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Processing and Classification of brain images based on deep learning techniques

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Abstract: Classifying brain images and diagnosing tumors using MRI is a difficult process due to the diversity and complexity of the cases. This research presents a model for classifying brain images and detecting tumors based on deep learning techniques.

The proposed model has been trained and tested on a database of MRI images consisting of 253 images. 155 of the images are images of healthy cases and 98 image are images of defected cases. The images have been pre-processed and prepared as suitable input for the designed neural network model. The proposed model has achieved outstanding results where the accuracy reached 94.5% with an AUC value = 0.95. The obtained results make the proposed model a suitable model to help specialist doctors in diagnosing brain images and identifying cases of malignant tumors.

Keywords: Deep learning, Classification, Convolutional Neural Networks, MRI images, brain tumor, image processing, Accuracy, AUC.

1 Introduction

Human health is one of the most important priorities in life. Therefore, a double and increasing amount of work has been constantly devoted to developing medical sciences, whether at the stage of diagnosing diseases or searching for treatment, until medicine has reached its current state of progress and is still seeking further development using all available means of technology. Medical images are usually digitized and processed based on the concepts of medical informatics in the practice of modern medicine for helping specialists in making sensitive decisions [1].

However, with the latest technologies, detailed interpretation of medical images poses a challenge from a time and accuracy perspective due to the specific nature of medical data and its need for precise processing. The challenge stands tall especially in regions with abnormal color and shape. This needs to be identified by radiologists for future studies, as the initial detection of the malignant area always helps in early diagnosis of the affected person and is one of the main factors for reducing mortality.

2 Research Objective

This research aims to design a diagnostic system based on convolutional neural networks (CNN). The proposed system classifies magnetic resonance images (MRI) for the purpose of detecting a brain tumor through analyzing medical images and extracting useful information.

3 Research materials and methods

The proposed model has been implemented using Anaconda software which is a data science platform that uses the Python programming language. Anaconda is one of the most important open source artificial intelligence languages. This is done with the help of Keras and Tensor Flow libraries in the stage of building CNN networks and machine learning library sklearn. These libraries are distinguished

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for their fast performance in the training process, in addition to reducing the size of the code and the number of procedures required from the user.

4 Image Processing

It is a series of operations performed on a digital image. The purpose of this process is to improve the image quality according to certain standards and to make it clearer and more accurate. The result of these operations is an image that is understandable to humans after making the necessary improvements [3].

This image represents an input to the computer vision process which is responsible for examining, processing, classifying and diagnosing objects in the external environment. Image processing is done by analyzing the images and extracting features and characteristics. Finally output signals are taken from the image. These signals are understood by the computer model (i.e. characteristics, features and measurements, not an image) with the aim of benefiting from them in various fields.

