Journal of Modern Technology
Vol. 01, No. 02, Dec 2024, pp. 141-149.

Homepage: https://review.journal-of-modern-technology.com

Enhanced Brain Tumor Detection from MRI Scans Using Frequency Domain Features and Hybrid Machine Learning Models

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Article Info

Article history:

Received: Dec 10, 2024
Revised: Dec 28, 2024
Accepted: Jan 06, 2025
First Online: Jan 08, 2025

Keywords:

Tumor characterization
Linear discriminant analysis
Magnetic resonance imaging
k-Nearest Neighbors (kNN)
Support Vector Machines (SVM)

ABSTRACT

This research proposes a machine learning-based approach to enhance the accuracy of brain tumor detection by incorporating advanced feature extraction techniques. Texture and shape information, which are critical for precise tumor characterization, were extracted from Magnetic resonance imaging (MRI) scans using Gabor and Radon features. The dataset used consists of 3,160 brain tumor images, categorized into three types of brain tumors and one category representing no tumor. Four classifiers were employed for classification: Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and AdaBoost. The results demonstrate that the recognition accuracies for Radon, Gabor, and combined features vary across classifiers. KNN achieved the highest accuracy of 95.50% with Radon features, SVM attained 96.65% with Gabor features, and SVM reported the best overall accuracy of 98.75% with combined features.

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1. INTRODUCTION

Brain tumor detection is a critical area of medical research due to its significant impact on human health and the associated morbidity and mortality rates. Brain tumors are abnormal growths of cells within the brain or central nervous system, which can disrupt normal brain functions. Early and accurate detection is essential for effective treatment and prognosis, as timely diagnosis significantly improves survival rates [1]. Advances in medical imaging techniques, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), have enhanced the visualization of brain abnormalities. However, the manual interpretation of these images is time-consuming and prone to human error [2]. Consequently, the integration of machine learning and image processing has emerged as a promising approach to automate and improve the accuracy of brain tumor detection.

Brain tumors can be benign (non-cancerous) or malignant (cancerous), affecting the brain's functions by disrupting tissues and exerting pressure on surrounding areas. Although the exact causes of brain tumors are not always clear, genetic mutations, exposure to certain chemicals, and family history may contribute to their development. Accurate identification and timely diagnosis are critical for effective treatment and improving patient outcomes.

Types of Brain Tumors:

1. Glioma Tumors: Gliomas originate from glial cells, which provide support and insulation to neurons in the brain. They are the most common type of primary brain tumor.
2. Meningiomas: Meningiomas develop from the meninges, the protective membranes surrounding the brain and spinal cord. They are typically benign but can occasionally be malignant.
3. Pituitary Tumors: Pituitary tumors form in the pituitary gland, a small organ at the brain's base responsible for hormone regulation. Most pituitary tumors are adenomas, which are benign and slow growing.

Machine learning algorithms, particularly deep learning models, have demonstrated exceptional performance in medical image analysis due to their ability to learn intricate patterns from large datasets. Techniques such as Convolutional Neural Networks (CNNs) have been widely adopted for their effectiveness in image classification and segmentation—key tasks for detecting and localizing brain tumors [3]. Additionally, feature extraction methods like Gabor filters and Radon transforms have been employed to capture the textural and structural details of brain tumor images, further enhancing detection accuracy [4]. These methods enable the extraction of features that may not be easily discernible by the human eye, aiding in the identification of malignant tissues.

Despite significant advancements, challenges remain in ensuring the robustness, generalization, and interpretability of these automated systems. Addressing these challenges is essential to make machine learning-based solutions reliable for clinical applications [5]. Continued research focuses on refining these algorithms by incorporating diverse datasets and advanced techniques to develop more precise, efficient, and user-friendly diagnostic tools for brain tumor detection. Given the significant societal impact of brain tumor detection, extensive research has been conducted in this area [13]-[25]. The authors of [6] have utilized Convolutional Neural Networks (CNNs) to segment tumors on. Chen et al., employing BRATS 2018 data and a modified U-Net model with a novel attention mechanism, improved segmentation accuracy to 94% [7]. Zhang et al. combined CNN and Gabor features in their deep learning model, which was evaluated on the BRATS 2019 dataset, achieving a classification accuracy of 93.5% [8]. Ahmad et al. proposed a hybrid model integrating CNN and Support Vector Machine (SVM) classifiers, attaining 90% accuracy in binary classification (tumor/no-tumor) using BRATS 2020 data [9]. In a BRATS 2021 experiment, employed 3D CNNs, achieving a Dice coefficient score of 0.88 for segmentation accuracy [10]. In [11], ResNet-50 for classification on a synthetic dataset generated from BRATS 2019, achieving an impressive accuracy of 94.7%. More recently, a multi-scale feature extraction technique combining deep CNNs with Radon transforms, achieving an accuracy of 95% on the BRATS 2022 dataset [12].

