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Classification and Prediction of Brain Tumors Using Deep Neural Networks

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Abstract:

Brain tumors are one of the leading causes of cancer-related death globally among children and adults. Precise classification of brain tumors at an early stage plays a key role in successful prognosis and treatment planning. In this paper, we used the Deep Neural Network classifier, which is one of the DL architectures for classifying MRI images of brain into meningioma, pituitary, glioma, and healthy brain types. The utilization of fuzzy C-means, principle component analysis (PCA), discrete wavelet transform (DWT), 7-fold cross-validation techniques, logistic regression, and SVM facilitates image segmentation. feature extraction, reduction, and classification, contributing to a more robust and reliable prediction system. The projected arrangement accomplished a noteworthy performance with the finest accuracy of 97.04%.

Keywords: machine learning; deep neural network; discrete wavelet transform; principle component analysis; fuzzy c-means; magnetic resonance image; SVM; PCA; logistic regression

1.INTRODUCTION

Brain tumors rank among the leading causes of cancer-related fatalities globally, as indicated by the most recent data from the World Health Organization. Swift identification of a brain tumor not only averts potential mortality but also facilitates timely therapeutic interventions. Unfortunately, accessibility to early diagnosis remains elusive for a significant portion of the population, posing a challenge to timely and effective treatment for affected individuals. The human brain, a remarkably intricate organ comprised of billions of cells, becomes susceptible to the development of tumors when there is an uncontrolled proliferation of cells, resulting in the formation of abnormal cell clusters in or around the brain. This cluster of cells has the potential to disrupt the normal functioning of brain activity and inflict damage on healthy cells. Brain tumors are broadly categorized into benign and malignant tumors. Benign tumors, characterized by their non-progressive nature, are considered less aggressive and non-cancerous. Originating within the brain, they exhibit slow growth and do not have the capacity to metastasize to other parts of the body. On the contrary, malignant tumors are cancerous, displaying rapid growth with poorly defined boundaries. These are further classified as meningioma, pituitary, and glioma glands.

Medical imaging technologies such as magnetic resonance imaging (MRI), computerized tomography (CT), ultrasound imaging (UI), and X-rays have been successfully adopted to view, analyze, diagnose, monitor, and treat diseases in the human body. These technologies help medical practitioners obtain more information regarding different areas of the human body. This information helps study, treats the particular disease or injury, and benefits from knowing the effect of existing medical treatment. Among these technologies, the radiologist has preferred MRI because, at the molecular level, it provides rich and typical microscopic chemical and physical information about the human anatomy. Compared to other technologies, MRI is more useful in disease detection and classification due to its high resolution. MRI uses a strong magnetic field and non-ionizing radiation in order to get a view of various organs and tissues.

The brain, a vital organ overseeing complex functions in the human body, is effectively scrutinized through the use of magnetic resonance imaging (MRI). This imaging technique has proven successful in detecting various brain-related diseases, with a particular focus on tumors. The early identification of brain tumors from MRI scans has gained immense significance, emerging as a life-saving measure for patients. However, beyond mere ,classification of brain tumors is equally pivotal. Understanding the specific type of tumor not only enhances the survival rate for patients but also guides appropriate treatment strategies. The categorization of brain MRI images into normal and abnormal, or specific tumor types, has been a subject of extensive research. Numerous methods have been proposed over the years to efficiently classify brain tumors, leveraging high-resolution MRI images with optimal contrast.