4.1 Steps for processing digital images

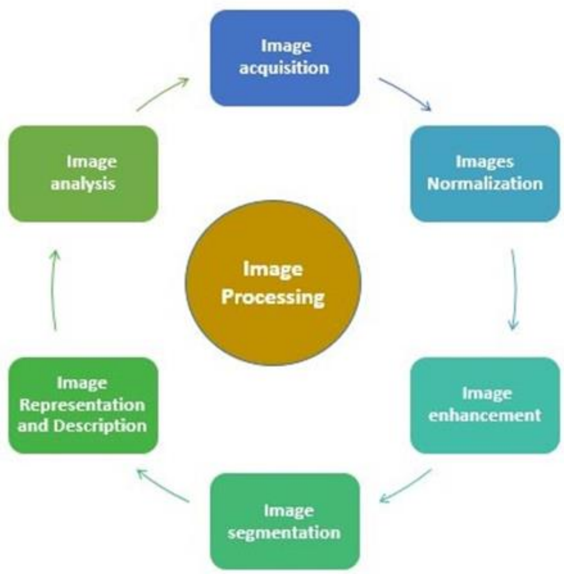

Figure 1: Image Processing Steps

- Image Acquisition: This involves capturing an image using a digital camera or scanner or importing an existing image into a computer.
- Image Normalization: This process is often used in data sets preparation for artificial intelligence (AI). In this process, multiple images are put into a common statistical distribution in terms of size and pixel values. However, a single image can also be normalized within itself [4].
- Image Enhancement: This involves improving the visual quality of an image, such as increasing contrast, reducing noise, and removing artifacts.
- Image Segmentation: This involves dividing an image into regions or segments, each of which corresponds to a specific object or feature in the image.
- Image Representation and Description: This involves representing an image in a way that can be analyzed and manipulated by a computer, and describing the features of an image in a compact and meaningful way.

- Image analysis: This involves using algorithms and mathematical models to extract information from an image, such as recognizing objects, detecting patterns, and quantifying features [5].
- Image synthesis and compression: This involves generating new images or compressing existing images to reduce storage and transmission requirements.

Digital image processing is widely used in a variety of applications, including medical imaging, remote sensing, computer vision, and multimedia.

4.2 Medical imaging and MRI

Medical imaging refers to several different technologies that are used to view the human body in order to diagnose, monitor, or treat medical conditions. Each type of technology gives different information about the area of the body being studied or treated, related to possible disease, injury, or the effectiveness of medical treatment [6], it is a central part of the improved outcomes of modern medicine.

Different types of medical imaging procedures include:

- X-rays.
- Magnetic resonance imaging (MRI).
- Ultrasounds.
- Endoscopy.
- Tactile imaging.
- Computerized tomography (CT scan).

Magnetic resonance imaging (MRI)

Magnetic Resonance Imaging (MRI) is a medical imaging procedure for making images of the internal structures of the body. MRI scanners use strong magnetic fields and radio waves (radiofrequency energy) to make images.
During an MRI exam, an electric current is passed through coiled wires to create a temporary magnetic field in a patient's body [7].
Radio waves are sent from and received by a transmitter/receiver in the machine. These signals are used to make digital images of the scanned area of the body. A typical MRI scan last from 20 - 90 minutes depending on the part of the body being imaged.

5 Deep Learning Techniques

Deep learning is a subset of machine learning, and is essentially a neural network with three or more layers. These neural networks attempt to mimic the behavior of the human brain allowing it to "learn" from large amounts of data with the help of additional hidden layers that optimize and refine for accuracy as shown in the Figure 2 [8].
Deep learning drives many Artificial Intelligence (AI) applications and services that improve the automation and performance of analytical and physical tasks without human intervention. Acknowledgement should be placed after the main body and before the references.

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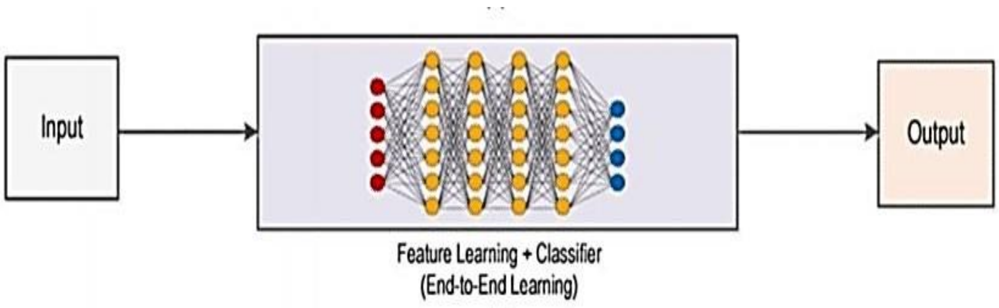

Figure 2: Deep Learning model

5.1 Convolution Neural Networks (CNN)

It is a special type of feed-forward neural networks. It derives its work from biological processes found in the visual lobes specifically in the human brain [9]. It is often used in image processing. The eye sees the image and then the brain analyzes it and extracts its characteristics. For example, the eye sees a car, then the brain deduces its color, shape, size... just as humans organize their thoughts and concepts in a hierarchical manner starting with simple concepts and reaching more complex ones. Convolutional layers extract properties starting from general properties all the way to complex ones. It was given this name because it contains convolutional layers, and convolutional networks are an effective solution to many computer vision and artificial intelligence problems [10].