The paper is structured as follows: Section II reviews the related literature, Section III describes the materials and methods used, Section IV presents the results and discussion, and finally, Section V concludes the study.

2. DATASETS AND METHODS

For the proposed method, the standard datasets are available [13]. The dataset contains the 3264 images belonging to four types: glioma tumor, meningioma tumor, Pituitary Tumor and no_tumour. Following figure 1 shows the sample images. For the proposed method the frequency domain features are used.

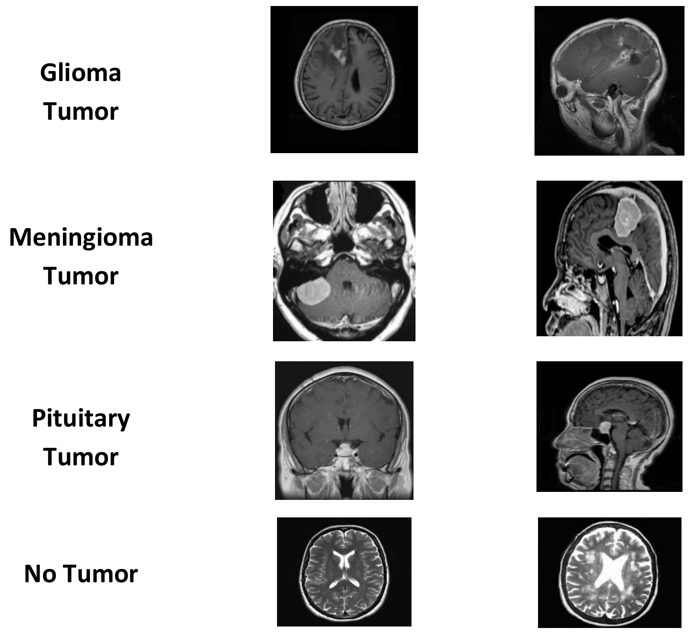

Fig. 1: Sample images of brain tumors.

Frequency domain features are a critical concept in signal processing, image analysis, and pattern recognition. In the frequency domain, signals are analysed based on their frequency components rather than their spatial or time-based representation. The idea is to transform data from its original domain (time or spatial) into a frequency domain using mathematical transformations, such as the Fourier Transform. Once transformed, specific characteristics of the signal's frequency components can be extracted and used for various applications, like image classification, texture analysis, and medical diagnostics. Thus, frequency domain features contain four kinds of features. Those are Fourier transform, Power spectrum, Filter banks, and Gabor features. For this work the Gabor features along with Radon features were considered.

Gabor features: Gabor features, based on Gabor filters, are widely used in image analysis. A Gabor filter acts as a band-pass filter for the frequency domain, allowing certain frequency ranges to pass while attenuating others. These features capture spatial frequency, orientation, and scale information, making them useful for texture analysis, face recognition, and pattern classification [14]. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image [15]. In the discrete domain, two-dimensional Gabor filters are given by (1).

$$\mathrm{Gc}[i,j] = Be - \frac{\left(i^2 + j^2\right)}{2\sigma^2}\cos(\pi f(\cos\theta + j\sin\theta)) \tag{1}$$

$$\mathrm{Gs}[i,j] = Ce - \frac{\left(i^2 + j^2\right)}{2\sigma^2}\sin(\pi f(\cos\theta + j\sin\theta)) \tag{2}$$

In (1) and (2), the B and C are normalizing factors to be determined.

2D Gabor filters have rich applications in image processing, especially in feature extraction for texture analysis and segmentation [16]. By varying *θ,* we can look for texture oriented in a particular direction defines the frequency being looked for in the texture. From this method 60 features were extracted.

