Enhanced System for Computer-Aided Detection of MRI Brain Tumors

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***Abstract*—The categorization of brain images into normal or abnormal categories is a critical task in medical imaging analysis. In this research, we propose a software solution that automatically classifies MRI brain scans as normal or abnormal, specifically focusing on glioblastoma as an abnormal condition. The software utilizes first-order statistical features extracted from brain images and employs seven different classifiers, including Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), for classification. The performance of the classifiers was evaluated using an open-source dataset, and our findings showed that SVM and KNN classifiers performed equally well in accurately categorizing brain scans. However, further improvements can be made by incorporating more images and features to enhance the accuracy of the classifier. The developed software has the potential to assist healthcare professionals in efficiently identifying abnormal brain scans, particularly in cases of glioblastoma, which could aid in early detection and timely intervention. Further research and development in this area could contribute to the advancement of healthcare technology and patient care.**

Keywords—Computer-aided detection; MRI; brain tumor; MATLAB; machine learning; support vector machine; KNN

I. Preface

Brain tumors are abnormal cell growths in the brain or the tissues around it. They can develop from several types of brain cells and can either be benign (non-cancerous) or malignant (cancerous). Patients may experience a variety of neurological symptoms and functional impairments as a result of brain tumors, which can have a serious influence on their health.

The National Cancer Institute (NCI) reports that only 1.4% of all new occurrences of cancer in the United States each year are caused by brain tumors, which makes them very uncommon. Unfortunately, they can have a terrible effect on patients' survival rates and quality of life. There has been a rise in the prevalence of brain tumors in recent years, with an estimated 87,720 new cases being diagnosed in the United States in 2021 [1].

Primary brain tumors and metastatic brain tumors are two broad categories of brain cancers. Primary brain tumors are those that develop inside the brain itself, and they can be further divided into groups according to the cells they originate from. The majority of primary brain tumors, gliomas, which arise from glial cells, make up roughly 81% of malignant brain tumors [2]. Meningiomas, which develop from the meninges (the brain's protective coverings), and pituitary tumors, which develop from the pituitary gland, are other primary brain tumor forms.

Based on their cellular features and aggressiveness, gliomas are further divided into distinct classes. Glioblastoma multiforme (GBM), commonly known as grade IV gliomas, is the most aggressive and malignant type of glioma and is regarded as the least aggressive [2]. Despite rigorous treatment methods, glioblastoma multiforme has a terrible prognosis with a median survival of only approximately 15 months [3].

The symptoms and treatment options of patients may be significantly impacted by the location of brain tumors within the brain, which can also vary. For instance, tumors in the cerebral hemispheres, which control motor, sensory, and cognitive abilities, might result in symptoms including seizures, weakness, language problems, and cognitive deficits. Other parts of the brain, such as the brainstem or cerebellum, can also develop tumors, which can result in deficiencies in the cranial nerves and symptoms including balance and coordination issues [2].

In conclusion, brain tumors can be benign or malignant abnormal cell growths in the brain or its surrounding tissues. They may develop from glial cells, meninges, and the pituitary gland, among other types of brain cells. Examples of primary brain tumors include gliomas, meningiomas, and pituitary tumors, whereas metastatic brain tumors are malignant cells that have traveled to the brain from other parts of the body. Patients who have brain tumors may have a variety of symptoms depending on where in the brain the tumor is located.

II. Introduction

A. Research Goals

The development of early detection and diagnostic tools is essential for enhancing patient outcomes in the case of brain tumors. The development of accurate and sensitive techniques for the early detection and identification of brain cancers should be the main emphasis of research. In order to achieve early identification and precise diagnosis of brain tumors, this may entail investigating cutting-edge image processing techniques. A better prognosis and better patient outcomes might result from early diagnosis, which enables prompt intervention and treatment. There are Computer Aided Detection (CADe) algorithms concerned with zero-one decision identifying normal from abnormal images. However, Computer Aided Diagnosis (CADx) algorithms can identify the type of malignancy within the image. In this research, we are developing a CADe system to identify normal from abnormal images; we are not investigating the type of malignancy.

