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Brain tumors recognition based on deep learning

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A R T I C L E I N F O

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A B S T R A C T

Brain tumors are fatal diseases that require proper treatment, making accurate and timely diagnosis critical for successful treatment. Deep learning (DL) has emerged as a powerful tool for improving the accuracy of brain tumor recognition and underscores the importance of optimizing training parameters and dataset size. These findings demonstrate the feasibility of using DL for accurate and efficient brain tumor recognition, which has significant implications for improving patient outcomes. Accurate and timely diagnosis can greatly improve treatment outcomes and potentially save lives. This paper investigated the impact of DL on brain tumor recognition by utilizing a convolution neural network (CNN) algorithm and Magnetic Resonance Imaging (MRI) dataset of 4000 samples, each with a size of (224×224). The results show that increasing the dataset size led to better performance, with increasing accuracy and generalization of the model. Furthermore, increasing the number of epochs during training improves the accuracy; with 60 epochs as our choice for the DL model, we achieved 97.28% accuracy.

Introduction

The brain is the most vital organ in the human body since it aids in decision-making and regulates all other organ functions. It considers the most critical and vital organ in the body. A mass or growth of aberrant brain cells is referred to as a "brain tumor." There are numerous varieties of brain tumors, and they can be either benign (noncancerous) or malignant (cancerous). [1]. Primary brain tumors start in the brain, whereas secondary (metastatic) brain tumors are the result of cancer that starts in another part of your body and moves to the brain. [2].

Nowadays, brain tumors are diagnosed in modern medical healthcare facilities using a variety of imaging modalities, such as Computed Tomography (CT) scanning, X-ray screening, Positron Emission Tomography (PET), MRI, and ultrasound screening. These imaging modalities assist doctors and radiologists in identifying brain tumors and other health-related diseases. [3].

In recent years, DL has emerged as a promising approach for automating the diagnosis of brain tumors. DL is a machine learning (ML) type that involves training artificial neural networks (ANN) on a large dataset. The neural network learns to recognize patterns and make decisions based on the data it has been training on. The advantage of using DL for brain tumor recognition is the ability to analyze accurately and quickly large amounts of data; it is particularly useful for analyzing medical images.

Problems and literature review

The Patient diagnosis by doctor manually based on a physician's assessment of the patient and the results of their tests; in the absence of automated tools to aid in diagnosis and with a shortage of physicians, there is a greater chance of misdiagnosis as well as longer wait times for patients to be seen by doctors. Physicians must spend more time to viewing the test results and images than actually spending time with patients; therefore, improved medical technology using automated tools required to improve patient care, enhanced medical technology in the form of automated tools is necessary to increase doctor efficiency and decrease patient time in hospitals and time toward recovery, and the initial detection, monitoring, and proper investigation can reduce the death rate and increase the survival rate. The invasive characteristics of the tumors increase the death rate, but with early detection, monitoring, and investigation can be reduce the death rate and raise the survival rate.

Researchers usually use a CNN to analyze CT and MRI scans of the brain. The high dose of radiation poses a risk to elderly patients and pregnant women, a high ionization of brain cells, and the risks to patients with pacemakers and implantable heart rhythms [4]. MRI pictures

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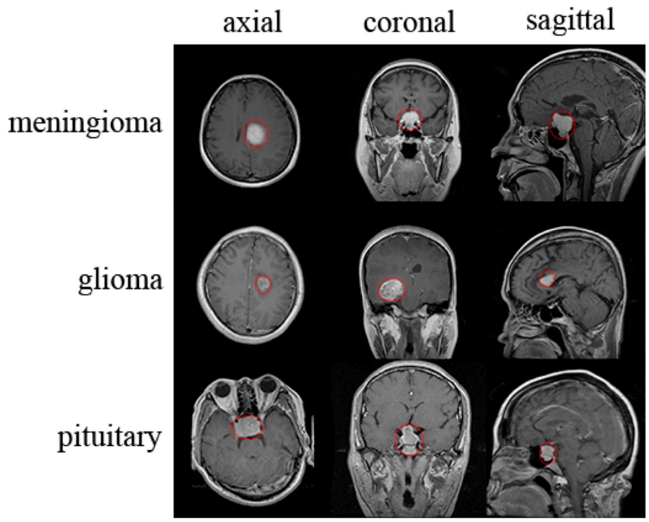

Fig. 1. Some of brain tumor types and their location.

produce a slice view of the bones, tissues, and organs by using radio waves and powerful magnets. MRI scans are the best option for obtaining a thorough, detailed view of tissues or organs, it is a clear images compared to a CT scan and better option than X-rays. The disadvantages of it MRIs cost, more time, any movement may produce blurred results; An additional restriction is that an MRI of cancer tissue and extra fluid seems identical. [5].

