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An Automated System for Detecting and Classifying Brain Tumors Using Convolutional Neural Networks (VGG16)

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نظام آلي للكشف عن أورام الدماغ وتصنيفها باستخدام الشبكات العصبية الالتفافية (*VGG16*)

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Abstract:
One of the most crucial strategies in managing brain tumors is early and accurate detection to enable timely intervention and stop their growth. In this research, it was research to use the deep convolutional neural network VGG-16, which is employed to extract deep features from brain MRI images from a dataset compiled from the (Kaggel) consisting of 7,023 MRI images These images were divided into four categories depending on the type main categories: glioma tumor, meningioma tumor, pituitary tumor, and healthy cases. Where the images are then passed through multiple convolutional layers, pooling layers, and fully connected layers to perform the final classification process. Where 80% of them were used for training, and 20% for testing. The final results of the accuracy obtained from the experiments of using the research mode is (95%).

Keywords: Brain Tumor Diagnosis, MRI Images, Deep Learning, Convolutional Neural Networks, VGG.

الملخص
يعدّ الكشف المبكر والدقيق عن أورام الدماغ من أهم الاستراتيجيات في علاجها، إذ يُتيح التدخل في الوقت المناسب وإيقاف نموها. في هذا البحث، استُخدمت الشبكة العصبية التلافيفية العميقة *VGG-16* لاستخراج خصائص عميقة من صور الرنين المغناطيسي للدماغ، وذلك من مجموعة بيانات مُجمّعة من *Kaggle* تضم 7023 صورة. قُسّمت هذه الصور إلى أربع فئات رئيسية حسب نوعها: ورم دبقي، ورم سحائي، ورم الغدة النخامية، وحالات سليمة. بعد ذلك، مُررت الصور عبر طبقات تلافيفية متعددة، وطبقات تجميع، وطبقات متصلة بالكامل لإجراء عملية التصنيف النهائية. استُخدم 80% من الصور للتدريب، و20% للاختبار. بلغت دقة النتائج النهائية المُتحصل عليها من التجارب باستخدام نموذج البحث 95%.

الكلمات المفتاحية: تشخيص أورام الدماغ، صور الرنين المغناطيسي، التعلم العميق، الشبكات العصبية الالتفافية.

Introduction
A brain tumor is an abnormal growth of cells in or around the brain, categorized as part of central nervous system tumors. These tumors can be malignant (cancerous) or benign (non-cancerous), with only about one-third being cancerous. Regardless of type, they can impair brain function and health by compressing nerves, blood vessels, and surrounding tissue. Tumors originating in the brain are primary, while those spreading from other body parts are secondary. Over 150 distinct brain tumors are

identified, classified by healthcare providers into gliomas (from glial cells) or non-gliomas (on or within brain structures), and as benign or malignant [1,2,3,12].
Traditional diagnosis relies heavily on advanced imaging like MRI, visual analysis by radiologists, and specific assessment protocols. While MRI provides detailed internal brain views, this manual process faces significant challenges: difficulty distinguishing among the three main tumor types in MRI images, radiographic similarity between different tumors, variability in specialist expertise across medical centers, and the time-consuming nature of detailed case analysis. Accurate classification is crucial as treatment strategies vary radically by tumor type [4,5,9,10].
Furthermore, some physicians may lack the necessary expertise, particularly in areas where specialists are unavailable. Therefore, this the System plays a vital role in improving tumor classification by analyzing MRI images using deep learning algorithms [6,7,8,11,13].
To address these limitations, this research proposes designing an automated system for brain tumor detection and classification using the VGG16 convolutional neural network. By training the model on a dataset of MRI images, the system aims to support physicians in making accurate diagnostic decisions, reduce the need for unnecessary invasive procedures like biopsies, and enhance healthcare quality.
Where the model was trained to classify four main categories, Glioma, Meningioma, and Pituitary tumor, healthy (No Tumor) cases, leveraging deep learning to identify subtle patterns in MRI scans that may elude human observation.

