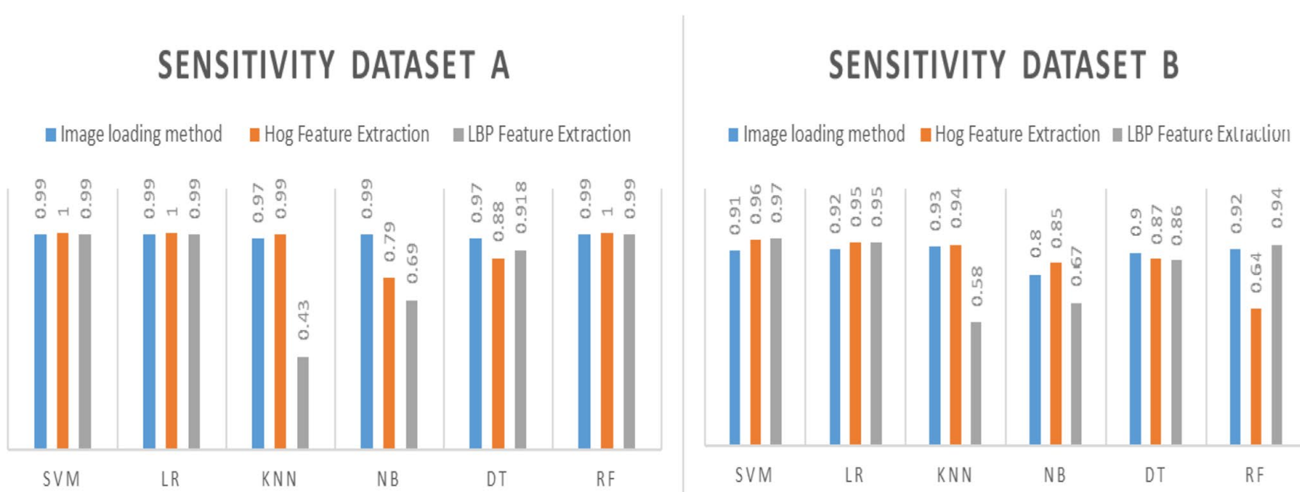


Fig. 5 Comparative analysis of ML Techniques on the basis of sensitivity of dataset A and B

these feature extraction techniques, Naive Bayes might not be as successful in identifying the positive instances in the data. Decision Tree achieved sensitivity ranging from 0.86 to 0.97 across all feature extraction methods.

5.3 Specificity

We examined the specificity scores of several machine learning algorithms as shown in Table 3 across a range of feature extraction techniques. The specificity chart in Fig. 6 provides an overview of the specificity scores for each combination of algorithm and feature extraction technique with both the datasets A and B.

Random Forest is the best performer, consistently attaining high specificity scores of 0.97 to 0.99 with across all feature extraction methods.. This suggests that, independent of the feature representation employed, Random Forest is very good at accurately identifying negative instances. With specificity scores ranging from 0.96 to 0.99, SVM and LR consistently achieved high specificity across all feature extraction techniques with both the datasets A and B. This suggests that, irrespective of the feature representation employed, both algorithms are very good at accurately identifying negative cases. KNN shows good specificity ranging from (0.96) to 1. This suggests that, irrespective of the feature representation employed, KNN is good at accurately identifying negative cases. Decision Tree achieved specificity scores from (0.90) to (0.97) performed reasonably well; however, with HOG Feature Extraction (0.90), it achieved slightly lower specificity with dataset A. Naive Bayes achieved specificity ranging from (0.80) to (0.98) with both the datasets A and B However, with LBP feature extraction in dataset A. it achieved (0.80) 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. The precision chart in Fig. 7 provides an overview of the precision scores for each combination of algorithm and feature extraction technique with both the datasets A and B. Random Forest is the best performer among all classifiers with high precision score of 0.99 across all feature extraction methods. This suggest that Random Forest is very good at correctly identifying positive instances while minimizing false positives. With precision scores varied from (0.90) to (0.988), both SVM and LR consistently demonstrate high precision across all features extraction methods. This suggests that, regardless of the feature representation employed, both algorithms are very good at correctly identifying positive instances while minimizing false positives. KNN shows good precision score varied from 0.95 to 1 across all features extraction methods. Naive Bayes achieved precision ranging from (0.68) to (0.97), but when using the Image loading method (0.68) dataset B and LBP (0.75) Feature Extraction methods dataset A, its precision noticeably decreased. 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. Decision Tree achieved precision scores varied from 0.83 to 0.93 performed reasonably well; however, with HOG method, precision slightly declined with dataset A. Decision Tree exhibits consistent performance across various feature extraction techniques.