Recent advancements in machine learning, especially within the realm of deep learning, have paved the way for the identification and classification of patterns in medical imaging. Noteworthy achievements in this domain include the ability to extract knowledge directly from data, eliminating the need for reliance on expert opinions or scientific texts. Machine learning is rapidly evolving into a valuable tool that enhances performance across various medical applications and fields. These applications encompass the prognosis and diagnosis of diseases, the identification of molecular and cellular structures, tissue segmentation, and image classification. Within image processing, deep neural networks (DNNs) currently stand out as the most successful techniques. With their intricate layers and heightened diagnostic accuracy, DNNs prove particularly effective when dealing with a substantial number of input images. Supervised methodologies, including artificial neural networks and support vector machines, along with unsupervised approaches and fuzzy c-means, are commonly employed to classify MR human brain images. This classification process is often enhanced through the integration of feature extraction techniques. Additionally, other supervised methods, such as principle component analysis, are utilized to group pixels based on their similarities across various features. The categorization of MR images into normal or abnormal can be effectively accomplished through the utilization of both supervised and unsupervised techniques. It is now feasible to scan and upload medical images to computers, with support vector machines (SVM) and neural networks (NN) having been widely utilized due to their commendable performance over the past few decades. However, a recent development has emerged with deep learning (DL) models, marking an exciting trend in machine learning. The deep architecture of DL models demonstrates efficient representation of complex relationships without necessitating an extensive number of nodes, a characteristic distinct from shallow architectures like SVM and K-nearest neighbor (KNN). Consequently, deep learning models have swiftly ascended to become the state-of-the-art in various health informatics areas, including bioinformatics, medical informatics, and medical image analysis.

This paper contributes by applying the deep learning paradigm to automate the classification of brain tumors using MRI images and evaluating its performance. The proposed methodology is designed to distinguish between normal brain tissues and specific types of brain tumors, such as meningioma, pituitary, glioma, and healthy brain, based on MRI images. To achieve this, the methodology employs a set of features extracted through the discrete wavelet transform (DWT) from segmented brain MRI images. These features are utilized to train a deep neural network (DNN), a 7-fold cross validation technique, and an SVM classifier for the purpose of brain tumor classification. The rest of the paper is organized as follows: Section 2 introduces the related work. The data collection and augmentation are given in Section 3. Section 4 introduces the methodology of the proposed differential DNN model for a brain tumor. The experiment results are given in Section 5. The conclusion and future works are given in Section 6. The references are given in Section 7.

2. RELATED WORK

In recent times, there has been a considerable focus on advancing and expanding techniques for the classification of brain tumors, encompassing meningioma, glioma, and pituitary tumors. The categorization of brain tumors stands as a crucial and exciting endeavor within the realm of medical image processing. Among various imaging modalities, magnetic resonance imaging (MRI) has emerged as a particularly promising technique for this purpose, offering numerous advantages in the medical field. Notably, it provides radiologists with a secondary opinion, facilitating the prompt and easy diagnosis of tumor intensity, diameter, position, and type. The early and accurate identification and classification of tumors further aid in devising effective treatment plans. While previous research has made substantial contributions to understanding various methods employed in image-based brain tumor classification, the majority of these approaches rely on high-quality MRI images with suitable contrast for robust tumor classification. Consequently, a primary objective of the current research is to develop a classification framework that can effectively handle low-quality MRI images. This involves a comprehensive examination of existing approaches and endeavors aimed at successfully classifying brain tumors, particularly those utilizing similar datasets for brain tumor classification.

In their work documented in [1], Shasidhar and colleagues introduced a modified version of the Fuzzy C-Means (FCM) algorithm specifically tailored for the detection of MR brain tumors. Their approach involves extracting texture features from brain MR images, followed by the application of the modified FCM algorithm for tumor detection. Notably, the modified FCM algorithm demonstrates an average speed-up of up to 80 times compared to the conventional FCM technique. This modification serves as a rapid and efficient alternative to the traditional FCM method for brain tumor detection. In the research outlined in [2], Ibrahim and collaborators introduced a neural network approach for classifying magnetic resonance human brain images. The feature extraction process involves utilizing principal component analysis (PCA), followed by employing a back-propagation neural network as the classifier to distinguish between normal and abnormal MRI brain images. They achieved a classification accuracy of approximately 96.33%.