Radon features: The Radon Transform is a math technique used in image processing to find features like lines, edges, and shapes in an image. It works by projecting the image from different angles and calculating the intensity of the image along those directions. This helps in identifying key patterns in the image. The Radon Transform is commonly used in areas like medical imaging, especially in CT (Computed Tomography) scans, as well as in other fields where recognizing shapes and patterns is important. The Radon Transform takes an image and transforms it from the spatial domain into a new domain that is based on the parameters of lines within the image. Mathematically it is expressed as (3).

$$R(\rho,\theta) = \int_L f(x,y)\, ds = \int_{-\infty}^{\infty} f(x\cos\theta + y\sin\theta - x\sin\theta + y\cos\theta)\, d\rho \qquad (3)$$

In (3), the ρ and θ define a line in polar coordinates, and the integral sums up the values of the image along that line. respectively. By using the radon equation, the 9 features are generated.

4. METHODOLOGY

In this section, the examination for the detection of brain tumors in MRI images using frequency domain features (Gabor and Radon). For the classification LDA, ADA boost, KNN, and SVM classifiers were employed. The following are the details of the classifiers used in the proposed work.

A. *LDA (Linear Discriminant Analysis):* Linear Discriminant Analysis (LDA) is a classification technique that finds a linear combination of features to separate classes effectively. It maximizes the ratio of between-class variance to within-class variance, enhancing class separation. LDA is widely used for dimensionality reduction and pattern recognition, especially in machine learning applications[17].

B. *B. Ada Boost (Adaptive Boosting):* This is a machine learning technique that combines multiple weak classifiers to create a strong classifier [18]. It assigns higher weights to misclassified instances and trains subsequent classifiers to focus on those harder cases. This iterative process improves accuracy by minimizing errors step-by-step works.

i. Initialize Weights: Start with equal weights for all training samples.
ii. Train Weak Learner: Train a simple classifier (like a decision stump).
iii. Update Weights: Increase weights for misclassified samples, so the next classifier focuses more on them.
iv. Repeat: Add more weak classifiers iteratively, combining them to form a stronger model.
v. Final Prediction: Use a weighted majority vote from all weak classifiers to make the final decision.

AdaBoost is widely used in image recognition, text classification, and other domains where boosting accuracy is crucial [19]. It's particularly effective when quick training and interpretability are needed.

C. KNN (K-Nearest Neighbours): This classifier is a simple, yet effective, machine learning algorithm used for both classification and regression tasks [20]. It is a non-parametric method, meaning it makes no assumptions about the underlying data distribution, which makes it flexible and applicable to a variety of real-world problems.

KNN operates on a straightforward principle: it classifies a data point based on the majority label of its nearest neighbours. Here's how it works step-by-step:

1. Choose the number of neighbours: The algorithm requires selecting a number, k, which represents how many neighbours should be considered for classification. For example, if k=5, the algorithm will look at the 5 nearest neighbours.
2. Compute distances: For a given test data point, KNN calculates the distance between this point and all points in the training dataset. The most common distance metric is Euclidean distance, although others like Manhattan or Minkowski can also be used.

$$\text{Euclidean distance} = \sqrt{\sum_i^n (x_i, y_i)^2} \quad (3)$$

3. Identify the nearest neighbours: The algorithm selects the top k data points with the smallest distances to the test point.
4. Vote for the class: In classification, KNN assigns the test point to the class most common among the k nearest neighbours. In regression tasks, it averages the values of the k nearest neighbours [21].

The KNN is widely used in image recognition, medical diagnosis, recommendation systems, and anomaly detection. It identifies patterns by comparing data similarities, aiding in tasks like classifying images, predicting diseases, recommending personalized content, and spotting unusual behaviours in datasets.
D. SVM (Support Vector Machine): It is a supervised machine learning algorithm primarily used for classification tasks, but it can also be applied to regression problems. It is a powerful tool, especially when dealing with smaller datasets and high-dimensional spaces. The main idea behind SVM is to find the optimal hyperplane that separates data points belonging to different classes with the maximum margin. This makes SVM effective at handling linearly separable data, and with the use of kernels, it can also manage non-linear data[22].