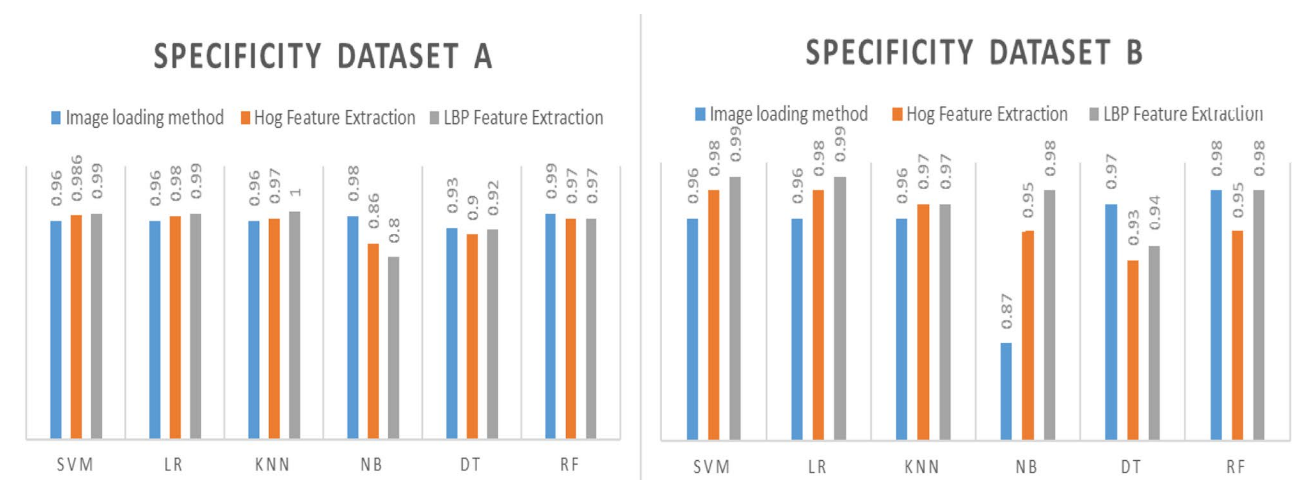


Fig. 6 Comparative analysis of ML Techniques on the basis of specificity of dataset A and B