Natarajan et al. presented a method for detecting brain tumors in MRI brain images, as outlined in [3]. The process involves the initial preprocessing of MRI brain images using a median filter, followed by segmentation through threshold segmentation. Subsequently, morphological operations are applied, and the tumor region is ultimately obtained using the image subtraction technique. This methodology accurately captures the exact shape of the tumor in MRI brain images. In a similar vein, Joshi et al. proposed a system for brain tumor detection and classification in MR images, detailed in [4]. The approach begins with the extraction of the tumor portion from the brain image, followed by the extraction of texture features from the detected tumor using the Gray Level Co-occurrence Matrix (GLCM). The classification is then carried out using a neurofuzzy classifier. Daljit Singh and colleagues, as detailed in [5], introduced a hybrid technique for the automatic classification of MRI images. The method involves an initial feature extraction step using principal component analysis (PCA) and a gray-level co-occurrence matrix (GLCM). Subsequently, the extracted features serve as input to a Support Vector Machine (SVM) classifier, which categorizes the brain image as either normal or abnormal.

Paul and collaborators, as presented in [6], proposed a brain tumor classification model based on deep learning. Their approach employed a convolutional neural network (CNN) to improve the accuracy of classification. The model achieved a 5-fold cross-validation accuracy of 90.26% in brain tumor imaging. Additionally, the study suggested that reducing the image size could enhance training performance, potentially aiding doctors in the patient's treatment process. Arunachalam and Savarimuthu, as outlined in [7], introduced a model designed to categorize normal and abnormal brain tumors in brain MR images. Their proposed model consisted of four main stages: enhancement, transformation, feature extraction, and classification. Initially, they enhanced the brain MR image using the shift-invariant shearlet transform (SIST). Following this, they extracted features utilizing Gabor, the gray level co-occurrence matrix (GLCM), and the discrete wavelet transform (DWT). Subsequently, the extracted features were fed into a feed-forward backpropagation neural network, resulting in a high accuracy rate. Moreover, we propose the incorporation of both machine learning (ML) algorithms and deep neural networks to address the limitations associated with traditional classifiers. In our study, we specifically explore the performance of two ML algorithms, namely Support Vector Machine (SVM) and logistic regression, leveraging ensemble learning techniques after the model is trained by a deep learning architecture. The selection of these algorithms is based on their proven effectiveness in various pattern classification tasks. Deep neural networks, represented by DNN architectures, offer an advantage with their ability to learn intricate mappings between input and output, making them well-suited for handling complex classification tasks. In situations where the exact modeling of certain rules is challenging, the support vector machine classifier, grounded in the concept of probability, emerges as a valuable alternative.

3. Proposed Methodology

Our proposed methodology relies on a deep neural network (DNN) learning architecture and ensemble learning methods for the classification task, specifically aimed at identifying brain tumors in brain MRIs. The step-by-step outline of our proposed methodology for classifying brain tumors in brain MRIs is as follows:

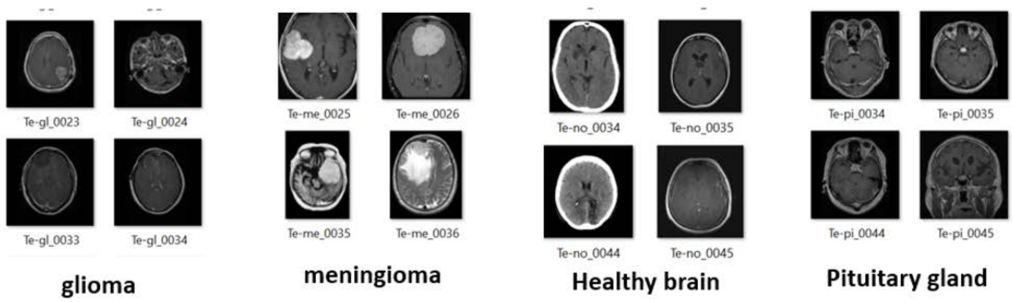
- dataset acquisition.
- image segmentation: fuzzy C-means clustering technique.
- Feature extraction: discrete wavelet transform (DWT) mechanism.
- Feature reduction: principle component analysis (PCA).
- Classification: DNN 7 hidden layer structure, CNN-SVM, logistic regression.