MilicaM. Badža and Marko C. Barjaktarovic presents a new CNN architecture to classify three types of brain tumors. This network is simpler than already-existing pre-trained networks, and test on T1-weighted contrast-enhanced MRI, the accuracy was 96.56 %. [6]. The Arkapravo Chattopadhyay and Mausumi Maitra segment the brain tumors from Two-dimensional (2D) MRI by a CNN which is followed by traditional classifiers and DL methods, the result obtained so far applied Support Vector Machines (SVM) classifier and other activation algorithms (softmax, Root Mean Square Propagation (RMSProp), sigmoid, etc.) to cross-check our work) [7]. Gokila Brindha P, detected the brain tumor by applying ML and DL algorithms. ANN and CNN. The ANN was applied to train data for 50 epochs; they got 97.13 % accuracy and 71.51% validation accuracy. Applied to the test data, it yields an accuracy of 80.77 %. [8]. Abdul Hannan Khan, etc. They divide brain tumors into meningioma, glioma, and pituitary using a hierarchical DL method, and using a CNN gives excellent results in this capacity. Based on the suggested model, a 92.13 % precision and 7.87 % miss rate, make it superior to earlier methods for detecting and segmenting brain tumors. [8,9]. Dheiver Santos and Ewerton Santos, Scientists understand brain tumors as the growth of abnormal cells in the brain, some of which may lead to cancer, and the traditional method to diagnose brain tumors is nuclear MRI. By reducing the size of the image, the Network can make predictions without losing information. More image data was provided, and the resulting model yielded an accuracy of 89 %. [10]. Last but not least, D C Febrianto, etc. In medical work, To determine whether a brain tumor has the potential to progress to cancer, an early diagnosis is crucial. DL is a 93 % accurate and efficient image categorization method. [11].

Brain tumor

An aberrant mass or development of cells in or near the brain is called a brain tumor. This category of tumors, known as the central nervous system (CNS) tumors, also includes spinal tumors. Brain tumors can be malignant (cancerous) or benign (non-cancerous). There are several different types of brain tumors, which can be classified based on the type of cell they originate from and their behavior. Some of the most common types of brain tumors are shown in Fig. 1: Glioma, Meningioma, Schwannomas, Pituitary Tumors, Medulloblastomas, and Other Brain Tumors [12,13].

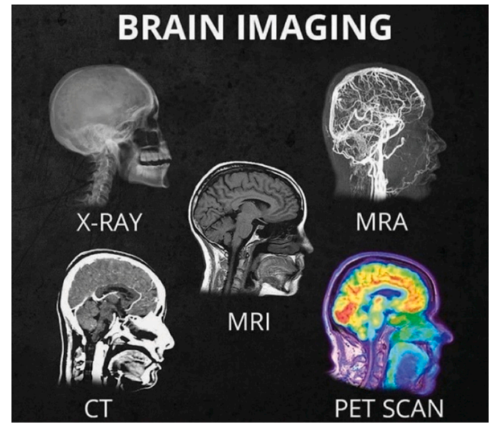

Fig. 2. Image types used to detect brain tumor.

If a brain tumor is suspected, the doctor may suggest a number of tests and procedures to identify the type of brain tumor and diagnose it. They may also perform certain tests to determine whether the tumor has spread to other parts of the body and where it originated. [14,15].

The doctors use imaging to see what there is inside the body; the tests send a form of energy (radioactive particles, sound waves, X-rays, or magnetic fields) through the body. The body tissues are changing the energy patterns to make an image to show how the inside body looks. Changes are caused by diseases like cancer. Some of these tests include many different kinds of scans used to get images of inside the body. Fig. 2 shows some of the common types of imaging tests [16,17].

Convolution neural network (CNN)

One of the most famous architectures of Deep Learning (DL) is CNN. It's a type of ANN that is widely used to recognize and classify images/objects, it has proven to be extremely effective in solving a wide range of computer vision problems, localization, segmentation, and video analysis [18]. In CNNs, a (convolution operation) does the calculations to extract the features of the images in the multiple hidden layers. In order to increase the computational efficiency of the network, the pooling layer shrinks the spatial dimensions of the feature maps that the convolutional layer produces. The rectified linear units are a non-linearity activation function in the network, allowing it to make complex decisions, and fully connected layers. The features are extracted from the input image in the first layer (convolutional). The object is identified and classed in the output layer by the fully connected layer [19–25]..