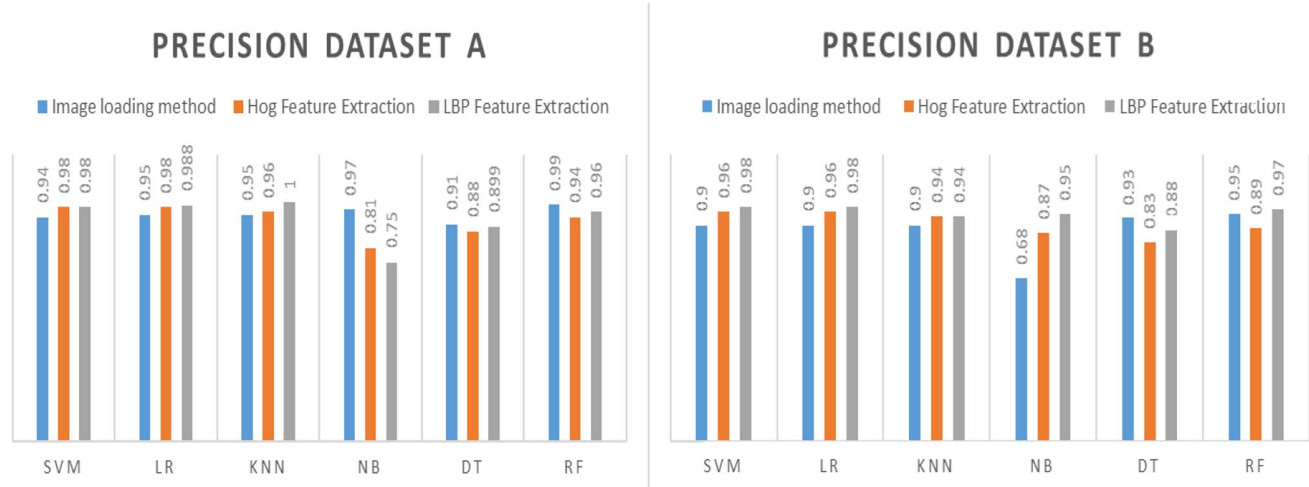


Fig. 7 Comparative analysis of ML Techniques on the basis of precision of dataset A and B

5.5 Area under curve

The True Positive Rate (TPR) and False Positive Rate (FPR) for each model and feature extraction technique must be determined in order to create the AUC (Area Under the Curve) curves for the provided data. Here is how to calculate the TPR and FPR:

- $$\mathrm{TPR}\,(\text{or Sensitivity or Recall}) = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{6}$$
- $$\mathrm{FPR} = \mathrm{FP}/(\mathrm{FP} + \mathrm{TN}) \tag{7}$$

These numbers allow us to plot the Receiver Operating Characteristic (ROC) curves and calculate the Area Under the Curve (AUC) for every combination of feature extraction technique and machine learning algorithm.

It is evident that Image Data outperforms all other algorithms, with the highest AUC values (0.79) for SVM, Random Forest, k-NN, and Logistic Regression. Both the LBP and HOG methods record moderate performance when used for feature extraction, with LBP generally outperforming HOG. On the other hand, compared to other techniques, Random Forest, SVM, and Logistic Regression consistently display higher AUC values under the Image Data method. Furthermore, KNN performed well with Image Data but inconsistently with the other techniques. Specifically, Naïve Bayes performs poorly for both Image Data and LBP, suggesting they might not be the best choices for these features. This demonstrates the importance of selecting the appropriate combination of machine learning algorithm and feature extraction technique to achieve high classification performance.

5.6 Comparison with previous work

In Table 4, a comparison of the proposed model with other studies is shown and result highlight its better performance, with an accuracy of 99% achieved using Random Forest on Kaggle datasets—outperforming many other studies. For instance, study [28], utilized SVM with cross-validation on MRI data, achieved 97.1% accuracy, an AUC of 0.98, a sensitivity of 91.9%, and specificity of 98.0%. Similarly, the study [71], utilized XGBoost and Naive Bayes on MRI dataset, achieving a 97% accuracy, Santos et al. [76], achieved 98% accuracy using Extra Trees. The study [50] combined Random Forest with Ant Colony Optimization (ACO) on the BRATS 2016 dataset and achieved accuracy of 98.01%, sensitivity 97.7%, and specificity 96.5%. In another study [30], implemented multiple models, found that XGBoost performed best with a 92.02% accuracy. So, as seen in Table 4, our proposed model's performance stands out best for its results and efficiency across complex MRI datasets, showing its potential as a reliable tool for brain tumor classification.

