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Brain Tumors Detection using Computed Tomography Scans Based on Deep Neural Networks

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Abstract: Brain tumors are one of the deadliest diseases, with numerous implications on human health. A brain tumor is an abnormal cell mass or growth in or around the brain. They are not all cancerous, as they might be benign or malignant. Doctors use a variety of diagnostic techniques to assess the presence of a benign or malignant brain tumor, as well as to estimate its size, location, and growth rate. The proper diagnostic modality is used to provide a complete view of the brain to detect any abnormalities. A computed tomographic (CT) scan of the brain shall be done to check the abnormalities. The benefits of CT scans include accurate detection of calcification, hemorrhage, and bone detail, as well as low cost compared to magnetic resonance imaging (MRI). Therefore, we examine a proposed CT-based detection method to determine whether brain tumor is present or not. The proposed method works on a CT image dataset that collected from Mansoura University hospital. Different pre-trained models are used: VGG-16, ResNet-50, and MobileNet-V2. Comparing the results, that pre-train model MobileNet-V2, despite having the lowest number of parameters, yields better results. It gives an accuracy 97.6%, while its precision, recall, and F1-score values are 96%, 95%, and 96%, respectively.

Keywords: Brain tumor, CT-based diagnosis, MobileNet-V2, VGG-16, ResNet-50, Pre-trained deep learning neural network.

1 Introduction

Brain tumor is the leading cause of death in females aged 20 and under and males aged 40 and under. According to WHO statics, brain cancers are exceedingly heterogeneous, which pose the fundamental challenge for brain tumor categorization and segmentation, and thus diagnosis and prognosis. A brain tumor is an uncontrolled growing clump of tissue that is stifling surrounding healthy tissue. Malignant (severe) and benign (soft) brain tumors are two different types of tumors that can develop in the brain. Since the symptoms that manifest depend on the location, growth rate, and impact of the tumor mass on the brain tissue, it can be difficult to distinguish between benign and malignant brain tumors (Fahmi et al., 2020; Shirazi et al., 2020).

The detection of brain tumors is critical in the field of biomedical application in terms of medical picture record diagnostics. The significance of detecting brain tumors has grown in recent years. The brain tumor categorization was created to assist medical personnel in diagnosing the condition. There are numerous steps that must be completed in the classification, such as preprocessing, feature extraction, and classification (Fahmi et al., 2020).

Brain tumors are diagnosed via a neurological examination of the tissues of the brain. The foundation of the examination is a reflexive and radiological evaluation of the brain tissues and a careful observation of muscle tone and movement. These examinations are conducted using medical imaging techniques. These techniques include computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET). The expansion and pressure of expanding tissue, which must also be seen on a medical imaging scan, harms vital brain tissues as well. One of the key issues is the buildup of water in the brain, which the tumors cause to happen and makes the cerebrospinal fluid circulate. Tumor symptoms get worse as they spread (Haq et al., 2022).

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Computerized tomography approach has been proven the most effective for the early diagnosis of tumors since it is the modality that is most frequently employed in the planning of radiotherapy for two major causes. The first is that scanner images carry anatomical information that can be used to design the direction and entrance points for radiotherapy beams, which must only target the tumors region and spare surrounding organs. The use of radiation to create CT scan images, which is similar to radiotherapy, is the second factor. This is crucial since the scanned image has been used to calculate the strength of the radiotherapy photons.

The use of CT has benefits such as effective calcification, bleeding, and bone detail detection in addition to cheaper costs, faster imaging times, and universal availability. These circumstances include patients, who are too large for an MRI scanner, patients who are claustrophobic, patients who have metallic or electrical implants, and patients who are unable to remain for the duration of the test because of age, pain, or a medical condition (Padma and Sukanesh, 2011). Images from full-slice brain CT scans with apparent lesions are typically selected by methods designed to detect disorders, however medical professionals must tag these images. This method is unreliable since, in real life, patients may have numerous concurrent diseases and doctors need a full sequence CT scan to detect brain disease. The technique is unable to account for the causal connections between distinct brain illnesses and the dependencies between the slices. Labeling photographs slice by slice also takes a lot of effort and money. Therefore, it is crucial study with real-world applications to identify numerous disorders from complete slice brain CT images (Chiang et al., 2021).