The dropout layer is a regularization method commonly used in DL to prevent overfitting and make the model more generalized. The dropout works by randomly dropping the output of some neurons in a layer during training (set to zero) to help the model learn in a better way and make it more robust, it also helps to speed up the training process [26,27].

The dense layer only accepts a one-dimensional array of information. The output from the convolution and pooling layers is transformed into a one-dimensional array using the flattening layer. The fully connected layer, also known as the dense layer, is a layer in a CNN responsible for making the final classification decision based on the features extracted from the image [28].

Activation functions are used in a CNN to introduce non-linearity into the network and help to prevent overfitting, the rectified Linear Unit (ReLU) and the Softmax activation function are the most common activation functions used in CNNs [24,25,29]. The ReLU and sigmoid activation functions are shown in Fig. 3, and the CNN architecture is

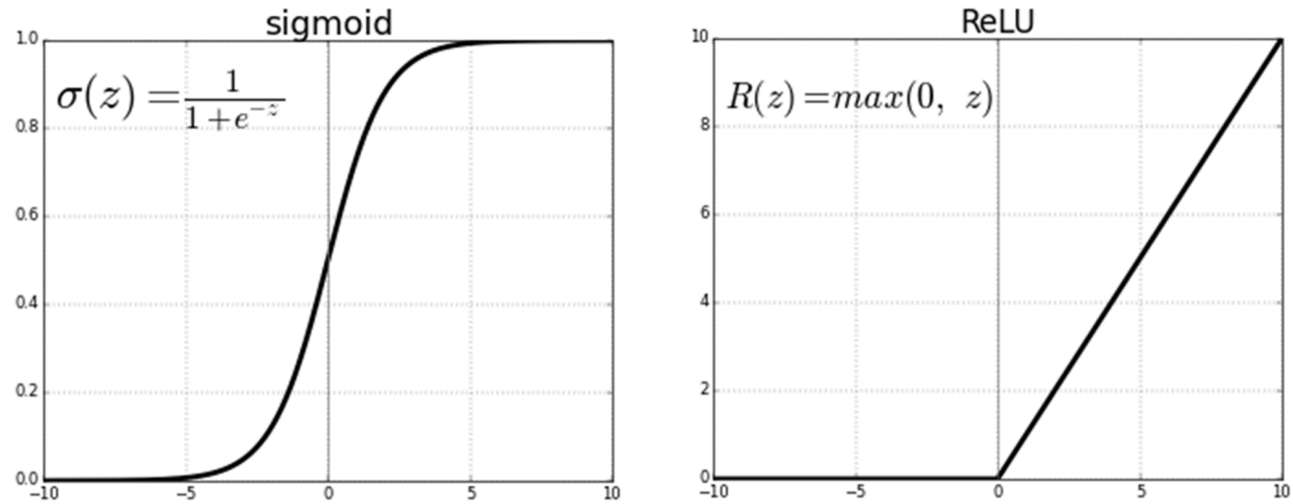

Fig. 3. ReLU and sigmoid activation functions. [30].

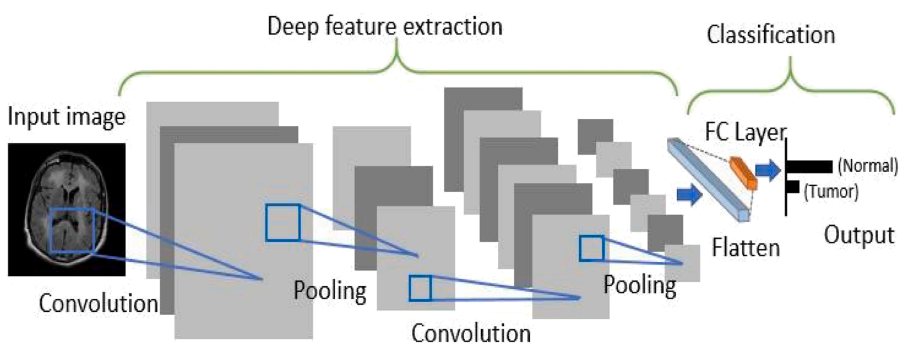

Fig. 4. CNN architecture. [31].

shown in Fig. 4.

Adam optimizer

Instead of the classical Stochastic Gradient Descent (SGD) procedure, an optimization algorithm (Adam algorithm) is used to update the weights of network iterative based on training data. It is a variation of the SGD optimization algorithm that adapts the learning rates of individual parameters based on their historical gradient information [32]. The learning rate determines how much the model adjusts its weights during each iteration of the training process, and the batch size determines the number of samples used in each iteration of the training process.