The figure 3, shows the main components of Convolution Neural Networks.

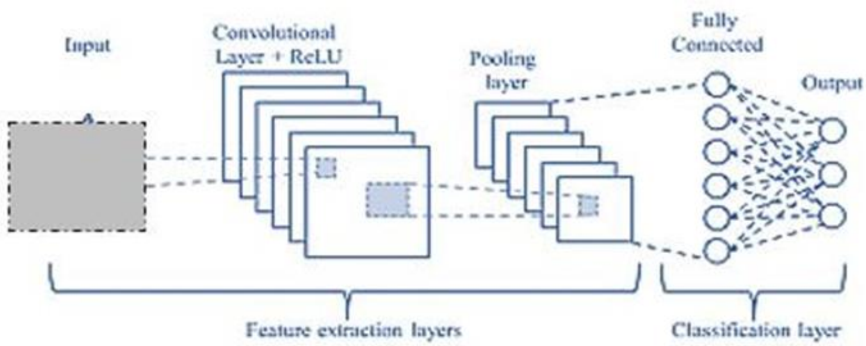

Figure 3: Structure of Convolution Neural Networks

6 The Experimental Results

The brain is considered the center of management of the central nervous system. It is a vital element that controls all vital functions including thinking, speech, and movement. Therefore, any type of damage to the brain or part of it may endanger human health, and tumors are among the most severe of these damages [11].

A brain tumor is the proliferation of abnormal cells in brain tissue. It occurs when a group of cells divides irregularly and spreads to the surrounding tissues uncontrollably and abnormally, at a time when they were supposed to die and new cells be born in their place, contrary to the nature of healthy cells.

The earlier the tumor is detected, the greater the chances of successful treatment and the patient's survival. Therefore, the death rate caused by this disease decreases where brain tumors can be detected using magnetic resonance images before clinical signs are observed. The final diagnosis is up to the specialist doctor who examines the sample. Taken from cells under a microscope, healthy cells are normal in terms of structure and size while cancerous cells appear abnormal and different in size and structure.

6.1 Practical Steps

The practical application goes through a set of steps according to two basic stages:

1) Obtain MRI images and apply processing to them to prepare them for use by a deep learning model.
2) Design a deep convolutional neural network model that achieves the best accuracy to make it more suitable for the required task.

MRI Image Processing

Based on figure 1, the following steps have been performed.

6.1.1 Images acquisition

The database was sourced from Kaggle, a subsidiary of Google LLC, an online community for data and machine learning scientists. (https://www.kaggle.com/brain- mri-images-for-brain-tumor detection) The database contains MRI images of the brain consisting of **253** images divided into two parts: **155** healthy (no) and 98 infected (containing a tumor) (yes). Figure 4, shows a sample of these images.