Artificial Intelligence (AI) and Machine Learning (ML) methods are important in biomedicine. We can use machine-learning models to handle ambiguous and time-consuming biomedical jobs with nearly the same precision as skilled specialists. Deep Learning algorithms (DL), a branch of machine learning, have proved their strength in biomedical data processing, particularly in cancer data that includes patients' scans and clinical information (Shirazi et al., 2020). A pre-trained neural network is one that has had its architecture and weights kept after being trained on a sizable dataset. The set of features that the pre-trained network has learned may be used as a general visual model if this first dataset is large enough. There are two approaches to use transfer learning from a pre-trained network: feature extraction and fine-tuning. Using the convolutional base of a previously trained network, features from the new dataset are extracted, and a new classifier is then trained using these outputs. The feature extraction method's fine-tuning step comprises unfreezing the final layers of the frozen convolutional base that was used for the feature extraction (Ezzat et al., 2020).

In this paper, we employ the MobileNet-V2 network as a pre-train model for feature extraction and transfer learning in order to diagnose/detect a brain tumor, comparing with other neural networks. The rest of the paper is organized as follows: Section 2 is devoted for the literature review. The model preliminaries are presented in Section 3. While Section 4 describes the materials and method. The Experimental results and discussion are illustrated in Section 5. Finally, Section 6 explored the conclusion.

2 Related Work

Researchers have worked hard to use artificial intelligence in general, and deep learning in particular, to diagnose various brain illnesses using various sorts of imagery deep learning is used by Kuo et al. (2021) to detect acute cerebral hemorrhage at an expert level on head computed tomography. Their algorithm demonstrated the highest accuracy to date for this clinical application, with a receiver operating characteristic (ROC) area under the curve (AUC) of 0.991± 0.006 for identification of examinations positive for acute intracranial hemorrhage and outperformed the performance as 2 of 4 radiologists. They trained a fully convolutional neural network with 4,396 head CT scans. They used a patch FCN with strong supervision and a relatively small training dataset.

Kalidindi et al. (2021) developed CT image classification of human brain using algorithm-based model that can be used to classify or detect hemorrhage in a CT images. They concluded that classifier model could distinguish between hemorrhage and non-hemorrhage images from human brain CT scans. A multi-label classification model was created by Li et al. (2020) for a complete slice brain computer tomography picture. The slice dependency-learning model (SDLM) was suggested. In order to anticipate abnormalities, it learns slice dependencies between various slices in a set of images and image attributes from a series of variable length brain CT images. Only the sickness visible in the full-slice brain scan can be labelled with the help of their model. The suggested model was tested using the CQ500 dataset, which contains 1194 complete sets of CT scans from 491 people. The evaluation's findings show that the F1 score is 0.6412, the precision is 67.57%, and the recall is 61.04%.

Gao et al. (2019) classified CT brain images based on deep learning networks. They employed a convolutional neural network (CNN) to classify CT brain scans, and they investigated the importance and impact of this application of developing deep learning techniques with the goal of supplying additional data for the early identification of Alzheimer's disease (AD). Three kinds of CT images, AD, lesion (such as a tumor), and normal aging, are grouped together, and a sophisticated CNN architecture is constructed that combines 2D and 3D CNN networks. This complex CNN architecture provides classification accuracy rates of 85.2%, 95.3%, and 80% for the classes of AD, normal, and lesion, respectively, with an average of 87.6%.

For brain tumor diagnoses, one of the common problems of working with CT imaging is the lack of the published dataset. Therefore, Hu et al. (2021) proposed Splicing Learning to complete the few-shot learning task without the need of large dataset. They achieved the best test accuracy of 90.81%. When they combined Splicing Learning and data augmentation, the test achieved 96.33% accuracy. Alqudah et al. (2019) worked on classification of brain tumors comparison of uncropped, cropped, and segmented lesion images with varying sizes. They employed CNN to grade (classify) the brain tumor into three categories using a dataset of 3064 T1 weighted contrast-enhanced brain MRI (Meningioma, Glioma, and Pituitary Tumor). The suggested CNN classifier was an effective tool with an overall performance of 98.93% accuracy and 98.18% sensitivity for the cropped lesions, 99% accuracy and 98.52% sensitivity for the uncropped lesions, and 97.62% accuracy and 97.30% sensitivity for the segmented lesion images.