Binary cross entropy function

For binary classification problems, binary cross-entropy is a loss function used in neural networks to classify inputs into one of two classes known as log loss, it evaluates each projected probability against the actual class result, which has two possible outcomes: 0 or 1. The score that penalizes the probability based on how close or far the actual value is from the expected value is then computed. [33,34].

$$\text{Loss} = \frac{1}{N}\sum_{i=0}^{n}[\text{yi} * \log(\text{pi}) + (1 - \text{yi}) * \log(1 - \text{pi})]. \tag{1}$$

Where yi is the true (0 or 1). pi: probability of class 1., (1-pi): probability of class 0.

Overfitting and underfitting

Overfitting and underfitting are two common problems in any DL and ML model. The overfitting will be occur when the model in DL is too complex. When the model does training too much on the training samples that it "memorize" the training data instead of learning general pattern, this leads to subpar performance on fresh, untested data. Stated differently, the model is unable to categorize new data because it fits the training data too closely. The model memorizes the training data instead of generalizing to new data, as seen by the overfitting scenario learning curve, which would show great performance on the training data but low performance on the validation data. In an underfitting scenario, the learning curve would show poor performance on both the training and validation data, indicating that the model is not able to capture the underlying patterns in the data [35,36].

Metrics in deep learning

In binary classification problems, a confusion matrix of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are the four probable outcomes of a forecast., While the Metrics in Deep Learning are [37]:

$$\text{Accuracy} = \frac{\text{number of correct predictions}}{\text{total number of predictions}} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{2}$$

$$\text{AUC} = \int \text{TPR } d(\text{FPR}). \tag{3}$$

Table 1
Dataset division for training, testing and validation.

Brain Tumor	Samples	Training Samples	Validation Samples	Testing Samples
YES	2488	1990	248	250
NO	2488	1990	248	250
Total	4976	3980	496	500

$$\text{Precision} = \frac{TP}{TP + FP}. \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{5}$$

MRI dataset

When using deep learning models for brain tumor diagnosis, the following are the primary ethical concerns and potential biases to be mindful of are:

- Informed Consent: Consent must be obtained before using patient data to build deep learning models. Patients have to have the option to opt-out and be fully informed about how their data will be used.
- Privacy and data security: To safeguard patient privacy, the patient data used to train deep learning models must be handled with extreme caution.
- Human Oversight: While deep learning models can enhance diagnostic capabilities, they should not replace doctors. Maintaining human oversight and integrating the models into the clinical workflow as decision support tools is necessary to ensure patient safety.

The dataset in this research consists of a collection of 4976 MRI brain tumor images Kaggle [38]. The number of images in this dataset divided into three categories, shown in Table 1. The following images shown in Fig. 5 are samples from the dataset.

Proposed model

The proposed model is developed using Google Colab, on a machine with 1.80 gigahertz (GHz) 2.30 GHz processer with Core i7 10th Generation. and 8.00 gigabyte (GB) random access memory (RAM).

The DL used in the proposed model was designed using CNNs, a popular DL architecture for image classification and object recognition. CNNs are equipped with convolutional and pooling layers, followed by a series of dense layers that perform classification to make predictions based on the extracted features.

The algorithm of the proposed model:

Algorithm: Proposed Algorithm
- Import the needed packages (Libraries and Functions).
- Resize the images into (224 × 224).
- Import the dataset folders with the help of google drive (MRI_DataSet)
- Read the images.
- Labels the images ("1″ brain tumor, and "0″ not brain tumor).
- Split dataset (using the split-folders package) into 80 % training, 10 % testing, and 10 % validation.
- Creating the model.
- Compiling the model (use "Adam optimizer", and" binary cross-entropy loss function")
- Learning model (use the train dataset).
- Evaluating proposed model (applying model use the test dataset).

Divide model into two phases; training phase, and testing phase, as shown in Fig. 6.