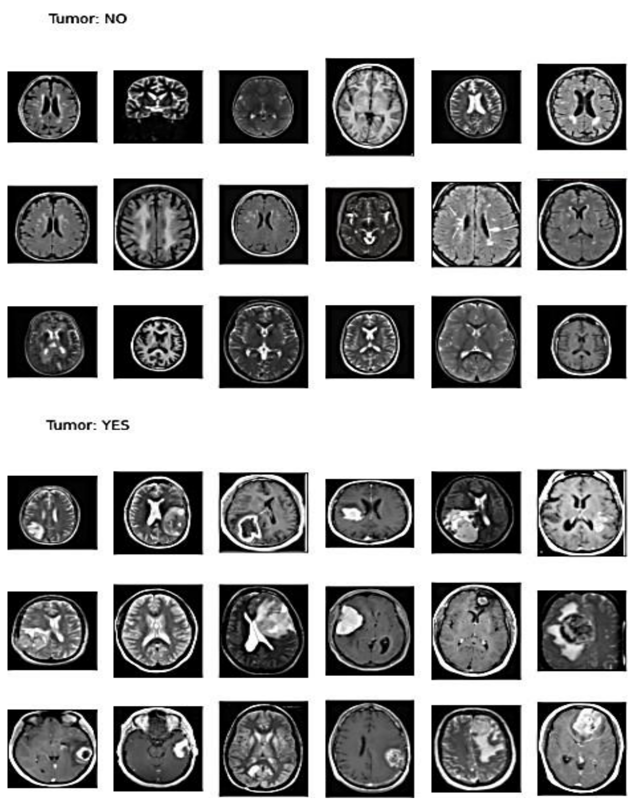

Figure 4: Sample of Data base images

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6.1.2 Images Normalization

At this stage, sizes and colors of the images are standardized according to the following steps.

a) Obtaining the important part of the image in which is the brain in this research.

b) Dispensing with the unimportant edges, by finding the frames in the image and challenging them. These frames are curves that include all the points connected to each other that have the same color or density. These points are found using the **findcontours** function in cv2 library) to perform the process of cropping the images at these points as shown in figure 5.

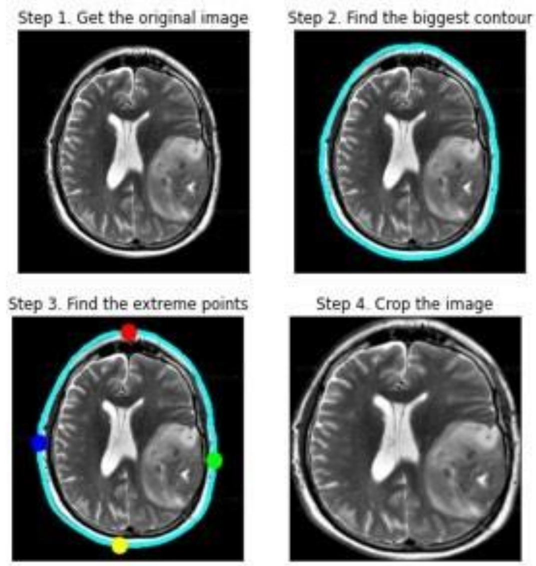

Figure 5: Image Normalization Steps

c) Standardizing the size of images and converting the pixel values so that they are all within the range [0-1].

6.1.3 Image Eenhancement

At this stage, noise and interference that affect the image quality have been eliminated. This step has been accomplished using linear filters (Gaussian filter), which is characterized by its ability to soften the image while preserving parts of the original image, most notably the edges. Figure 6 shows an MRI image before and after applying the filter.

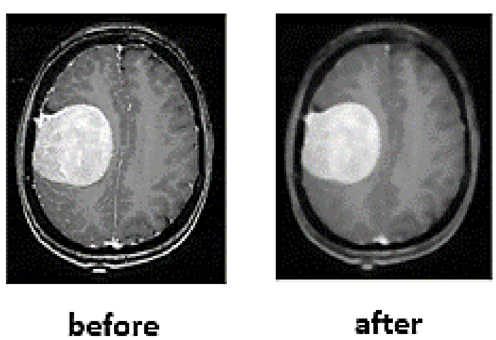

Figure 6: Applying the Gaussian filter to the image

6.1.4 Image Segmentation

Image segmentation process takes place in two stages

1. **Image Thresholding**: This is displaying a specific color level in the image to convert the grayscale image into binary for the purpose of applying formal operations to it.

2. **Morphological transformations**: brain images contain gray and white matter. The part affected by the tumor is more dense (white color). Therefore, to extract the tumor area, morphological transformations have been performed. These transformations are set of simple procedures applied to the shape of the image for extracting useful image elements.

This stage includes two processes

- **Erosion:** Its aim is to smooth the boundaries of the front surface (which is white). This is accompanied by a reduction in the area of the white body in the image.

- **Dilation:** It is the opposite of the erosion process, as it works to increase the area of the object that has been eroded, and thus the eroded white parts of the image are restored.