Table 4 Comparison with state of the art previous work

Refs.	Dataset	Model	Accuracy
Amin et al. [28]	MRI Images	SVM with cross-validation	Accuracy:97.1%, AUC:0.98, Sensitivity:91.9%, Specificity: 98.0%
Shilaskar et al. [30]	MRI Images	SVM, Gradient Boost, KNN, XGBoost, Logistic Regression	Accuracy: 92.02% (XGBoost)
Vijithananda et al. [31]	1599labeled MRI brain	Random Forest	Accuracy: 90.41%, F1: 92.02%
Gajula et al. [42]	The ADNI-1 and ADNI-2 datasets	Logistic Regression	Accuracy: 97%, Precision: 97.9%, Recall: 97%
Rajagopal et al. [50]	BRATS 2016	Random Forest + ACO	Accuracy:98.01%, Sensitivity:97.7%, Specificity: 96.5%
Tseng et al. [71]	250 MRI Images	XGBoost, Naive Bayes, ID3	97% (XGBoost)
Pattanaik et al. [72]	Figshare	SVM, KNN, NB, DT, and Ensemble ML	91.1% (KNN)
Vidyarthi et al. [73]	MS Medical College Jaipur, Rajasthan, India	KNN, mSVM, NN	95.86% (NN)
Asiri et al. [74]	Kaggle	RF, NB, Neural Networks, CN2 Rule Induction, SVM, DT	95.3% (SVM)
Uvaneshwari et al. [75]	Not Mentioned	TDC-MOML (XG-Boost)	97.83% (XGBoost)
dos Santos et al. [76]	Kaggle	RF, KNN, SVM, XGBoost, CatBoost, Extra Trees, Naive Bayes	98.00% (Extra Trees)
Sandhiya et al.	Brain Tumor Classification MRI (Kaggle)	PSO-KELM	Accuracy: 96.17% and 97.92% for datasets 1 and 2
Proposed Work	Kaggle [57, 58]	SVM,LR,DT,NB,KNN,RF	99%(RF)

6 Case study: interpretable machine learning for brain tumor classification

It is very difficult to diagnose, treat, or predict brain tumors, whether benign or malignant. This is mainly because of their diversity and location within the brain, hence requiring sophisticated tools for analysis. Machine learning (ML) and deep learning (DL) have come up with many powerful techniques that enhance the accuracy of brain tumor detection, segmentation, and classification from medical imaging data, especially MRI and CT scans [18, 21, 77, 78].

Although, despite the high performances of the models, one critical issue arises: their "black-box" nature. In many instances, the underlying decision-making process by the model is unintelligible to clinicians, which means that models are unreliable and untrustworthy in practical clinical practice. It lacks transparency and trust, which could greatly affect the application of such technologies because physicians need both accuracy and interpretability to make informed decisions [79].

The field of explainable AI(XAI) is aimed to address these problems, serving mechanisms for making the outputs of machine learning and deep learning models more transparent and understandable to human users. This study is focused on the integration of some of the XAI techniques, including LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), and Grad-CAM (Gradient-weighted Class Activation Mapping), into the brain tumor analysis models to enhance their performance and interpretability. This integration will close the gap between advanced computational methods and the practical needs of clinicians, providing a more accurate diagnosis, understandable to increase outcomes for patients [80–83].

The objective of this work is to show how explainability and interpretability can be integrated into a machine learning model for brain tumor classification. It is meant to give a clear interpretation of the process by which decisions are made in the ML model in such a manner that health professionals will be assured and understand the predictions being made.

In this case study, we will explore a machine learning pipeline designed to classify brain tumors using a dataset that contains various features extracted from MRI images. The process includes data preprocessing, model training using random forest, and model interpretability using LIME (Local Interpretable Model-agnostic Explanations) with dataset [84]. After the training, model performance is evaluated using the metrics such as accuracy, sensitivity, specificity, precision, and F1-score.