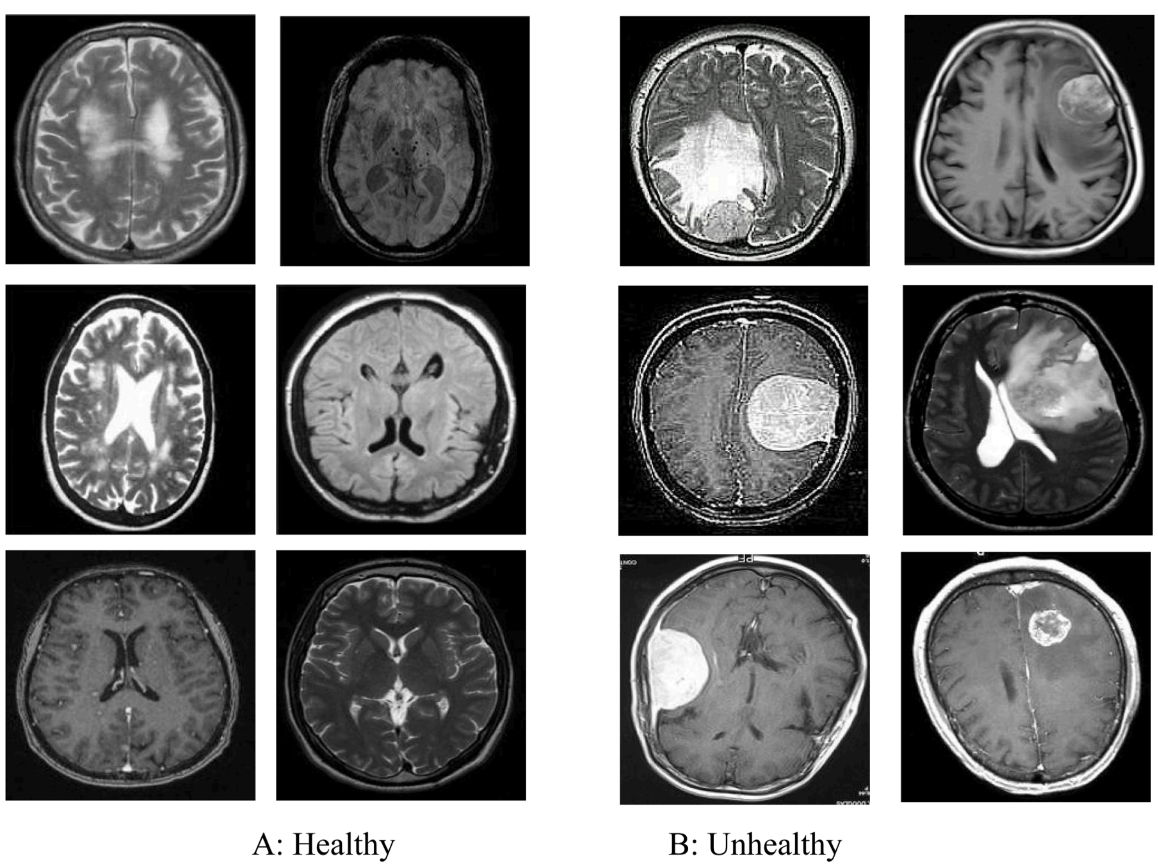

Fig. 5. Samples for MRI images.