3.1. Dataset acquisition:

According to the World Health Organization (WHO) classification system used for identifying brain tumors, there are over 100 types of brain tumors that vary in terms of origin, location, size, and characteristics of the tumor tissues [8,9] This paper, however, focuses specifically on three types of malignant tumors, which are:

- **meningioma**: A common type of benign brain tumor that originates in the meninges, the layers of tissue covering the brain and spinal cord. It typically grows slowly and is often successfully treated with surgery.
- **Glioma**: This is a type of malignant brain tumor that arises from glial cells, which provide support and protection for neurons. Gliomas can vary in aggressiveness and are classified into different grades, with higher grades indicating more aggressive behavior. Treatment options often include surgery, radiation, and chemotherapy.
- **pituitary gland**: The term pituitary gland type is not a specific classification of brain tumor. However, tumors can develop in the pituitary gland, and these are often referred to as pituitary tumors. These tumors can be benign (non-cancerous) or, in rare cases, malignant (cancerous). They are typically categorized based on the cell type; they originate from within the pituitary gland and can affect hormone production, leading to various health issues.
- **No tumor**: This implies the absence of abnormal growth or mass in a particular area. In a medical context, this is a reassuring condition, indicating the absence of pathological tissue in the specified region.

Fig.1 : Brain MRI image Sample Dataset



The dataset comprises 5000 real human brain MRIs, consisting of images featuring meningioma, pituitary, glioma, and healthy brains. The images were obtained from the Kaggle and Git websites. All brain MRIs are split into training and testing folders. A representative sample of the dataset is depicted in Fig. 1. The dataset is 164MB in size.

Dataset-Link:

https://github.com/sartajbhuvaji/brain-tumor-classification-dataset
https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri

3.2. Image Segmentation:

Image segmentation is crucial in computer vision and medical imaging, as it enables the identification and delineation of distinct objects or regions within an image. This process enhances the understanding of complex structures, facilitates feature extraction, and supports accurate analysis. In medical applications, segmentation aids in the precise localization of abnormalities, such as tumors, providing valuable insights for diagnosis and treatment planning. Overall, image segmentation plays a pivotal role in various fields by enabling efficient and meaningful interpretation of visual information.

Fuzzy C-Means (FCM) is widely employed in image segmentation due to its ability to handle uncertainty and the partial membership of pixels of different classes. Unlike traditional clustering algorithms, FCM assigns membership degrees to pixels, allowing them to belong to multiple clusters simultaneously. This flexibility is advantageous in scenarios where pixel boundaries are ambiguous. FCM's adaptability to capture fuzzy relationships makes it suitable for applications like medical image segmentation, where boundaries between tissues may not be well-defined. Its role extends to enhancing the accuracy and robustness of segmentation outcomes in various image processing domains. Image segmentation is a challenging task involving the separation of distinct normal brain tissues like gray matter (GM), white matter (WM), cerebrospinal fluid (CSF), and the skull from tumor tissues in brain MR images [10]. In this study, we employed the fuzzy C-means clustering technique to partition the image into five sections, leveraging its successful performance in previous work and for comparative analysis [18]. Figure 2 illustrates the results of segmenting a sample image using fuzzy C-means.