In the simplest case of a two-dimensional dataset, an SVM classifier finds a line (called a hyperplane in higher dimensions) that divides the data into two categories[23]. The goal is to select the hyperplane that maximizes the margin—the distance between the closest points from each class (called support vectors) and the dividing line. The wider this margin, the better the generalization performance of the classifier.
Steps of SVM Classification:
1. Identify Support Vectors: Points from each class that are closest to the hyperplane.
2. Maximize the Margin: Find the hyperplane that maximizes the distance to the nearest support vectors.
3. Use Kernels for Non-linear Data: If the data is not linearly separable, transform the data into a higher-dimensional space using a kernel function (e.g., polynomial, radial basis function). In this transformed space, a linear separator can be identified, which corresponds to a non-linear boundary in the original space.

The SVM classifier's effectiveness in handling high-dimensional data and its flexibility with kernel methods make it a popular choice for diverse classification tasks [24]. Support Vector Machine (SVM) classifiers are widely used in various fields due to their robust performance in high-dimensional spaces. In medical diagnosis, SVMs are effective for classifying diseases like cancer based on genetic data, distinguishing healthy and pathological tissue with high accuracy [25]. They are also prominent in their image.

5. RESULTS AND DISCUSSIONS

This section presents the results obtained from frequency domain features along with four different type of widely used machine learning methods. Here, the result is showing in the individual features with combined features. Table 1 indicates the test results of Radon Features for various classifiers and the accuracy of of the same represented in Fig 2. Radon features result analysis is shown in Fig 3.

This section presents the results obtained from frequency domain features, analyzed using four widely used machine learning methods. The results are shown for individual features as well as for combined features. Table 1 provides the test results of Radon features for various classifiers, with their accuracy represented in Figure 2. The analysis of Radon features is illustrated in Figure 3, while the combined analysis of Gabor and Radon features is shown in Figure 4.

Table 1. Radon Features Results.

Classifiers	Accuracy in percentage (%)
LDA	89.32%
ADA BOOST	92.33%
KNN	95.50%
SVM	93.22%

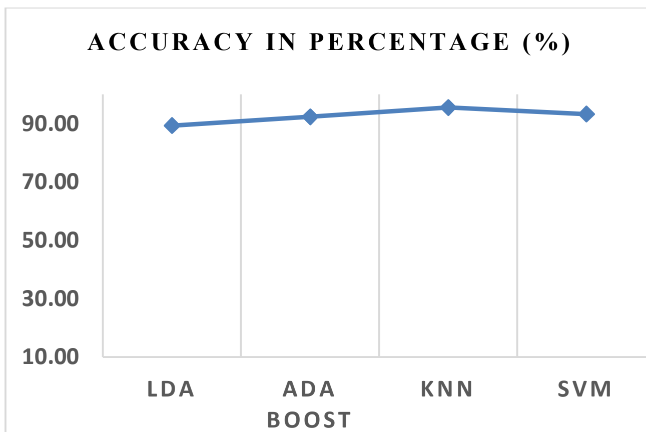

Fig. 2: Radon Features result analysis.

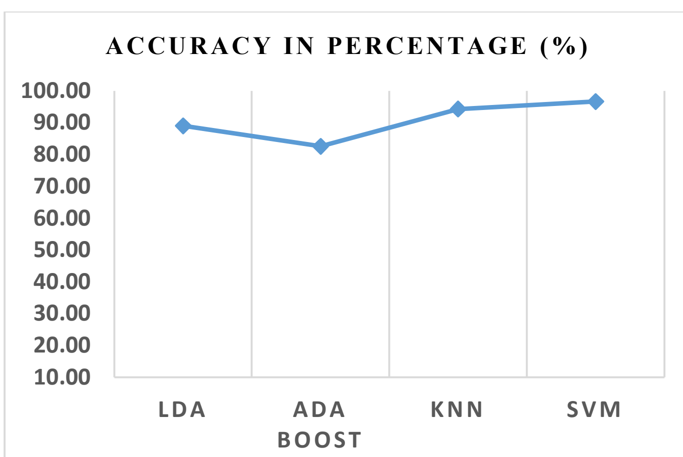

Fig. 3: Gabor Features result analysis.