6.1 Models interpretation with LIME

LIME [85] (Local Interpretable Model-agnostic Explanations) is used to explain the predictions of the models. LIME helps in understanding which features contribute most to a particular prediction, which is crucial in healthcare scenarios like brain tumor detection. Understanding these features can provide insights into why a model might predict a tumor is present or absent. We used two instances of dataset with top eight features contributing in prediction of class in the following example as shown in Table 5. Results of Random forest model is shown in Table 6.

6.1.1 Lime explanation based on prediction probabilities

The LIME (Local Interpretable Model-agnostic Explanations) output visualization is shown in Figs. 8 and 9 illustrates the output of LIME a machine learning model's prediction. On the left, it shows prediction probabilities for two classes, 0 and 1, on the right, the feature importance analysis highlights each feature's contribution to the prediction. This kind of visualization is valuable for identifying the features that influence the model's decision, especially in critical areas like brain tumor detection.

In this case, actual output for instance 1 of dataset is class 0(No Tumor) and predicted Class is also 0(with probability of 0.98). Top features which are pushing the prediction towards Class 0(No Tumor) are visible in Blue color and one feature contributing to Class 1(Tumor) are visible in orange color as shown in above figure.

In this case, actual output for instance 3 of dataset is class 1(Tumor) and predicted Class is also 1(with probability of 1). Top features which are pushing the prediction towards Class 1(Tumor) are visible in orange color as shown in Fig. 10.

7 Discussion

The significance of our suggested methodology for classifying brain tumors is highlighted by our research. By combining image pre-processing, image enhancement, feature extraction and machine learning models, we were able to distinguish brain tumor and non tumor with remarkable accuracy. This approach has significantly improved the accuracy and reliability of brain tumor detection, demonstrating its potential as a valuable tool in medical diagnostics.

Table 5 Shows the five instances of dataset

Image	Class	Mean	Variance	Standard deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimilarity	Correlation	Coarseness
1	0	6.535339	619.5878	24.89152	0.109059	4.276477	18.90057	98.61397	0.293314	0.086033	0.530941	4.473346	0.981939	7.46E−155
2	0	8.749969	805.9576	28.38939	0.266538	3.718116	14.46462	63.85882	0.475051	0.225674	0.651352	3.220072	0.988834	7.46E−155
3	1	7.341095	1143.808	33.82023	0.001467	5.06175	26.47956	81.86721	0.031917	0.001019	0.268275	5.9818	0.978014	7.46E−155
4	1	5.958145	959.712	30.97922	0.001477	5.677977	33.42885	151.2297	0.032024	0.001026	0.243851	7.700919	0.964189	7.46E−155
5	0	7.315231	729.5406	27.01001	0.146761	4.283221	19.07911	174.9888	0.343849	0.118232	0.50114	6.834689	0.972789	7.46E−155

Table 6 Result of Random forest model

Algorithm	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Random Forest	0.98	0.97	0.99	0.99	98