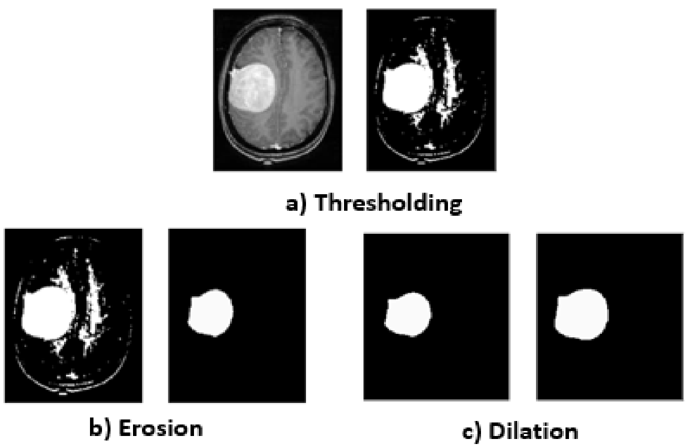

Figure 7. Steps of Image Segmentation

6.1.5 Image Restoration

From the images in Figure 7, location and size of the tumor are determined. At the same time, these operations led to the removal of edges from the image. These edges represent thin threads separating the heterogeneous areas in the image. Therefore, the image has been restored by retrieving the edges.

a) Edge detection process

This procedure is performed on the **original image** by applying the canny algorithm to detect edges. Applying this algorithm has been done by finding the edge gradient and direction of each pixel in the image based on the following equation (1), (2) [12]:

$$\text{EdgeGradient}\,(\boldsymbol{G}) = \sqrt{\boldsymbol{Gx}^2 + \boldsymbol{Gy}^2} \quad (1)$$

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$$\text{Angle}\ (\boldsymbol{\alpha}) = \mathbf{tan}\ \mathbf{-1}\left(\frac{Gy}{Gx}\right)\ (2)$$

G_x: Gradient image in horizontal direction.
G_y: Gradient image in vertical direction.

b) Images merging

The final processed image is composed by merging the image obtained after applying Morphological operations with the edges of the original image. Figure 8 shows the merging process and the resulting image.

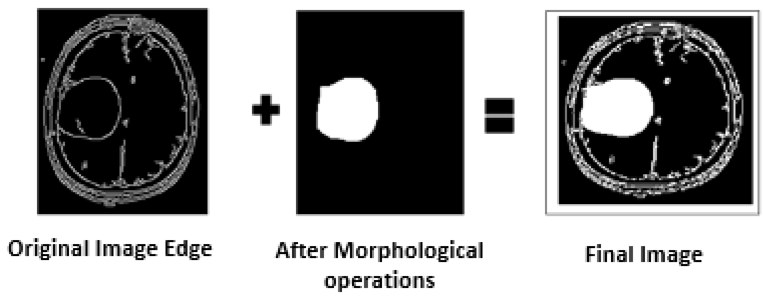

Figure 8: merging process and the resulting image

6.2 Steps of Building CNN

Figure 9, shows the main stages of building a convolutional neural network model:

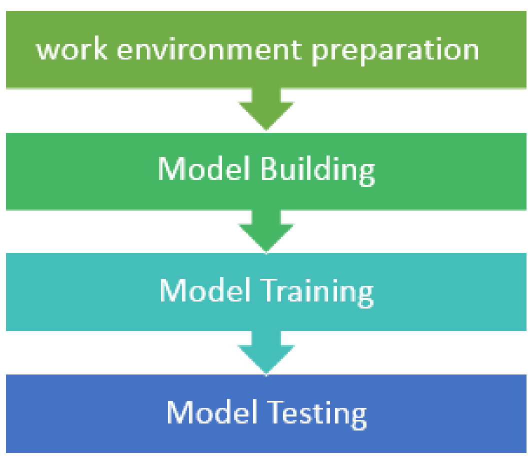

Figure 9: Steps of designing the proposed classification Model

6.2.1 Work environment preparation

a. Import libraries

First, the work environment has been prepared by calling the libraries necessary for the program to work. These libraries are as follows.