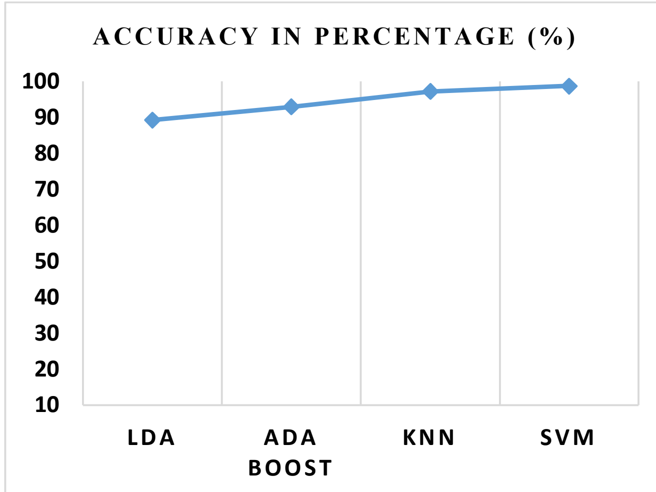

Figure 4. Gabor and Radon combined Features result analysis.

The proposed study employs an advanced machine learning-based approach to detect brain tumors from MRI images, focusing on improving detection accuracy using frequency domain features. Specifically, Gabor and Radon features, which are well-established tools for texture and shape analysis, are utilized to extract key information from MRI scans. These features are combined to form a comprehensive set of characteristics that capture both structural and textural variations indicative of tumors.

The research utilizes a dataset comprising 3,160 brain tumor images, categorized into three tumor types—glioma, meningioma, and pituitary—along with non-tumor images. This dataset was analyzed using four classification algorithms: Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and AdaBoost. The results indicate that different features and their combinations yield varied levels of accuracy. Gabor features processed with SVM achieved an accuracy of 96.65%, while the combined use of Gabor and Radon features with SVM achieved a remarkable accuracy of 98.75%. These findings underscore the efficacy of feature fusion in capturing intricate patterns within brain MRI scans.

The use of frequency domain features, particularly Gabor filters and the Radon transform, plays a critical role in this research. Gabor filters, as frequency-sensitive tools, effectively capture spatial orientation and scale, making them ideal for identifying texture variations in MRI images. Conversely, the Radon transform emphasizes structural elements such as lines and shapes, which are essential for detecting tumor outlines and boundaries. This dual approach of texture and shape analysis provides a robust feature set that enhances the classifier's ability to distinguish between healthy and pathological tissues.

Regarding classification, the study highlights the varying strengths of different machine learning algorithms. The KNN classifier demonstrated strong performance with Radon features, achieving an accuracy of 95.5%. Meanwhile, the SVM classifier excelled with Gabor features, showcasing its ability to handle complex, high-dimensional data effectively. The combination of Gabor and Radon features produced the highest accuracy, emphasizing the advantages of integrating multiple feature extraction methods to improve classification performance. This multi-feature approach is particularly valuable in medical diagnostics, where subtle variations in images can indicate critical clinical conditions.

5. CONCLUSION

This research explored the use of frequency domain features, specifically Gabor and Radon features, for the detection of brain tumors from MRI images. The analysis demonstrated that combining these features significantly improves the classification performance of machine learning algorithms. The findings show that while individual Gabor and Radon features yield high accuracies (up to 96.65% and 95.50% respectively), their combination with SVM produced the highest accuracy of 98.75%. The results underline the importance of integrating multiple feature extraction techniques to capture both texture and structural details for robust tumor identification. This comprehensive approach enhances diagnostic reliability, paving the way for automated systems that can support medical professionals in early and accurate brain tumor detection. The study affirms that machine learning methods, when augmented with diverse feature sets, can effectively improve the diagnostic potential of MRI analysis, contributing to better clinical outcomes and more efficient diagnostic workflows.

Future research could expand on this foundation by incorporating larger and more diverse datasets to test the model's generalizability across different patient demographics and imaging conditions. Enhancing the current approach with deep learning techniques, such as Convolutional Neural Networks integrated with advanced feature extraction, could yield further improvements in accuracy and robustness.

DECLARATIONS

Conflict of Interest: The authors declare that there is no conflict of interests.

Funding: This research received no external funding.

Availability of data and materials: No data is available in this article.

Publisher's note: The Journal and Publisher remain neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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