For CT-based brain tumor detection, Woźniak et al. (2021) suggested a unique correlation learning mechanism (CLM) for deep neural network topologies that mixes convolutional neural network (CNN) with traditional design. The support neural network assists CNN in identifying the most suitable filters for the pooling and convolution layers. As a result, the primary neural classifier learns faster and reaches a greater level of efficiency. The results indicate that the CLM model may achieve approximately 96% accuracy, along with approximately 95% precision and recall. Moreover, Kaur et al. (2022) designed hybrid techniques model using the combination of metaheuristics and ML algorithms for tumor ad normal images, they achieved a 98.61% for the classification accuracy. Kang et al. (2022) used MRI images to differentiate between normal and tumor images; they concatenated three deep features from pre-trained CNN models and trained nine ML classifiers. DenseNet-169, Inception-v3, and ResNeXt-50 produced the best deep features, achieving an accuracy of 96.08%, 92.16% and 94.12%, respectively.

3 Preliminaries

3.1. Computed Tomography scan

Sir Hounsfield, an engineer who was working for EMI in England when he invented the first computed tomography (CT) scanner, is widely regarded as one of the most influential and well-known pioneers in the field of medical imaging. A head-only scanner first appeared in London, England, in 1971; the Mayo Clinic in Rochester, Minnesota, also adopted the technology. Rapid propagation of multiple articles on CT scanning's ability to detect brain tumor, intra- and extra-axial hematomas, abscesses, and hydrocephalus revolutionized the way we assess patients and identify neurological illnesses (Castillo, 2014).

The first full-body CT scanners were developed in 1975. Only one imaging study out of 35 patients with glioma was false-negative (an optic chiasm glioma), and only one was technically unsatisfactory because of motion, according to the first study to focus solely on CT imaging of primary and secondary intracranial malignancies (600 patients) (Castillo, 2014). Images from computed tomography (CT) offer more detailed information than images from regular X-rays. Since its introduction, the CT scan has been widely endorsed and utilized. CT scans display the bones, blood arteries, and soft tissues of various human body parts (Amin et al., 2022).

3.2. Deep Learning NN

Artificial neural networks (ANN) are based on biology, namely the human brain's neural network. Neural networks are made up of single neurons that are coupled to one another and so create a network (Deng, 2012). The fundamental building block of a neural network is the neuron, which can be viewed as a straightforward model to itself. A neuron is a computing unit that processes several xi (i=1, 2, 3) inputs to produce the activation, also known as the output, as

$$Output = f\left(\sum_{i=1}^{3} w_i x_i + b\right) \quad (1)$$

where w_i denotes the weights, b denotes the bias, and *f(.)* denotes the nonlinear activation function (Abdel-Hamid et al., 2013). Each x_i in the input vector is assigned its own weight w_i, which is multiplied by x_i to give the final result. The bias parameter b is applied to the weighted input values to produce an offset in the data. The neuron's output is not only the result of this linear combination but rather the transformation of this result by a nonlinear activation function *f(.)* (Deng, 2012). The logistic sigmoid function (Eq. 2) and hyperbolic tangent function (Eq. 3) are two of the most frequent nonlinear activation functions used in ML, as

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

$$f(x) = \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad (3)$$

i. Convolutional Neural Networks (CNNs):

CNNs are a critical component of deep learning architecture (Wu et al., 2014; Karimpanal and Bouffanais, 2019); each neuron in the first hidden layer is related to all neurons in the input. When the input *x* is high dimensional (for example, an image of 100×100 pixels, each neuron requires 10000 parameters), it does not function since each neuron requires numerous connections. An effective technique is to limit each neuron of input connections to a restricted number of neurons. There are numerous ways to create a connection technique. In the case of pictures, for example, we can force each neuron to only look at nearby pixels in the input image. This concept can be developed further by imposing the preceding process across multiple layers, resulting in a deep locally connected network.

There are multiple layers in a CNN, a convolutional layer (CL) is the first layer, and it consists of a group of neurons. Each neuron takes input from a different section of the previous layer. A weight sharing strategy is utilised to accomplish even more reduction, in which each neuron in the CL has the same weights for this specific section. The convolution filter is specified by these weights. Multiple filters can be placed in the same position using the convolution. Two filters referring to the same input, for example, could exist at one place. A feature map is a collection of the output provided by each filter. The use of many filters helps in the discovery of diverse aspects of the image.

ii. A Pre-trained model:

To demonstrate the notion of transfer learning, a neural network is trained on a set of data. This data is compiled as the "*weights*" of the network, from which it learns. These weights can be retrieved and implemented in any neural network. Rather of starting from scratch, we "*transfer*" the learnt attributes to the other neural network. Using pre-trained models that have already been trained on huge datasets, we may directly use the weights and architecture obtained and apply the learning to our problem statement, that means "*transfer learning*". We "*transfer the learning*" from the trained model to the particular problem, we are trying to solve.