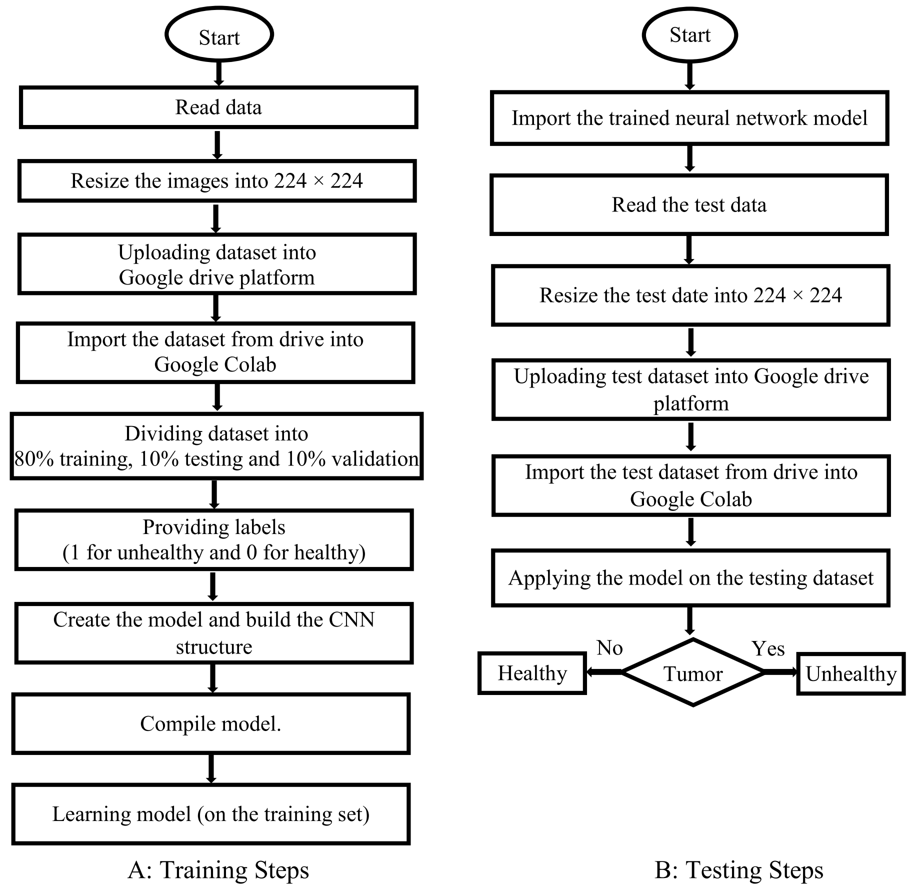

Fig. 6. Deep Learning Implementation.

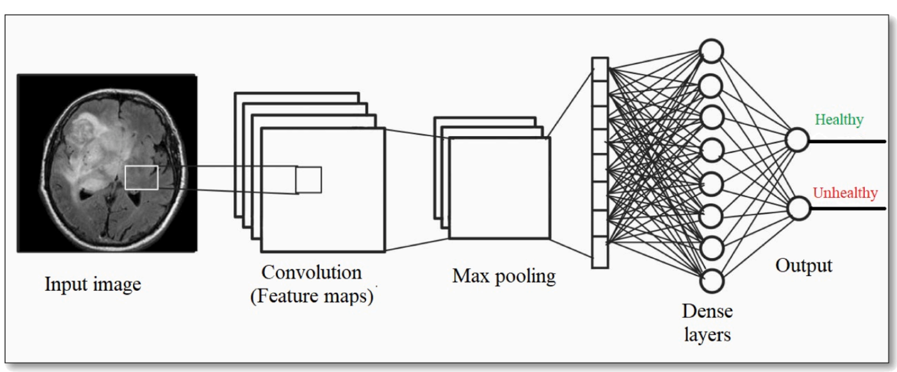

Fig. 7. CNN model architecture.

CNN structure

The proposed model built using four convolution layers:

The first layer has 16 filters (the number of feature maps generated by this layer). 36 filters make up the second layer, 64 filters make up the third, and 128 filters make up the final layer. The filters measure (3 × 3), strides = 1, and a 'ReLU' as an activation function. The convolution layers followed by a pooling layer with (2 × 2) to reduce the size of the feature maps from the previous convolution layers. A dropout layer used (it is a regularization technique). After that, a flattened layer followed by a dense layer with 256 units (number of neurons in the layer) which has a 'ReLU' activation function as well, then another dropout layer is applied with a 25 %, and finally, the last layer is a dense layer which contains a one unit with 'sigmoid' activation function for classification as the input image has or has not brain tumor. Fig. 7 shows the CNN model architecture.

- Data Augmentation

Data augmentation is a technique used in the DL model to improve its performance by reducing the overfitting and increasing the ability to identify and correctly classify the new data. The concept of the data augmentation is to increase the number of samples by creating new training data for the existing one. Applies various transformations such as rotating, scaling, flipping, cropping, or even adding noise to the original data.

- Model Compilation

Table 2
Epochs metrics calculation.

Epochs	Accuracy%	Validation Accuracy%	AUC%	Precision%	Recall%	Training Loss%	Validation Loss%
10	80.84	79.64	87.41	78.93	84.77	43.87	42.05
20	91.46	87.70	95.88	90.34	92.27	25.65	29.41
30	92.39	91.53	96.42	90.61	94.87	24.99	25.91
40	95.42	94.35	98.7	94.4	96.05	14.67	17.96
50	96.67	95.56	99.34	95.69	97.99	9.93	15.66
60	97.4	97.25	99.6	96.41	98.37	8.06	12.14