- **Keras** and **Tensorflow:** library for working with CNNs.
- **OpenCV:** for image processing functions.
- **Matplotlib:** for graphs.
- **Numpy:** libraries for working with arrays.

b. Data Loading

The previously processed data set consisting of **253** samples, has been divided into two groups.

- **Training set:** includes 80% of the dataset (202 images).
- **Testing set:** includes 20% of the data set (51 images).

Each group includes healthy and infected images as shown in figure 10. Number of infected samples is (**98**) and number of the healthy samples is (**155**).

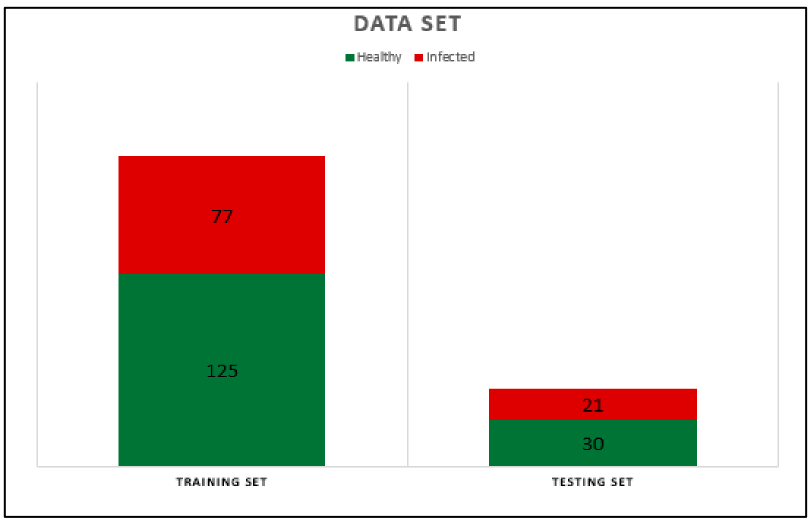

Figure 10: Healthy and infected images in dataset

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6.2.2 Model Building

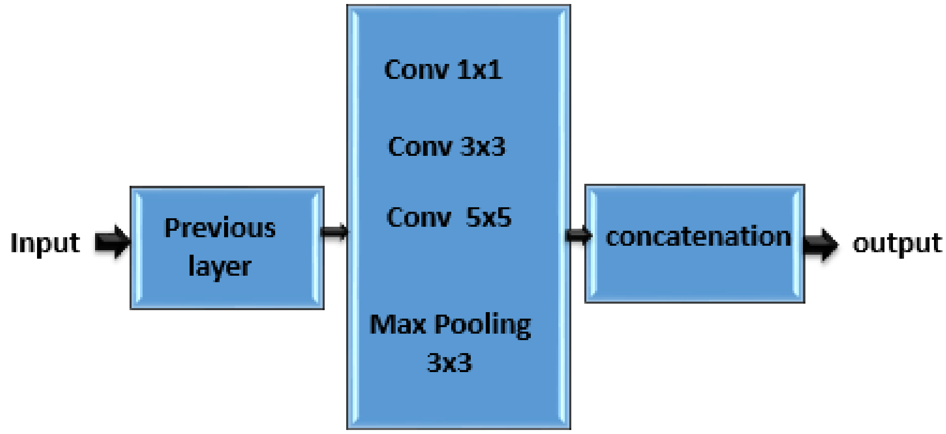

Figure 11: Classification model structure

The process of building the classification model has been done in two basic stages.

1. **Feature extraction:** The convolutional and secondary layers work to extract the most obvious image features for collecting information that helps in classification process such as color, edges, shape, and contrast.

2. **Classification:** The fully-connected layers, especially the output layer, are responsible for the classification process based on the image information provided by the internal layers.

Table 1 shows components of the designed neural network and the details of its layers.