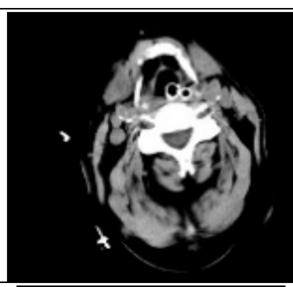
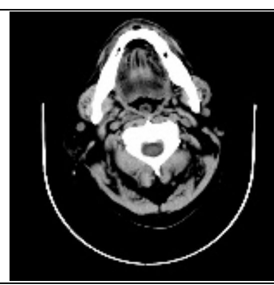
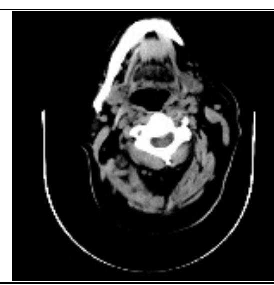
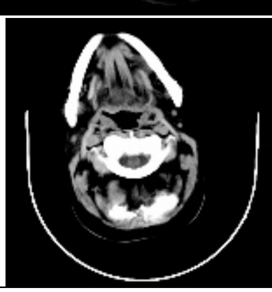
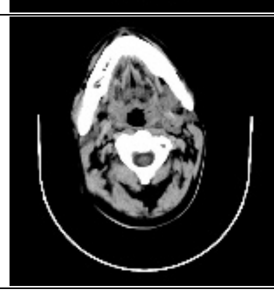
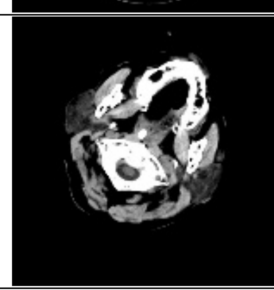
A pre-trained model is one that has already been taught to address a similar problem. Instead of creating a new model to handle a comparable problem, you utilize the model trained on the previous problem as a starting point (Web 1). A pre-trained model can be used as a mechanism for feature extraction. In order to use the complete network as a fixed feature extractor for the new dataset, we can first remove the output layer (Web 1). The core of object detection models, for instance, is frequently pre-trained using ImageNet classification. Today, it is simple to access a number of well-trained networks, such as ResNet, VGGNet, and AlexNet (Chen et al., 2021).

4 Material and Methods

4.1. Dataset:

The dataset consists of CT images with slice of 5 mm, which contains normal and abnormal brain images. The dataset was gathered from Mansoura University hospital that includes images of 90 patients: 60 without brain tumors for 3093 images and 30 with brain tumors for 1034 images. Table 1 shows samples of the dataset.

Table 1: Sample of the brain CT dataset.

Brain CT images				No. of images
Normal image				3093
Abnormal image				1034

4.2. The proposed model for brain tumor diagnosis:

There are five stages of the model after data acquisition as shown in Figure (1), namely, image preprocessing, data preparing, feature extraction, transfer learning and classification. We will explain each stage as follows.

i. Image preprocessing phase

The input dataset images have the raw DICOM format, and it needs to be normalized and balanced as in the following stages:

a) Convert DICOM images into jpg images

The input dataset's images are formatted according to the global standard for the storage and transmission of medical imaging, known as Digital Imaging and Communications in Medicine (DICOM). Utilizing the DICOM standard serves to ensure that all medical images produced by different devices, hospitals, or companies may communicate in the same language and hence operate in the same environment. However, there is a problem with DICOM files. Each DICOM file has a header that contains details on the patient, the acquisition settings, and the image dimensions. These DICOM images may occasionally be converted into alternative file types like JPEG (Joint Photographic Experts Group) or PNG (Portable Networks Graphics) in order to display easily and to hide the patients' personal information (Chiang et al., 2021). Hence, we converted the DICOM images into JPG in order to remove the text information and create compact images.