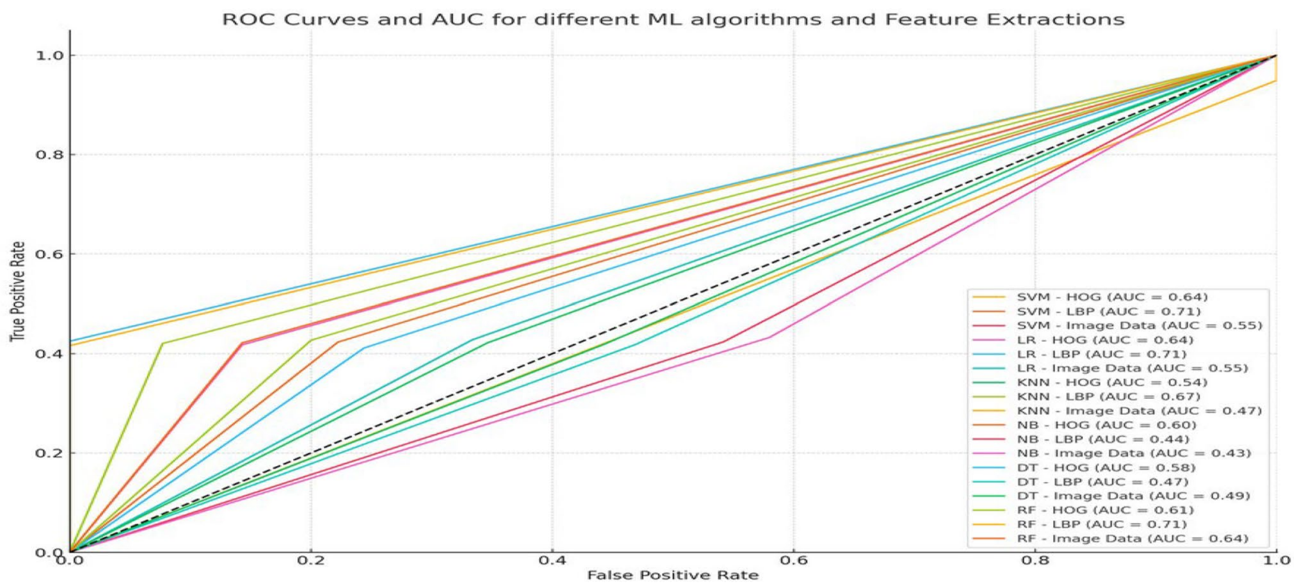


Fig. 8 Shows the ROC curves for the different machine learning algorithms and feature extraction techniques. The algorithm and feature extraction technique, as well as the corresponding AUC values, are labeled on the curves

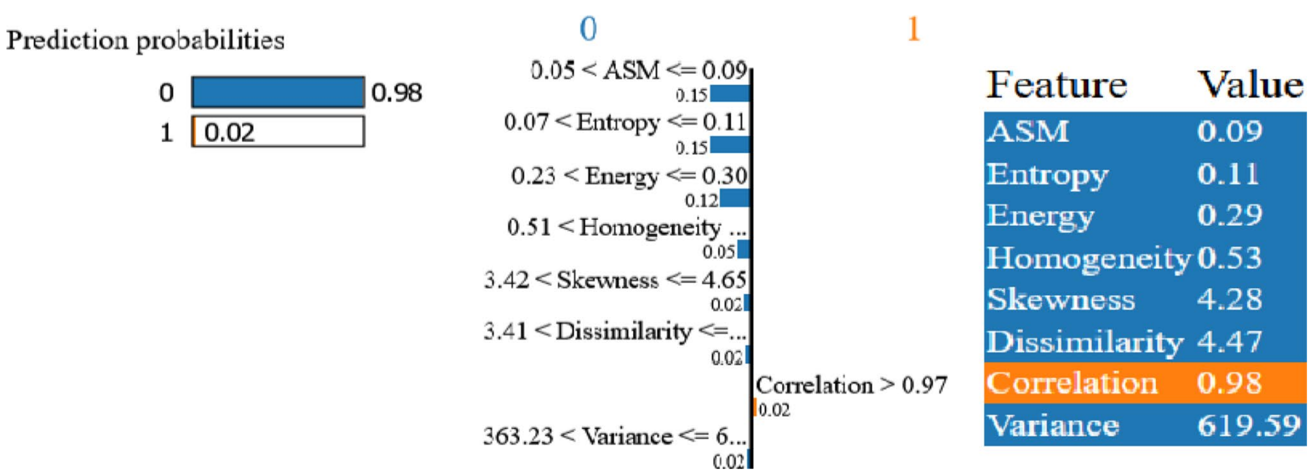


Fig. 9 Lime output for instance 1 of dataset

In Table 4, we performed the comparison of machine learning models applied to various medical imaging datasets gives the essential insights. For example, Random forest had the highest accuracy, 99%, on Kaggle dataset [57] and was consistently effective. With accuracy scores varying from 0.97 to 0.99, SVM and LR also achieved high accuracy across all feature extraction methods. Still, XGBoost and other ensemble methods were efficient solutions to problems with high-dimensional data. Our Case study highlights how Interpretable machine learning can help physicians diagnose brain tumors with accuracy and transparency thus increasing the trustworthiness in AI applications. This strategy has a lot of potential for improving patient outcomes and practical clinical applications. Future