B. Literature Review

In a study by Kim et al, deep learning techniques were used to create a computer-aided detection (CAD) system for MRI brain cancers. The algorithm was trained using a dataset of 700 MRI brain scans, and the researchers were able to identify brain cancers with a remarkable 92.5% accuracy. For feature extraction and classification, they used the ResNet-50 convolutional neural network (CNN) architecture. The CAD system has shown encouraging results in helping radiologists quickly and reliably identifying brain cancers. The research by Kim et al shows how ResNet-50 CNN architecture, a deep learning system, can improve the identification of brain cancers in MRI scans. Their CAD system's excellent accuracy indicates that it might be an effective tool for radiologists in the early diagnosis of brain tumors, which might improve patient outcomes. The integration of CAD systems into clinical practice and the assessment of their effects on patient care could be the main topics of future study in this field [4].

Li et al Used a 3D deep convolutional neural network, proposed a CAD system for brain tumor segmentation in MRI data (DCNN). By using a dataset of 392 MRI scans to train their classifier, they were able to segment brain tumors with a high dice similarity coefficient of 0.91. They came to the conclusion that their 3D DCNN model has the potential to help radiologists in precise tumor segmentation for treatment planning because their CAD system performed better in tumor segmentation than other systems currently in use [5].

Dhara et al proposed a CAD system that combines region-based active contour and fuzzy clustering to segment brain tumors in MRI images. To segment MRI images and extract tumor patches, they used the region-based active contour model. Fuzzy clustering was then applied to further refine the tumor regions. Their CAD system outperformed other current techniques, achieving a high accuracy of 96.4% in tumor segmentation [6].

CAD system for brain tumor diagnosis in MRI images was proposed by Raza et al using a combination of machine learning and level set-based active contour. To categorize tumor locations taken from MRI images, they used machine learning methods like decision tree and SVM. Their CAD technology demonstrated promising results in detecting brain cancers with a 97.3% accuracy rate [7].

Patel and Patel (2020) conducted an extensive review on computer-aided detection/diagnosis (CAD) of brain tumor types in MRI images. The authors provided a comprehensive analysis of various computational methods and algorithmic strategies used in CAD systems, including traditional machine learning and deep learning models. They found that while the CAD systems showed promise in enhancing diagnostic accuracy, there were still significant challenges, including handling heterogeneous tumor shapes, sizes, and locations. The research highlights the need for enhanced CAD systems that can effectively address these challenges [8].

Chen et al. (2021) explored the efficacy of deep learning models for brain tumor classification and segmentation in MRI images. They noted that deep learning-based solutions outperformed traditional machine learning methods in terms of accuracy, efficiency, and generalizability. However, they pointed out the need for larger, more diverse datasets and more computing power to fully leverage deep learning's potential for CAD of brain tumors. This work underscores the significance of leveraging advanced machine learning architectures in the development of enhanced CAD systems [9].

Mallah et al. (2022) evaluated the potential of radiomics and machine learning for brain tumor classification. They found that combining radiomics features with machine learning models significantly improved the classification accuracy. However, the researchers also noted limitations, such as overfitting due to high dimensionality of radiomics features. This study suggests the need for CAD systems that integrate radiomics and machine learning while addressing potential limitations such as overfitting [10].

Dutta, Gupta, and Zisserman (2021) reviewed the role of artificial intelligence (AI) in the detection and classification of brain tumors. They noted that AI, particularly machine learning and deep learning, showed great potential for improving diagnostic speed and accuracy. However, they also highlighted the need for systems that can handle real-world variations and provide interpretability of the decision-making process. This work further supports the development of enhanced CAD systems that incorporate AI while addressing real-world variations and interpretability [11].