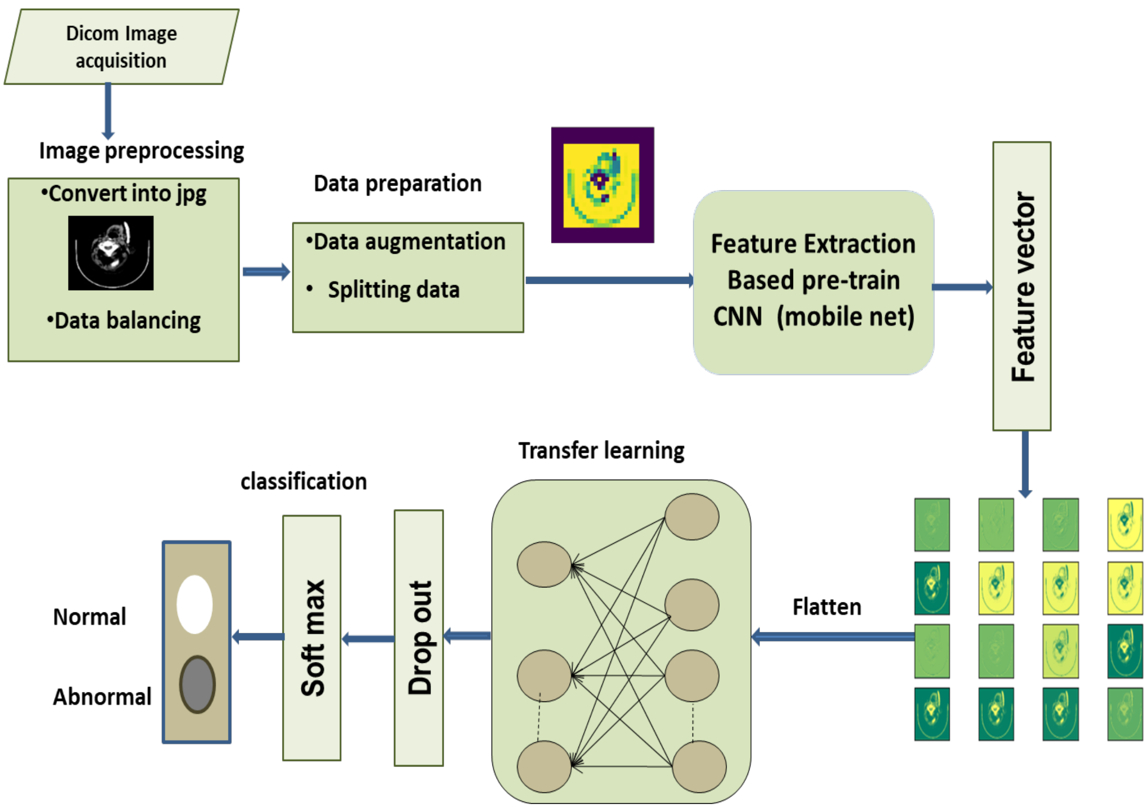


Fig.1: The proposed CT-based diagnosis model of brain tumors.

b) Data balancing and normalization

If the classes are not roughly equally represented, the dataset is unbalanced. This is useless if the data is manipulated (Abou El-Magd et al., 2022a). The most straightforward oversampling-based approach is class weight. With biased class data, the majority of machine learning algorithms perform poorly. Changing the current training procedure to account for the skewed class distribution giving the majority and minority class's different weights, and this can be resolved. The categorization of training will be impacted by the weight difference. The goal is to penalize minority misclassification by elevating the weight of the minority and lowering that of the majority (Web 2).