Research Methodology and Design

This Chapter introduces the methodologies used to conduct this thesis, briefly discussing materials and tools used, the selection of the appropriate model for classification, the architectural design of the research model, and evaluation techniques. It deals with the methodological analysis of diagnosing brain tumors from healthy and infected brain MRI images from the brain and preparing the necessary data set using different mechanisms. Then this chapter shows the design of a Layers of the convolutional neural network model(VGG16) detect and classify the tumor, train and test the model, and finally, evaluate the effect of learning parameters.

Research Algorithm Methodology

To deploy (VGG16) for classification and to compute the features for a given image, the following steps are used:

1. Reading brain MRI images of the dataset obtained from (Kaggle) web consists of 7023 brain MRI images.
2. Images were resized to 224x224 pixels, the color system was converted from BGR to RGB, and standardization processes were applied to ensure the quality and consistency of the inputs, making them ready for analysis and feature extraction.
3. Feature extraction is performed using the VGG16 algorithm, with the resulting feature vectors serving as the input for the training and testing phases.
4. The brain MRI images are classified in the testing phase into four classes.
5. Model Evaluation: The model's performance was measured using performance metrics, including:

Accuracy, Precision, Recall, and F1-Score, through the use of the Confusion Matrix and ROC curves to accurately analyze the performance.

Research Algorithm Design

The research algorithm design consists of three stages: conversion, feature extraction, and classification, as shown in Figure (1).

DATASET AND EXPERIMENTATION

Our model was constructed using a dataset of brain MRI images; 7023 brain MRI images were utilized for training and testing, and a system capable of diagnosing brain tumor was then created. The brain tumor MRI images with the most prevalent tumor types are depicted in Figure (2) below, and Table (1) lists the image numbers for each class. We tested our system using a few test image examples, where the outcomes of our tumor recognition vary from one tumor to the next. For instance, the brain tumor sample for the Glioma Tumor sickness the results in the below Table (3) both had precision measures of 91.54% when compared to other brain tumors. The wide variation in appearance amongst tumor is the cause of the wider disparity. The precision, recall, F-measure, and accuracy curves of that

VGG16 model are shown in Figure (7). in Table (3), we show that our model, which produces encouraging results on brain tumor. The classification Accuracy for all classes was 95%.