Table 1: CNN layers

Layer (type)	Output Shape	Param #
inception_v3 (Functional)	(None, 5, 5, 2048)	21802784
flatten (Flatten)	(None, 51200)	0
dropout (Dropout)	(None, 51200)	0
dense (Dense)	(None, 1)	51201

As shown in Figure 11, the network is a block of parallel convolutional layers with different filter sizes (1×1, 3×3, 5×5) and a pooling layer according to the maximum value**, max pooling**, with a dimension of 3×3. Then all the results are collected. The filters in convolutional layers operate in a three-dimensional space (width and height) and a third dimension is the color channel, which makes feature extraction easier and more efficient.

6.2.3 Model Training

Training the proposed model has been done according to the following.

- Using the **Back Propagation** algorithm, which is an iterative process that starts from the last layer and calculates the error on the output by finding the difference between its value and the desired output value.
- Working to reduce the error value using **Adam optimization** algorithm. This algorithm makes the model converge to the desired output faster as it works very efficiently with less memory consumption.

6.2.4 Model Testing

The proposed model has been tested using the test data. The confusion matrix has been calculated. This matrix contains values representing the number of true and false positives and negatives as shown in Figure 12.

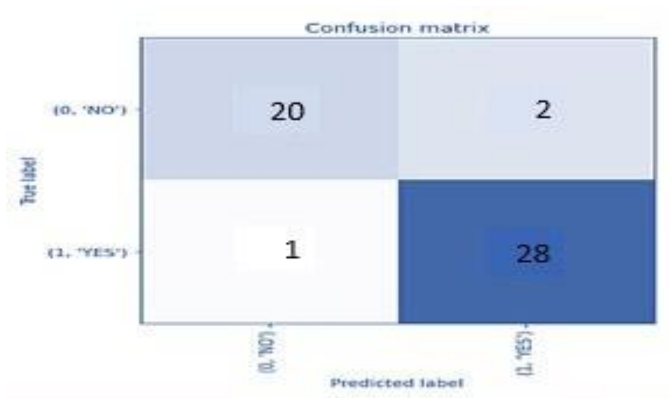

Figure 12: confusion matrix for evaluation model

Accordingly, the values of accuracy, sensitivity, and specificity have been calculated. The model has been evaluated according equations [13]:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

A comparison has been conducted between the results obtained from applying the proposed classification model to the test data set with the results of applying classification models **VGG19** and

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ResNet, which are pre-trained models that are used to solve tasks or issues other than that were trained on [14]. Evaluation values are shown in the table 2.

Table 2: Evaluation values

	Accuracy	Specificity	Sensitivity
VGG19	83%	80%	90%
ResNet	84%	89%	81%
Proposed Model	94.5%	95%	93%

In addition, **ROC** (receiver operating characteristic curve) is a graph that shows the diagnostic ability of a binary classification system, which is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR), whose values are calculated according to the equations (6) And (7).

$$TPR = \frac{TP}{TP+FN} = 1 - Sensitivity \quad (6)$$

$$FPR = \frac{FP}{TN+FP} = 1 - Specificity \quad (7)$$

This graph has been drawn and shown in figure 13.

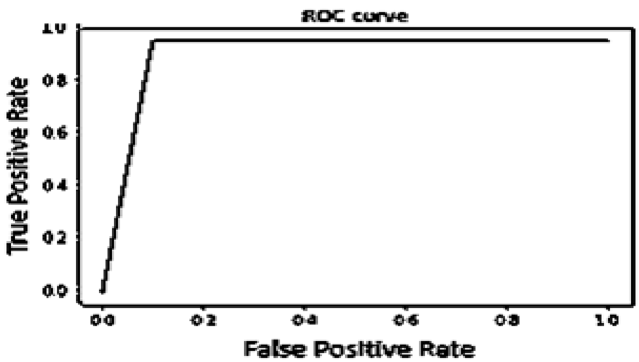

Figure 13: ROC graph

AUC (Area under the ROC Curve) is a good measure of performance as it measures how good the model's predictions are across all possible classification thresholds. It takes a value within the range of [0 -1]. The closer the ROC curve to the upper left corner is, the better the performance of the classifier. The obtained value of AUC = 0.95.