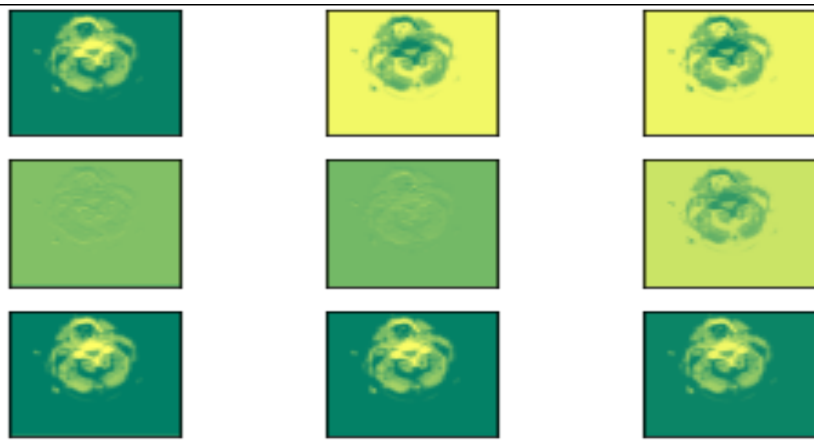
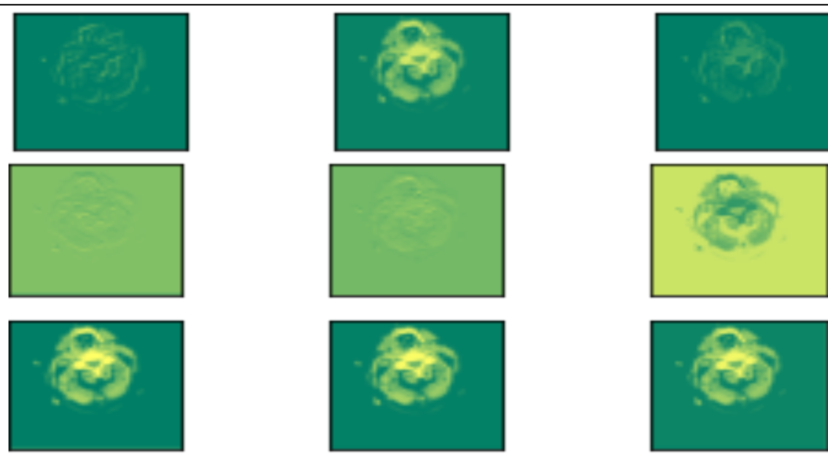
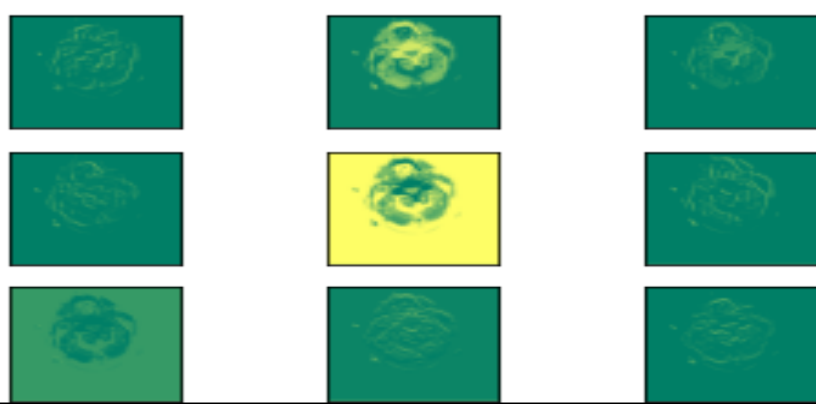
ii. Data Preparation phase

Several data augmentation techniques, such as rotation, width shift, height shift, shear, zoom, and horizontal flip, were performed on the training samples during this phase to reduce overfitting and boost generalization. The dataset is divided into 10% for testing and 90% for training. The second step in this phase is to divide the training data into two sets, one for training and one for validation. A validation set will be formed by splitting the training set group by 20%.

iii. Feature extraction-based pre-train network

The pre-trained model is used as standalone software to extract features from brain CT scans. An image's extracted features could be a vector of numbers that the model uses to represent the features of the image as a whole. The categorization step can then incorporate these traits as an input for the classifier. The output features of the three pre-trained models: MobileNet-V2, ResNet-50, and VGG-16 are put in Table 2, which are put to the test in the experimental part. These features are flatten and passed to the transfer-learning phase.

Table 2: The output features of the re-train CNN.

Pre-train CNN	Output Features
MobileNet-V2	
ResNet-50	
VGG-16	

iv. Transfer learning

For the suggested model, a pre-train CNN MobileNet-V2, ResNet-50-50, and VGG-16- model is followed by extra task-specific layers. It is pre-loaded with ImageNet pre-trained weights. Transfer learning was utilized to recognize the brain tumor using CT brain images once the model was fine-tuned. The extra layers replace the pre train CNN; MobileNet-V2, ResNet-50, and VGG-16- model entirely linked layer. They are two dense layers separated by a Rectified Linear Unit (ReLU) activation layer. The following layer is a dropout layer with a dropout probability of 30%, which eliminates 30% of the parameters at random and reduces overfitting.