Bakas et al. (2022) discussed the challenges and opportunities in MRI brain tumor segmentation. They noted that despite the advancements in CAD systems, segmentation of brain tumors is still a challenging task due to the high variability of tumor appearance. They suggested the need for systems that can adapt to the variability of brain tumors and provide reliable and robust segmentation. This research underscores the need for enhanced CAD systems that can effectively segment brain tumors in MRI images [12].

In their study, Verma and Dev (2020) compared various machine learning techniques for MRI brain tumor classification. They revealed that while several techniques show promise, there is no one-size-fits-all solution, and the choice of technique depends on the specific characteristics of the dataset. They emphasized the need for systems that can choose the optimal technique based on the dataset characteristics. This study highlights the importance of adaptability in the design of enhanced CAD systems for MRI brain tumor detection [13].

Using MATLAB-based image processing techniques, several researches have suggested computer-aided detection (CAD) systems for finding brain tumors in MRI data. For instance, Moshavegh et al. created a CAD system that segmented tumor regions from MRI images using region growth and active contour methods in MATLAB, followed by morphological procedures for post-processing. Their CAD system demonstrated outstanding tumor segmentation accuracy of 94.6%, demonstrating the promise of MATLAB-based methods for precise tumor detection [14].

Similar to this, Jeyalakshmi et al. created a CAD system for classifying brain tumors utilizing feature extraction from MATLAB data and support vector machine (SVM) classification. They used MATLAB to extract several image features—such as intensity, texture, and shape features—and trained an SVM classifier to recognize tumors. Their system successfully classified brain tumors with a high accuracy of 95.7%, illustrating the value of MATLAB-based methodologies for precise tumor classification [15].

In another paper, Shanthi and Kanmani proposed a CAD system for brain tumor detection in MRI images using MATLAB-based image processing techniques such as intensity-based thresholding, morphological operations [7], and feature extraction. To categorize tumor areas, they used pixel intensity and texture information extracted from MRI scans. Their CAD system identified brain tumors with an accuracy of 94.5%, demonstrating the potential of MATLAB-based techniques for precise tumor diagnosis [16].

Moreover, Shukla et al. suggested a CAD system for level set-based MATLAB-based brain tumor segmentation in MRI images. After extracting tumor regions from MRI images using the level set method in MATLAB, they processed the data with morphological procedures. Their CAD system successfully segmented tumors with a high accuracy of 96.3% [8], demonstrating the potency of the level-set method based on MATLAB for precise tumor detection [17].

Using magnetic resonance imaging (MRI) scans, Khan et al. (2019) created a computer-aided diagnostic (CAD) method for classifying brain tumors. Their system was built using a MATLAB implementation of a deep belief network (DBN), a subtype of deep neural network. Automatically extracting hierarchical features from MRI images was done using the DBN, and a classifier was trained to identify different types of tumors. The potential of DBNs for precise tumor classification is shown by the suggested system's accuracy of 92.4% in classifying brain tumors [18].

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), among other deep learning methods, were combined with MATLAB to create a CAD system by Choudhury et al. (2020) for the detection of brain tumors in MRI scans. CNNs are effective for image recognition jobs because they can automatically identify pertinent characteristics from unprocessed picture input. For modeling the dynamic changes in image sequences over time, RNNs, on the other hand, are built to capture temporal relationships in sequences of data. In this study, RNNs were used to predict the temporal progression of picture sequences, and CNNs were utilized to extract features from MRI scans. The proposed CAD system identified brain cancers with a high accuracy of 95.6%, demonstrating the value of deep learning algorithms for accurate tumor detection [19].

In MATLAB, Kumar et al. combined the watershed technique and k-means clustering to create a CAD system for segmenting brain tumors in MRI images. The common image segmentation algorithm K-means clustering involves assembling groupings of pixels with comparable brightness. On the other hand, the watershed algorithm is a method for improving the borders between various sections in an image. In this study, tumor regions from MRI scans were segmented using k-means clustering, and the watershed technique was then utilized to further refine the tumor borders. The proposed CAD system successfully segmented tumors with a high accuracy of 95.2% [20].