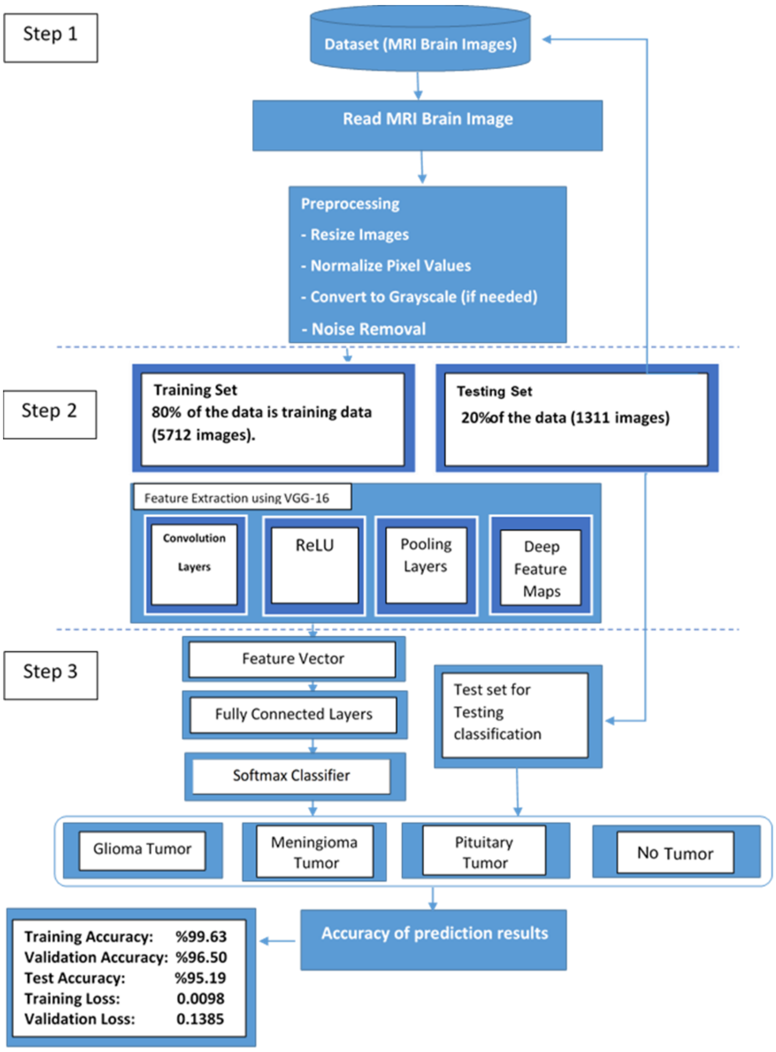


Figure 1: Diagram of the Research system by using VGG16.

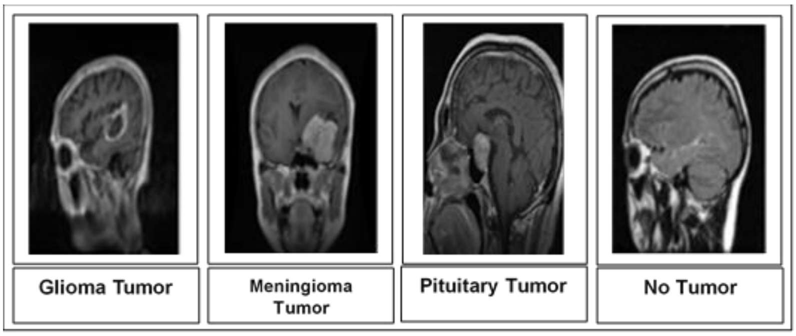


Figure 2: Brain MRI images, both with and without tumors.

Table 1: Dataset of Brain MRI images.

	Percentage	Glioma Tumor	Meningioma Tumor	Pituitary Tumor	No Tumor
Training	80%	1321	1339	1457	1595
Testing	20%	300	306	300	405
Total	100%	1621	1645	1757	2000