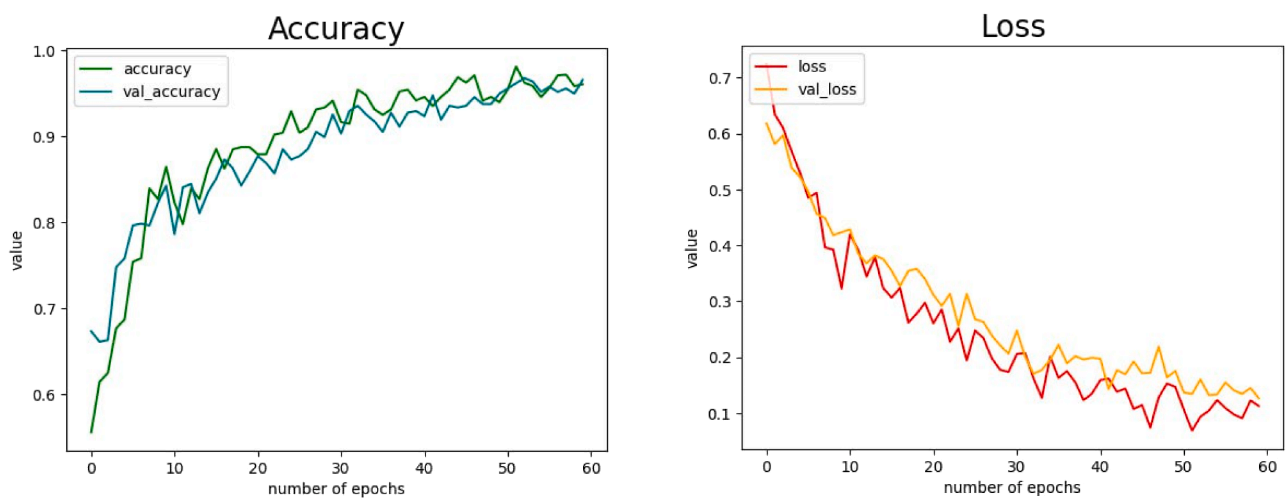

Fig. 8. Accuracy and Loss curves.

Compile the mode using Adam Optimizer, and binary cross entropy as a loss function to calculate the metrics: accuracy, AUC, precision, and recall.

- Model Training

The training done in several number of epochs. Table 2. shows the effect of increasing the number of epochs.

- Prediction

The prediction done by passing the testing images to the trained model, we made various changes in the number of epochs and the number of samples as will be explained in more detail in the following paragraphs.

Analyzing results for different epochs

The epoch refers to one complete pass of the training dataset through the neural network. In a single epoch, the model will iterate over the entire training dataset once, meaning it will see the whole dataset and update the weights using the optimizer algorithm. Increasing the epochs will make the model learn better and adjust to weights and biases, but choose a number to suit the size of the dataset, meaning if the dataset is small size and the number of epochs is large, this might lead to overfitting. Therefore, choosing the number of epochs is a trade-off between better accuracy and avoiding overfitting; this is why using a technique like dropout layers and data augmentation can help prevent overfitting and allow more value of epochs without sacrificing the accuracy.

The following table shows the results of the metrics for different numbers of epochs, calculates each metric value, and also does a prediction for healthy and unhealthy images.

The curves for accuracy and validation accuracy values, as well as for loss and validatio n loss, are shown in the Fig. 8 below.

Table 3
Simulation time for the difference between the use of GPU vs CPU in training process.

Number of epochs	Training Time GPU (Minutes: Second)	Training Time CPU (Minutes: Second)
10	03 :20	10 : 21
20	05 : 21	24 : 01
30	08 : 43	35 : 31
40	11 : 14	44 : 56
50	14 : 37	58 : 31
60	17 : 10	66 : 47

- The loss and accuracy curves are important to monitor the training of the proposed model and give a clear view of its performance. In these figures, the increase of the epochs lead curves become more accurate and has more values.
- The validation and training losses demonstrate how well the suggested model matches the training data set. In the best cases, the training loss should decrease as the number of epochs increases.
- The training and the validation accuracies indicate how well the proposed model is classifying training data in the training period. Ideally, the training accuracy should increase as the number of epochs increases, this means that the proposed model is gaining the ability to classify.

To calculate the training time, we used a GPU (Graphic Processing Unit) that provided by Colab. GPUs designed to perform many operations in parallel makes them well-suited for DL and CNN calculations and very useful because GPUs can perform the matrix multiplication used in any DL algorithms that can be executed on virtual machines. However, using GPU can speed up training by a factor up to 4 or 5 times or even more (depending on model complexity, dataset, and other factors). Table 3 shows the comparison of the training times using GPU vs

Table 4
Evaluation Matrices.