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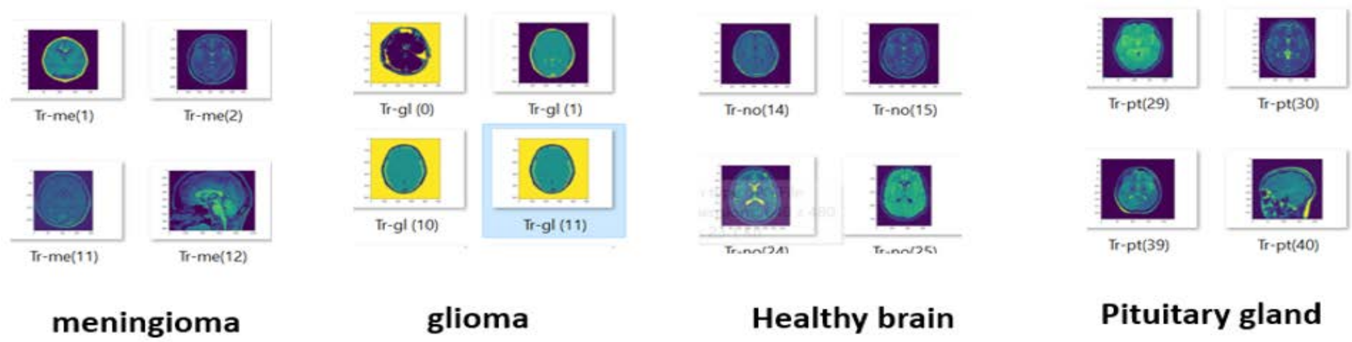
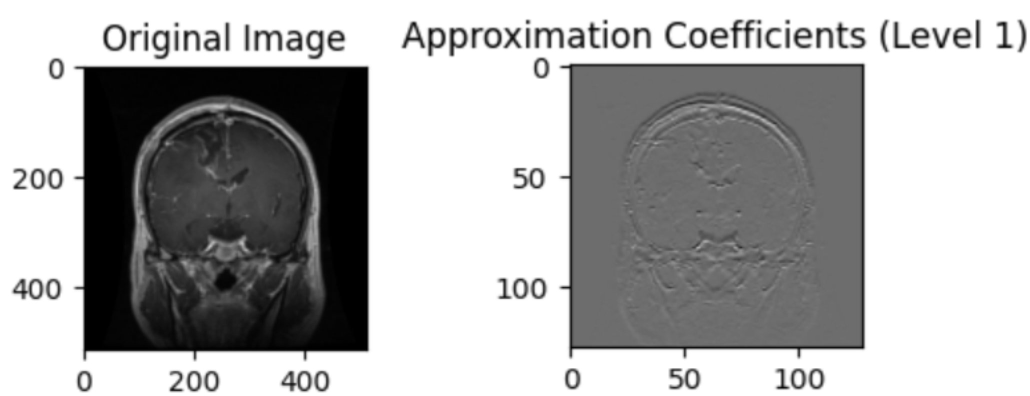
Fig.2: **Image segmented using FCM**