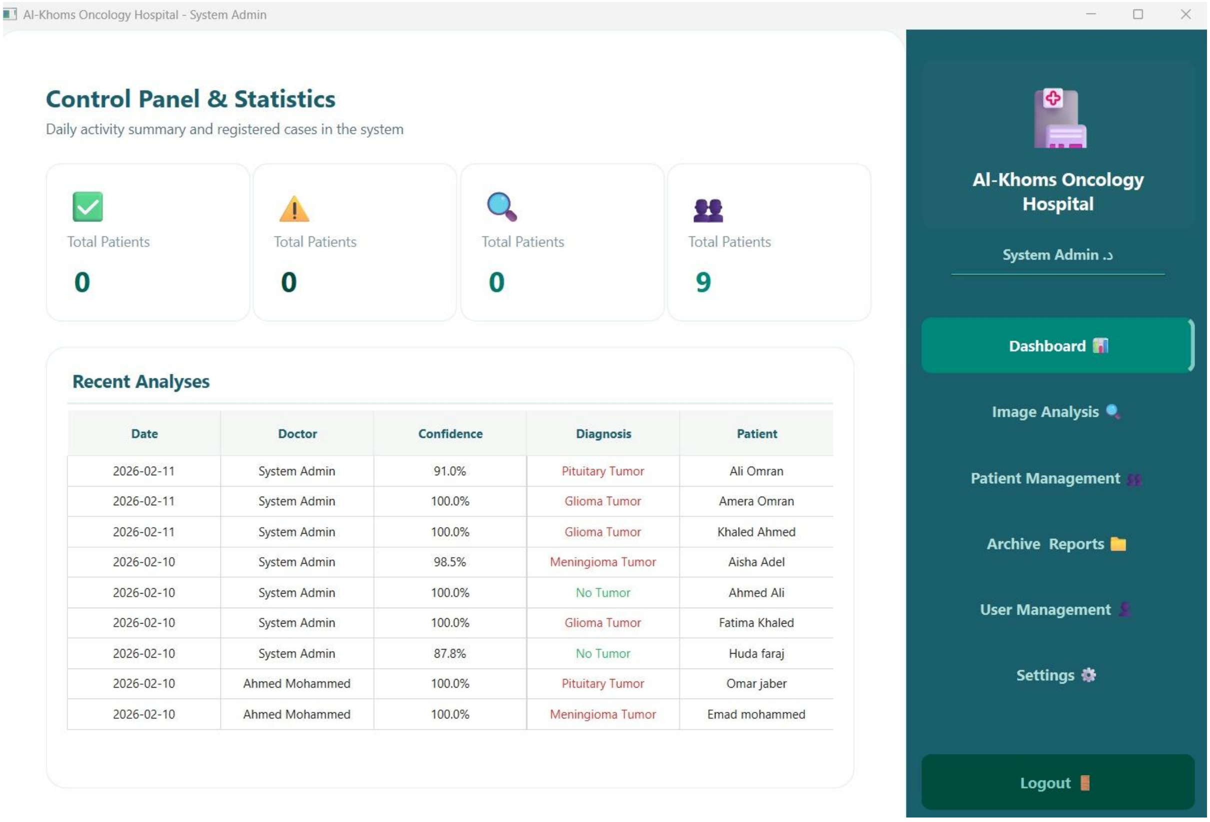


Figure 3: The system's main interface

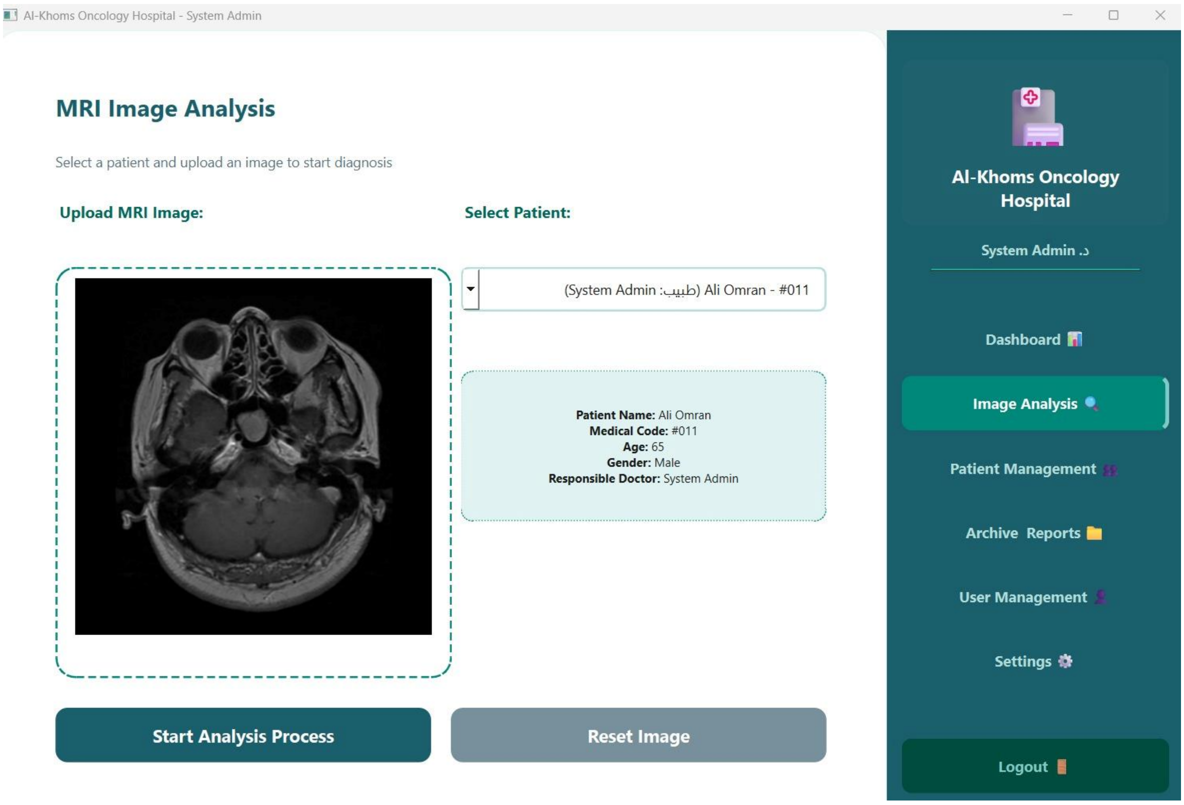