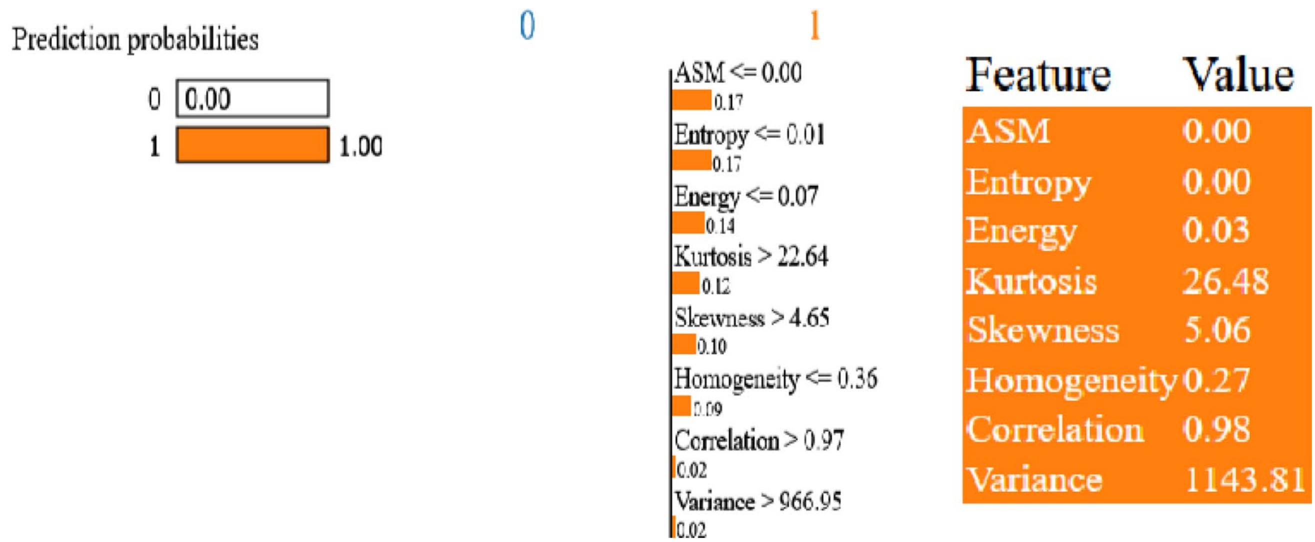


Fig. 10 Lime output for instance 13of dataset

research needs to be focused on achieving better model interpretability and exploring transfer learning to enhance performance across medical imaging applications.

So, the novelty of our research study lies in the fact that this study helps to fill various research gaps such as Lack of Explainability through Interpretable Machine Learning (LIME) and Explainable AI, Computational Challenges, Generalizability Issues with Utilization of Multiple Datasets, as most of the previous study utilized a single dataset, Inconsistent Performance Metrics, and Results Reproducibility through open source code availability. This research study will provide a pathway for research scholars looking to solve these problems.

8 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.

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Author contributions Krishan Kumar: the main author, took part in the conception, design, and implementation of the study; data collection and analysis; and drafting and revision of the manuscript. Dr. Kiran Jyoti: Right from the conception to the final version of the work—contributed to the design and methodology of the study; critical revisions and feedback on the paper were given; ensured overall quality and integrity of the work.

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Declarations

Ethics approval and consent to participate No.

Competing interests The authors declare no competing interests.

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