Samples	Accuracy%	Validation Accuracy%	AUC%	Precision%	Recall%	Training Loss%	validation Loss%
1000	97.71	92.66	99.62	97.41	97.84	7.72	22.03
2000	96.67	95.18	99.68	95.78	97.42	7.08	21.27
3000	98.33	97.11	99.76	98.32	98.32	5.78	10.8
4000	97.08	96.57	99.04	96.37	97.95	9.9	12.74
4976	97.4	97.25	99.6	96.41	98.37	8.06	12.14

Table 5
Comparison Evaluation Matrices with related works.

Ref. No.	Samples	Training Accuracy	Validation Accuracy	AUC	Precision	Recall	Training Loss	validation Loss
6	3064	96.56 %	–	–	95.79	96.51	–	–
7	2473	99.74 %,	–	–	–	–	–	–
8	2065	97.13 %	71.51%.	–	–	–	–	–
9	2870	92.13 %	–	–	92.13 %	–	–	–
10	3762	91.72 %	89.24 %	–	89.20 %	89.20 %	21.79	27.08
11	2065	93 %	–	–	–	–	23.264	–
Proposed	4976	97.27	97.25	99.6	96.41	98.37	8.06	12.14

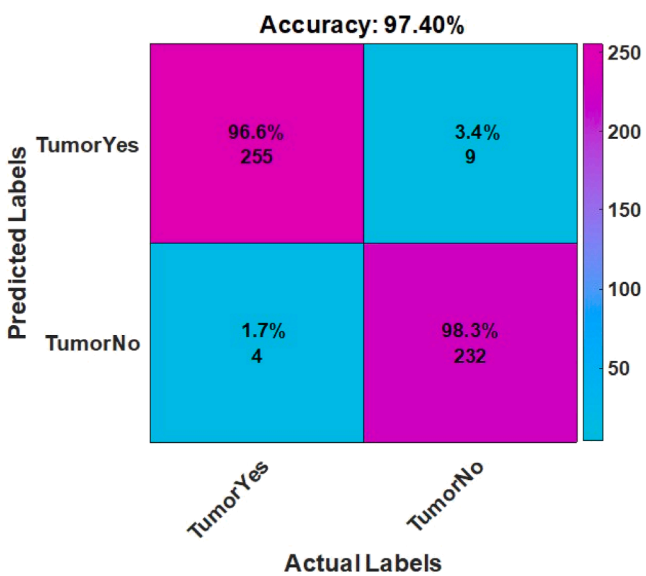

Fig. 9. Confusion matrix for the testing model testing: array ([255, 9,4, 232]).

CPU (Central Processing Unit) to show how the use of GPU can affect the training time.

Challenges in utilizing deep learning for brain tumor recognition

- Limited data availability: To overcome this, medical institutions can work with you to gather and interpret a wide variety of brain tumor images.
- Class imbalance: There may be an unbalanced distribution of brain tumor images in the dataset, with some tumor types having a lower representation than others. The deep learning model is biasedly trained as a result of this class imbalance, which affects how well it performs on tumor types that are underrepresented.
- Requirements for computation: Training and inference of deep learning models, particularly those with intricate structures, demand a large amount of computing.

Analyze effects of dataset size

The accuracy and resilience of deep learning models used for brain tumor identification can be a strongly impacted by differences in the preprocessing methods for MRI data. Image normalization, noise reduction, image registration, feature extraction, and data augmentation are effective keys to deep learning accuracy.

The size of a dataset can have a significant impact on the outcomes. A larger dataset requires more time and computational resources to analyze, which can be a challenge with limited resources. On the other hand, smaller datasets may be easier and faster to compute and analyze, but they may not provide a complete or representative view of the data. Therefore, it is important to consider the size of the dataset based on the research question and available resources. Table 4 shows the effects of dataset size on the matrices. And the comparison of the Evaluation Matrices of the proposed model with related works is shown in Table 5.

The proposed model was evaluating by applying the test MRI dataset. The confusion matrix for the predicted output show in the Fig. 9.

Conclusion

DL is an important field in data science with a vast range of applications that are constantly expanding. Through this paper, The DL Improves the diagnosis of brain tumors. Increasing the number of epochs during training results in higher accuracy. Using 60 epochs led to a high accuracy, along with high values in other metrics. Thus, we consider 60 epochs to be the optimal choice for the model. The size of the dataset is another critical factor that can greatly affect the training results. Increasing the dataset size improves accuracy and generalizes the model resulting in overall better performance. Through the experiment results, using 4976 samples resulted in a 97.4 % accuracy.

CRediT authorship contribution statement

Mohammed H. Al-Jammas: Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Emad A. Al-Sabawi:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis. **Ayshaa Mohannad Yassin:** Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Aya Hassan Abdulrazzaq:** Writing – original draft, Software, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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