Figure 4: Select and upload an image of the patient

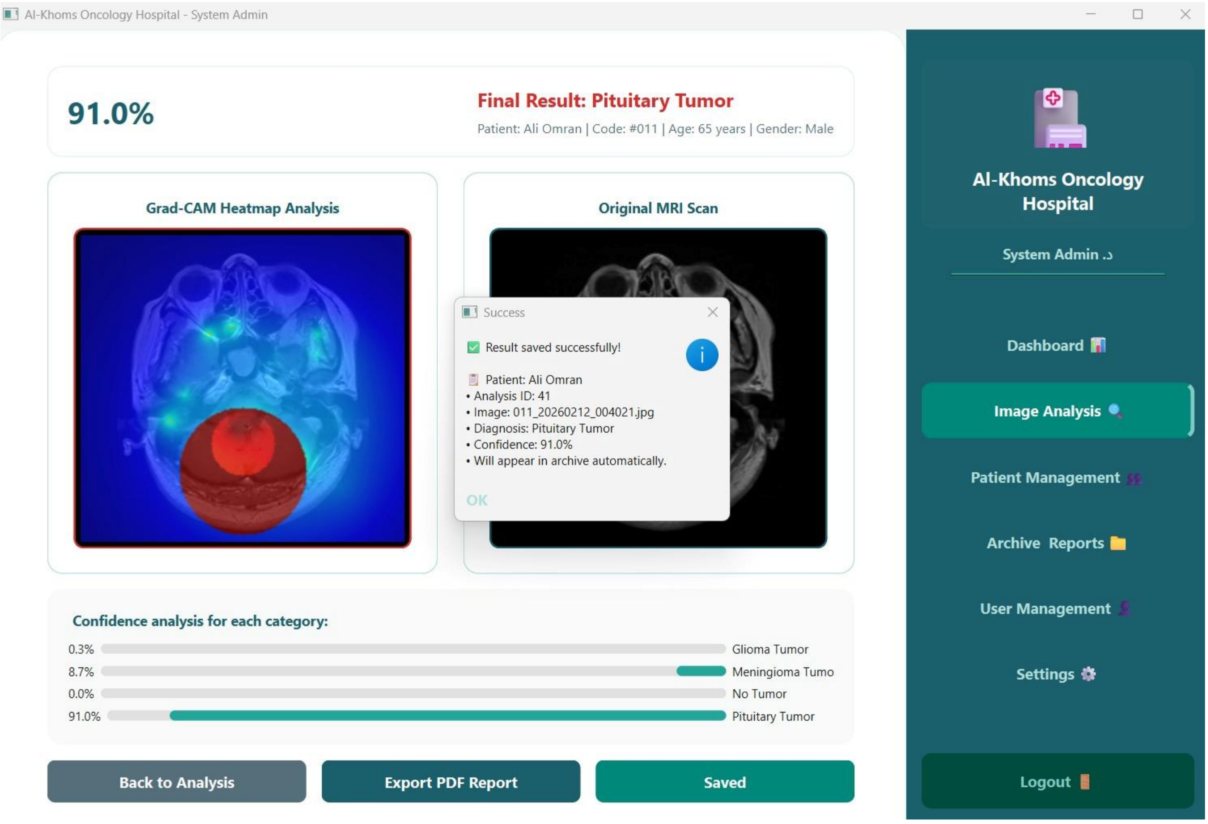
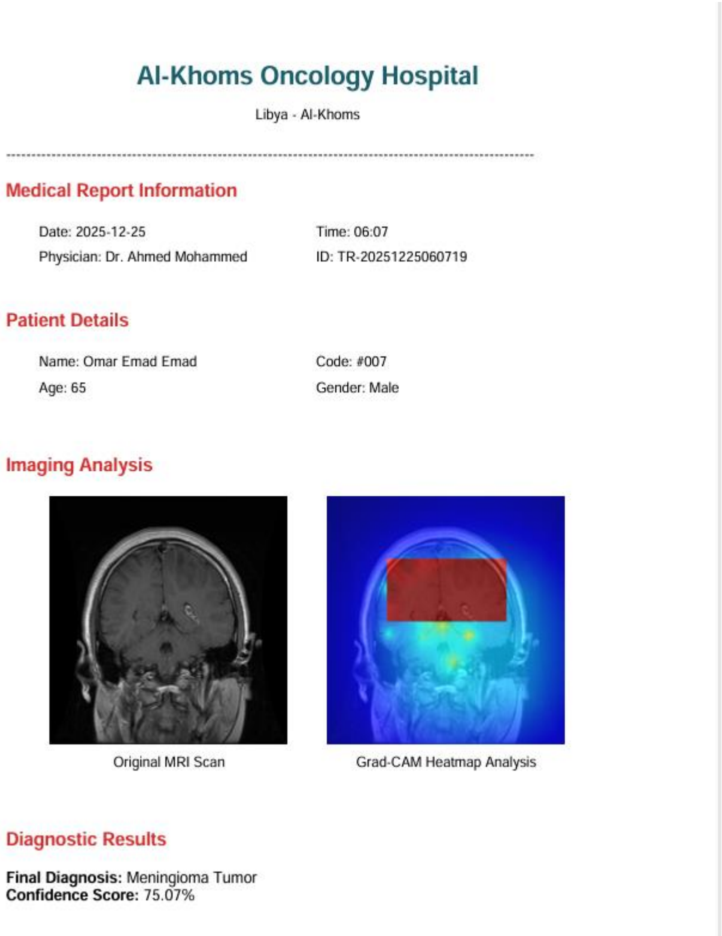