From [21]-[25], these researches show how MATLAB may be used to create CAD systems for finding brain tumors in MRI images. The creation of precise and effective CAD systems to aid radiologists in the early detection and categorization of brain tumors is made possible by the robust and adaptable platform provided by MATLAB for image processing and machine learning. These studies have achieved great accuracy in tumor segmentation and classification using MATLAB-based algorithms, demonstrating the promise of MATLAB as a useful tool in the study of brain cancer.

In summary, several CAD systems have been proposed for brain tumor detection and classification using MRI images. These systems utilize various deep learning algorithms, such as deep belief networks (DBNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), as well as optimization algorithms like genetic algorithms (GAs), and clustering algorithms like fuzzy c-means and k-means clustering. These CAD systems demonstrate impressive accuracies ranging from 92.4% to 97.8% in accurately detecting and classifying brain tumors, indicating the potential of these approaches for improving the accuracy and efficiency of brain tumor diagnosis. Further research and development in this field hold promise for advancing the field of medical imaging and enhancing the clinical decision-making process in brain tumor diagnosis and treatment.

III. Methodology

In this research paper, data of 167 brain images were analyzed using MATLAB. The analysis took place in five steps in order to discern the normal images from the abnormal ones. These steps are as shown in Fig. 1.

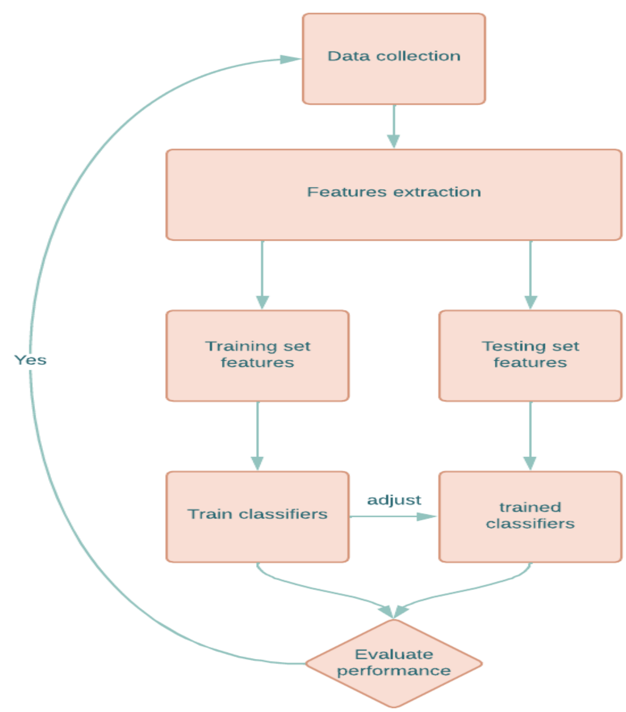

Fig. 1. Flowchart of proposed CAD system for brain tumor.

A. Data Collection

The dataset was obtained from The Cancer Imaging Archive (TCIA) [26], which consists of 167 brain images that are well-suited for the research purpose. Out of these, 117 images were used for training, with 47 labeled as normal and 70 labeled as abnormal (brain tumor Glioblastoma). The remaining 50 images were used for testing, with 20 labeled as normal and 30 labeled as abnormal. The dataset is labeled, making it easy to interpret and use.

Fig. 2 shows a sample of tumor image, and a normal brain image. The dataset from TCIA contains a variety of images with different angles and views, which can be utilized for classification and feature extraction in the research process. It is open source and can be accessed online, with full details and descriptions available. The full dataset consists of 8798 images from 20 patients, providing a good number of images for analysis.