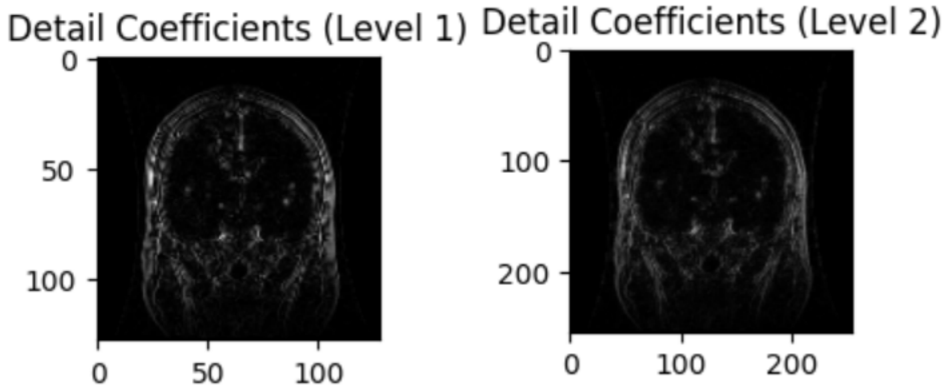


3.3. Feature extraction:

Feature extraction in image processing involves capturing relevant information from raw data to represent it more effectively. In brain tumor classification from MRIs, features like texture patterns, shape characteristics, and intensity variations are extracted. These features serve as distinctive elements for distinguishing between normal and abnormal tissues, enabling machine learning algorithms to make accurate predictions. Effective feature extraction is critical for enhancing the discriminative power of classifiers and improving overall diagnostic accuracy in medical image analysis. The discrete wavelet transform (DWT) plays a crucial role in feature extraction, particularly in image processing and analysis. DWT decomposes an image into different frequency components, providing a multi-resolution representation. In feature extraction, DWT is employed to capture essential information related to texture, edges, and patterns at varying scales. The coefficients obtained from DWT can be utilized as features, offering a compact representation of image characteristics. This helps enhance the efficiency and effectiveness of various image processing tasks, including pattern recognition and classification. Following the segmentation of brain MR images into 5 sections, features of the segmented tumor are extracted using the discrete wavelet transform (DWT). DWT excels at extracting relevant features at various directions and scales, providing localized time-frequency information through cascaded filters banks of high-pass and low-pass filters, and facilitating hierarchical feature extraction.