Figure 5: Image analysis result



Al-Khoms Oncology Hospital

Libya - Al-Khoms

Medical Report Information

Date: 2025-12-25	Time: 06:07
Physician: Dr. Ahmed Mohammed	ID: TR-20251225060719

Patient Details

Name: Omar Emad Emad	Code: #007
Age: 65	Gender: Male

Imaging Analysis

Original MRI Scan

Grad-CAM Heatmap Analysis

Diagnostic Results

Final Diagnosis: Meningioma Tumor
Confidence Score: 75.07%

Figure 6: Patient's medical report

Figure 7: VGG16 algorithm Performance metrics chart for classes

The Results Classification

The convolutional neural network algorithm in VGG16 was used to classify brain MRI images (Glioma Tumor, Meningioma Tumor, No Tumor, Pituitary Tumor) in classifying the data collecting in a dataset of brain MRI images. The proposed algorithm was used to extract the features of brain MRI images. The classification results were extracted as values and distributed on the confusion matrix for four classes as presented in Table (2):

Table 2: Confusion matrix – Brain Tumor Classification.

		Predicated Label			
Actual Label		Glioma Tumor	Meningioma Tumor	No Tumor	Pituitary Tumor
	Glioma Tumor	292	8	0	0
	Meningioma Tumor	19	279	7	1
	No Tumor	1	1	403	0
	Pituitary Tumor	7	18	1	274

VGG16
Performance Evaluation

The system's performance is measured using quantitative metrics such as Precision, Recall, F-measure, and Accuracy [14]. The following are examples of calculating Measures by using matrix terms for brain MRI images of a Glioma Tumor. images shown in Table 3.

$$\text{Precision} = \frac{TP_i}{TP_i + FP_i} \times 100 \qquad = 292/(292+27) \times 100 \approx 91.54\%$$

$$\text{Recall} = \frac{TP_i}{TP_i + FN_i} \times 100 \qquad = 292/(292+08) \times 100 \approx 97.33\%$$

$$\text{F-measure} = \frac{2 \times precison \times recall}{precision + recall} \qquad = 02\times91.54\times97.33/(91.54+97.33) \approx 94.36\%$$