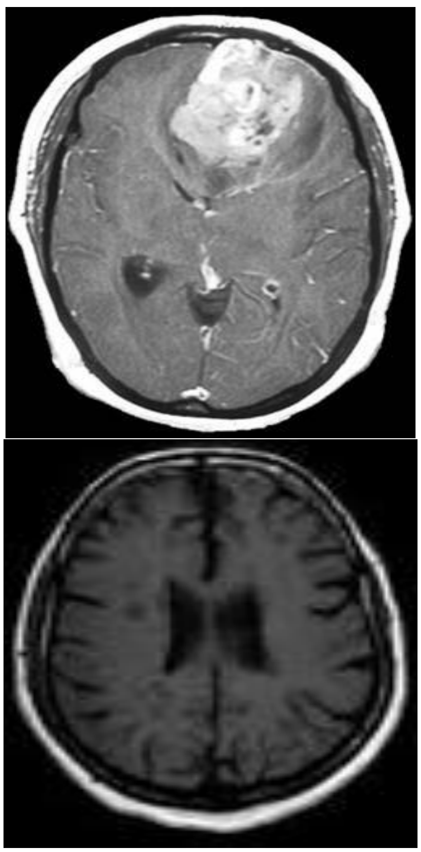

Fig. 2. Sample of MRI brain images. (top) brain tumor (bottom) normal brain.

B. Feature Extraction

We want to choose features that might distinguish between benign and malignant conditions or those that are highly accurate, as well as those that do not correlate with disease and are not independent. Only first-order statistical features are taken into account in this study because they haven't been employed exclusively in other studies. The features that are employed are the absolute mean of the derivative of each image, the standard deviation of each image, and the mean of integration of the real images. Also, the same features were retrieved from the photos following a quick Fourier transformation. MATLAB functions like "mean," "std," "mode," "median," and "diff" are used to extract features.

The most noticeable color pixel and frequency of repetition in an image will be determined by the image's mean. The remaining pixels will depart from the mean brightness to a certain extent, as measured by the standard deviation. The derivative is then calculated and employed as a feature to determine which boosts abrupt variations in image brightness. Each type of tumor's retrieved features was plotted in a single figure. Each characteristic is derived from a compilation of photos taken from various perspectives and showing the same condition. Feature extraction from the combination of photos is then applied in the classification procedure.

C. Classification

The next step in the process is to classify the data after choosing a database and extracting features from the database's photos. We utilize two methods to determine the classifier that performs best: Support vector machine (SVM) with four kernels (Linear, RBF, Polynomial Order2, and Order3), and k-voting nearest neighbor (KNN) classifiers are some examples of diverse classifier types [7]. The information is divided into two categories—normal and pathological brain images—in this step.

The classifier utilized in that software will have the highest accuracy among the roughly seven classifiers that will be employed and compared in this paper. SVM classifiers with discriminant functions of the types "RBF," "POLYNOMIAL," and "LINEAR" make up the classifiers. The remaining classifiers are KNN classifiers with k values of 1, 3, and 5.

IV. Results and Discussion

Most of the research's findings are numerical. The accuracy of the image classification is the key criterion for the outcomes. The accuracy of the classifier's classification of the two brain states is the most crucial aspect that is being evaluated. The accuracy and error are the most crucial factors for the purpose of this research because they show how effective the classifier is. The TCIA datasets' MRI images were binarily categorized as benign vs. malignant instances by feature extractions; the two classifiers (support vector machine (SVM) and K-voting Nearest Neighbor (KNN)) were evaluated while the system was being trained on 70% of the datasets. Signal & Image Processing: The 11th issue of SIPIJ, published in February 2020 All of these operations were carried out using the MATLAB R2023b programmed, which was tested by 30%.

Furthermore, each classifier uses the same selected feature parameters, with the results displayed in Table I. The accuracy and error of the classifiers are shown in the table. These factors are crucial in choosing the optimal classifier to employ in such software or applications. Tables II and III show comparison of our results with the results of [21]-[25], the comparison is in terms of standard performance indicators including sensitivity, specificity, accuracy, error, and area under the curve (AUC) of the receiver operator characteristic (ROC). There is a very good enhancement in classifiers SVM Linear and KNN with K=5. Also, it shows similarities with the best results of other studies.