Figure 14 shows the chart comparing the results of evaluating the three classification models applied to the data set used within the research. Superiority of the proposed model in all criteria is noticed in figure 14.

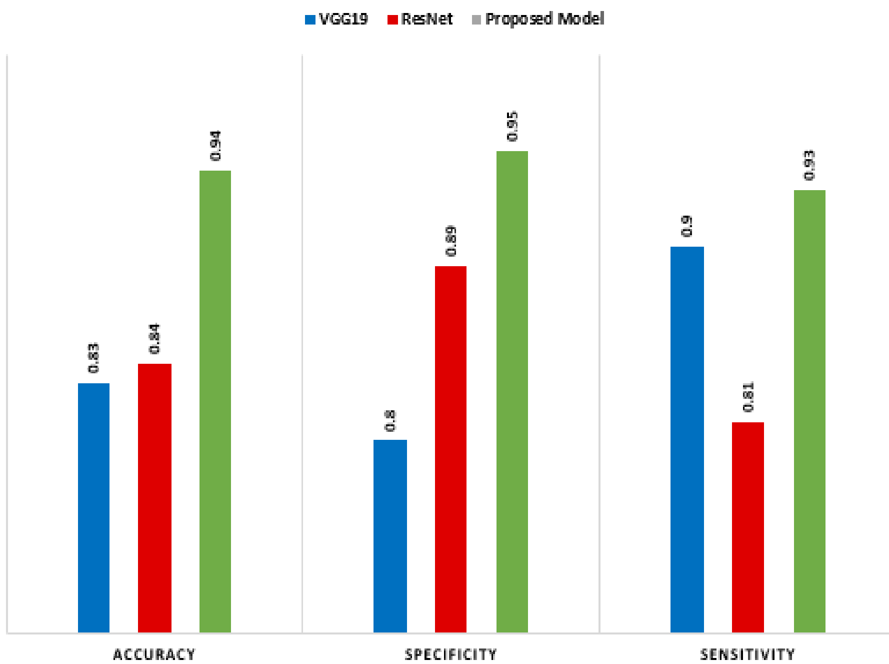

Figure 14: Evaluation results of the applied classification models

7 Conclusions

Automatic brain tumor classification is a very difficult task due to the large spatial and structural variability of the area surrounding the brain tumor. The obtained results show that deep learning techniques especially CNNs achieve high classification accuracy with low complexity. They do not require detailed feature extraction operations as is the case in machine learning algorithms or traditional neural networks in which features are extracted manually which saves training time.

During this research, a system for classifying magnetic resonance images after performing all image-processing stages has been proposed and implemented. Based on the concept of convolutional neural networks and their features, classification model has been built and trained. By evaluating the designed system based on studying the evaluation criteria, it is noticed that it achieves a high degree of accuracy that reaches 94.5% with a high AUC value that reaches 0.95. These values indicate the efficiency of the proposed classification model. By comparing the proposed model with pre-trained modelsAGG19 and ResNet, superiority of the proposed model is noticed in terms of classification accuracy and the sensitivity value which is 93%. The overall conclusion indicates the model's recognition rate for images that belong to infected cases from all infected images within the database.

8 Future work

The research suggests conducting a more detailed study of pre-trained deep learning models and modifying the structure of their basic layers, while trying to benefit from it in obtaining results that are more accurate in less time.

Working on the possibility of diagnosing a brain tumor at different stages, for example the first and

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second stages of the tumor, with the aim of detecting it in earlier stages and thus increasing the chance of recovery from it. This requires the existence of databases for each stage.

Developing the proposed model for brain tumor detection by working on supplementing it with other data such as neurological examinations and specialized medical analysis evaluations for the purpose of helping to diagnose the disease more accurately and quickly.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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