Fig.3: Brain images of coefficient levels

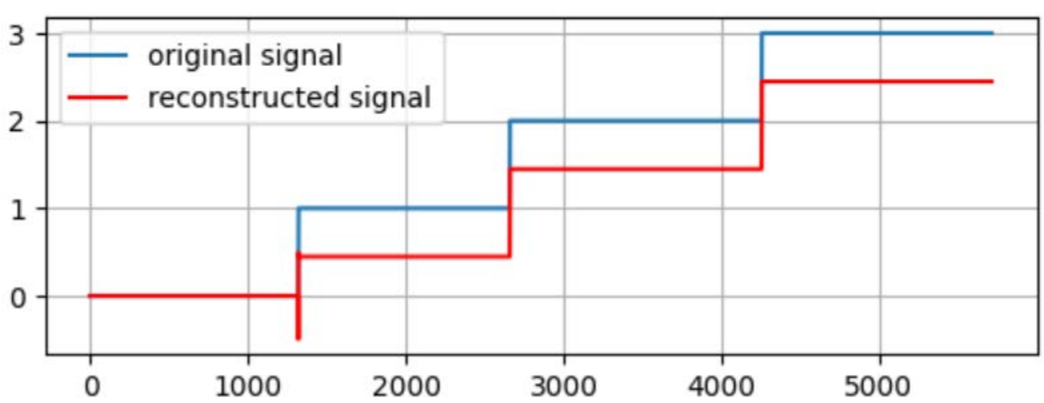




3.4. Feature Reduction:

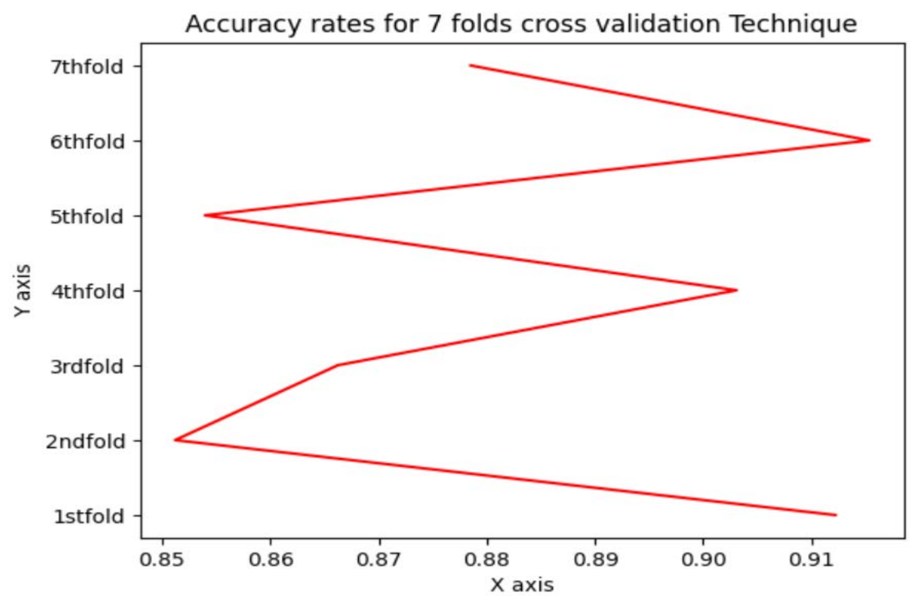
Feature reduction is a critical step in data analysis and machine learning to enhance efficiency and model performance. It involves selecting or transforming a subset of the most relevant features while discarding redundant or less important ones. Techniques such as principal component analysis (PCA), feature selection algorithms, and dimensionality reduction methods aim to streamline the dataset, improving computational efficiency, minimizing overfitting, and often enhancing the interpretability of the model. Effective feature reduction is especially important in scenarios with high-dimensional data, where it can contribute to faster model training and improved generalization to new, unseen data. Our methodology employs a 3-level decomposition of the Haar wavelet, a technique consistent with our prior work [11] to extract 12000 features (600 x 200) for each brain MRI. While this feature count may seem modest compared to the numerous feature maps generated by convolution filters in CNNs, we employ principal component analysis (PCA) [11] to approximate the original features with lower-dimensional feature vectors. This approach helps streamline the dataset and reduce dimensionality for improved efficiency and model interpretability.

Fig.4: Signal transformed during feature extraction



3.5. Classification:

Following the extraction and selection of features, the classification step utilizing a deep neural network (DNN) is executed on the resulting feature vector. The classification is conducted through a 7-fold cross-validation technique, involving the construction and training of the DNN with a 7-layered structure. To assess the performance of the chosen classifier, additional machine learning classification algorithms from WEKA [12] are employed under the same criteria. The selected classification algorithms include logistic regression and CNN-SVM for better accuracy.