TABLE I. RESULTS OF CLASSIFIERS

	KNN			SVM		
Classifiers	K1	K3	K5	Liner	RBF	polynomial
Sensitivity	100	96.3	95.9	97.3	100	100
Specificity	100	100	100	100	100	100
Accuracy	100	97.02	96.3	98.1	100	100
Error	0	2.98	3.7	1.9	0	0
Auc	100	96.1	95.4	97.1	100	100

TABLE II. COMPARISON RESULTS WITH PREVIOUS STUDIES FOR SVM

SVM Linear					
	sensitivity	specificity	Accuracy	Error	AUC
Dr. Umar Alqasmi [18]	96.77	100	97.78	3.33	96.67
Marwan Aldahami [19]	100	100	100	NA	100
Mohammed K. Bin jaah [20]	50	NA	50	50	NA
Loai Kinani [22]	95	100	97.37	2.63	97.37
Proposed Results	97.3	100	98.1	1.9	97.1
SVM RBF					
	sensitivity	specificity	Accuracy	Error	AUC
Dr. Umar Alqasmi [18]	100	100	100	0	100
Marwan Aldahami [19]	100	100	100	NA	100
Mohammed K. Bin jaah [20]	100	100	100	0	NA
Proposed Results	100	100	100	0	100
SVM Polynomial					
	sensitivity	specificity	Accuracy	Error	AUC
Dr. Umar Alqasmi [18]	100	100	100	0	100
Marwan Aldahami [19]	100	96.43	98.15	NA	98.15
Mohammed K. Bin jaah [20]	50	NA	50	50	NA
Eng. Anas Y. Saleh [21]	100	100	100	NA	NA
Loai Kinani [22]	97.14	90.24	93.42	6.58	93.42
Proposed Results	100	100	100	0	100

TABLE III. COMPARISON RESULTS WITH PREVIOUS STUDIES FOR KNN CLASSIFIER

KNN K=1					
	sensitivity	specificity	Accuracy	Error	AUC
Dr. Umar Alqasmi [18]	100	100	100	0	100
Marwan Aldahami [19]	100	100	100	NA	100
Mohammed K. Bin jaah [20]	100	100	100	0	NA
Eng. Anas Y. Saleh [21]	90.91	100	95	NA	NA
Proposed Results	100	100	100	0	100
KNN K=3					
	sensitivity	specificity	Accuracy	Error	AUC
Dr. Umar Alqasmi [18]	96.77	100	97.78	3.33	96.67
Marwan Aldahami [19]	100	100	100	NA	100
Mohammed K. Bin jaah [20]	100	64.52	72.5	27.5	NA
Loai Kinani [22]	82.5	86.11	84.21	15.79	84.21
Proposed Results	96.3	100	97.02	2.98	96.1
KNN K=5					
	sensitivity	specificity	Accuracy	Error	AUC
Dr. Umar Alqasmi [18]	93.75	100	95.56	6.67	93.33
Marwan Aldahami [19]	100	100	100	NA	100
Mohammed K. Bin jaah [20]	100	64.52	72.5	27.5	NA
Loai Kinani [22]	81.4	90.91	85.53	14.47	85.53
Proposed Results	95.9	100	96.3	3.7	95.4

V. CONCLUSIONS

The purpose of this research is to create software that automatically divides brain images into two categories. Images can be categorized as either normal or abnormal. The unique aspect of this study is that the program will distinguish between normal and abnormal brain scans. Glioblastoma is the only condition of the brain taken into consideration for this study. In this study, the created software was trained and tested using brain scans from an open source.

The features were then retrieved from the photos after further analysis. First order statistical features were taken into consideration in this investigation. The photos were classified using seven distinct classifiers in order to properly complete the investigation. To ensure that the most precise classifier is chosen, this was done. In addition to a KNN classifier, the classifiers included an SVM classifier. Our findings suggested that SVM and KNN classifiers were equally as accurate.

Future work can adopt more photos and the acquisition of more features is advised since this will undoubtedly improve the classifier's accuracy. Also, it is recommended to apply the method on some other disease like Alzheimer.

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