The Accuracy for all classes is:

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} TP_i + \sum_{i=1}^{n} FP_i} \times 100$$

=292+279+403+274/1311

1248/1311×100 ≈ 95.19%

Accuracy = 95.19%

Table 3: VGG16 Performance evaluation

Types of brain tumors	Measures			Accuracy
	Precision	Recall	F-measure	
Glioma Tumor	91.54	97.33	94.36	95.19%
Meningioma Tumor	91.18	91.18	91.18	
No Tumor	98.05	99.51	98.77	
Pituitary Tumor	99.64	91.33	95.29	

The performance evaluation of the VGG16 convolutional neural network algorithm Performance evaluation, as shown in Table 3, indicates that the model achieved a strong overall accuracy of 95.19% with balanced results across precision, recall, and F-measure. The classifier performed exceptionally well in detecting for Brain Tumor such as Glioma Tumor, Pituitary Tumor, where both precision and recall were consistently high, reflecting the effectiveness of VGG16 algorithm layers in extracting discriminative features. Clearly, Glioma Tumor Perfect Recall (97.33%) and a high F-measure (94.36), while Pituitary Tumor reached perfect Precision (99.64%) with a strong F-measure (95.29%), highlights the model's reliability in identifying these tumor categories. Similarly, healthy class (No Tumor) showed robust classification performance with F-measures above 97%. However, the model exhibited relatively lower performance in classifying Meningioma Tumor (F-measure = 91%), where reduced precision suggests possible overlaps with other categories or misclassification due to similar tumors symptoms.

These variations imply that while the model is highly effective for most tumors, further refinement is needed to reduce false positives in certain cases. Overall, the results demonstrate that the VGG16 convolutional neural network algorithm is a powerful approach for Brain Tumors detection and offers significant potential for practical application in hospitals and specialized clinics for brain tumors, though improvements in differentiating visually similar classes remain important.

Discussion

In the Implementation phase, the efficiency of detection and classification for MRI images for brain tumors as Glioma Tumor, Meningioma Tumor, No Tumor, Pituitary Tumor using VGG16 convolutional neural network algorithm to create features vectors for classification by VGG16. The proposed approach's performance was evaluated using several measures: Accuracy, Precision, Recall, Specificity, and F-measure. Based on the analysis of the results of the algorithm, the most important results were:

- Accuracy: when using VGG16 algorithm it was (95.19%). Regarding the detection of Glioma Tumor, the percentages of all measures were as follows: the Precision was (91.54%). For the Recall, it was (97.33%). The percentage of the F-measure was (94.36%).
- For the detection of Meningioma Tumor, the percentages of all measures were as follows: Precision was (91.18%). Sensitivity (Recall) was (91.18%). The percentage of the (F-measure) was (91.18%).
- To detect the Healthy cases (No Tumor), the percentages of all scales were as follows: The Precision was (98.05%). The Recall was (99.51%). For the percentage of F-measure, it was (98.77%).
- For the detection of Pituitary Tumor, the percentages of all measures were as follows: The Precision was (99.64%). Also, the recall was (91.33%). Similarly, the percentage (F-measure) was (95.29).
- Mindful of the above, the results evidenced that the proposed system is more effective in detection and classification for MRI images for brain tumors when using VGG16 convolutional neural network algorithm to extract features.

Conclusion

In this research, the efficiency of detection and classification for MRI images for brain tumors as Glioma Tumor, Meningioma Tumor, No Tumor, Pituitary Tumor using VGG16 convolutional neural network algorithm created features vectors to be used classification by VGG16 algorithm. The performance of the research approach was evaluated using several measures: Accuracy, Precision, Recall, Specificity, and F-measure. During the analysis and comparison of the results of the VGG16 algorithm, the most important results were:

The efficiency and accuracy of the research system were measured by comparing the results research technique. Several measures were used, namely: Accuracy, Precision, Recall, and F-measure, and by analyzing and comparing the system results. Using the research technique, where the most important results were: Accuracy when using VGG16 algorithm is (95.19%).

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