4. EXPERIMENTAL RESULTS

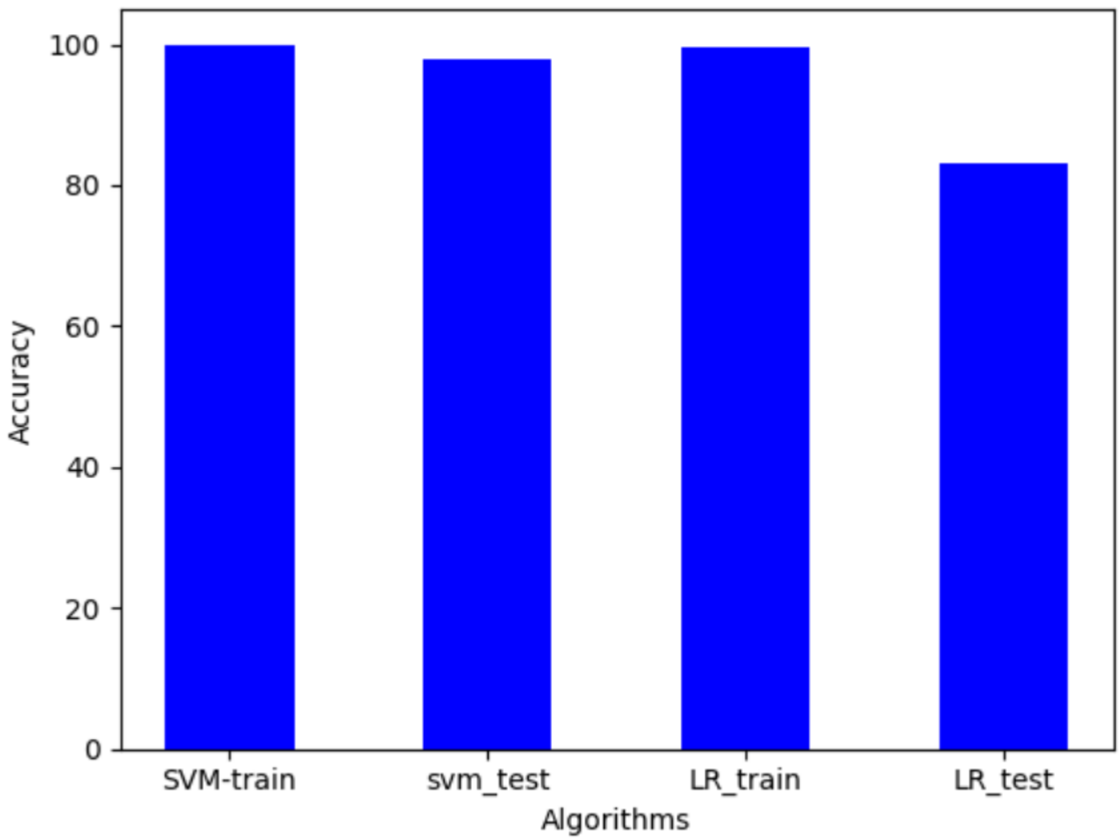
The study involved the analysis of approximately 5000 brain MR images. Texture-based features, including energy, contrast, correlation, and homogeneity, were extracted from each image using the Discrete Wavelet Transform Mechanism. The 7-fold cross-validation technique was employed for classification purposes. The classification models utilized in this study were support vector machines (SVM) and logistic regression. The dataset was split into training and testing sets, with 5000 Mri images in the training split and 1150 images in the test folder. This approach allowed for the evaluation of the classification performance on unseen data.

Table 1. Experimental result Analysis

ML Algorithm	Total Samples	Training Accuracy	Testing Accuracy
SVM Algorithm	5712	100%	97.89%
Logistic Regression	5712	99.64%	83.04%

From Table 1, we can find the classification rate of brain MR images using SVM and Logistic Regression. The accuracy of about 97.89% and 83.04% is obtained,respectively.

Fig 6. Graphical representation of accuracy



As evident from the data presented in Table 1 and the graphical representation in Figure 6, the SVM classifier trained with 7-fold cross validation technique demonstrated superior performance when coupled with the DWT feature extraction and PCA feature reduction algorithms.

5. Conclusion and future work

Brain tumor classification remains a crucial area of investigation within the medical sciences, and several methodologies have been presented for the categorization of three tumor types. While these methods have achieved acceptable classification accuracy, there is a continued need for effective solutions to enhance the accuracy further. This manuscript introduces a proficient brain tumor classification model specifically designed to classify meningioma, glioma, and pituitary tumors from brain MRI images. The primary objective is to develop a model that attains high classification accuracy with low complexity.

The proposed model follows a multi-step approach. Firstly, it enhances the visual quality of images through dataset acquisition and preprocessing. Tumor locations are then identified through segmentation and clustering techniques, and these locations are scored and utilized for feature extraction by discrete wavelet transforms. Subsequently, the refined locations contribute to improved detection performance. The model aligns and processes these locations to determine tumor categories and locations, with the classification accuracy benefiting from the transfer of features from detection layers to classification layers.

Although the proposed model exhibits high efficiency on a large image dataset, its computational cost is acknowledged. The suggestion is to reduce computational costs and broaden the model's applicability to diverse clinical applications. Future enhancements may include the incorporation of multi-channel classifiers and the introduction of a callback function for stopping criteria based on minimum loss and maximum accuracy to determine the optimal number of epochs. Additionally, weakly supervised techniques may be explored to enhance tumor localization accuracy. The ultimate goal is to generalize the proposed model for various medical image modalities, such as CT, PET, and X-rays, facilitating accurate tumor classification across different clinical scenarios.

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