v. Classification and evaluation phase

The accuracy, precision, recall, and F1-score, four-evaluation indices that are frequently used in the classification problem are used to assess the predictive power of the suggested model (Khalifa et al., 2021). The ratio of correct forecasts to all guesses is called accuracy, and it is commonly expressed as a percentage and derived in equation (4). Equation (5) measures the precision as the capacity of a model to accurately predict values for a specific category. Recall is calculated using equation (6) and measures the percentage of positive patterns that are categorized correctly. The F1-score is the equation's weighted average of precision and recall, and given by equation (7).

$$\text{Accuracy} = \frac{\text{Number of correct prediction}}{\text{Total number of prediction}} \tag{4}$$

$$\text{Precision} = \frac{\text{particular category predicted correctly}}{\text{all category predictions}} \tag{5}$$

$$\text{Recall} = \frac{\text{Correctly Predicted Category}}{\text{All Real Categories}} \tag{6}$$

$$\text{F1} - \text{score} = 2.\frac{(\text{Precision .Recall })}{(\text{Precision+Recall})} \tag{7}$$

5 Experimental Results and Discussion

Three experiments are done for brain tumor recognition using CT images. The experiments were performed using tensor flow and Keras with a TPU google COLAB. Next sub sections illustrate these experiments.

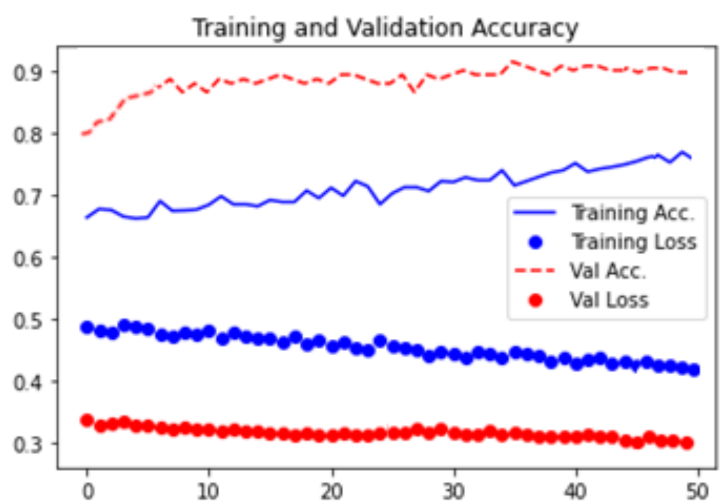


Fig. 2: The training performance based VGG-16 model

5.1 Experiment 1: using pre-train VGG-16 model

Simonyan and Zisserman's CNN model is called VGG-16 (Abou El-Maged et al., 2020). The model was applied to a dataset with about 14 million categories of photos and 1000 classes. Its test accuracy on the ImageNet dataset is 92.7%. By sequentially substituting three smaller kernel-sized filters (3×3 kernels) for the larger ones used by AlexNet, VGG-16 outperforms it. By making minute adjustments to the CNN's structure, fine-tuning aims to improve or maximize the output of a process or function. Despite image type differences, the CNN architecture can be applied to new datasets (Abou El-Maged et al., 2020). Consequently, we can employ fine-tuning to deal with this scenario, and the features of the images are extracted using VGG-16, followed by the classification phase using SoftMax activation function with Adam optimizer. Figure 2 shows the performance of the trained model in terms of accuracy and loss during the training period

(50 epochs).

5.2. Experiment 2: Using pre-train ResNet-50 model

The core idea behind ResNets, a deep convolutional network, is to use shortcut connections to bypass blocks of convolutional layers. When the size of the feature map is cut in half, the number of filters in the basic blocks known as "bottleneck" blocks doubles. These blocks adhere to two simple design principles. Convolutional layers with a stride of two perform down sampling and batch normalizing after each convolution and before activating the ReLU.

When the input and output dimensions are the same, the identity shortcut is used. The dimensions can be matched using 1×1 convolutions utilizing the projection shortcut. Stride lengths of two are employed in both cases where the shortcuts traverse feature maps of various dimensions. The network culminates with a softmax-activated layer (Abou El-Maged et al., 2022b). In this training experiment, the features of the images are extracted using ResNet-50, followed by the classification phase using softmax activation function with Adam optimizer. Figure 3 depicts the training performance in terms of accuracy and loss during the training period.

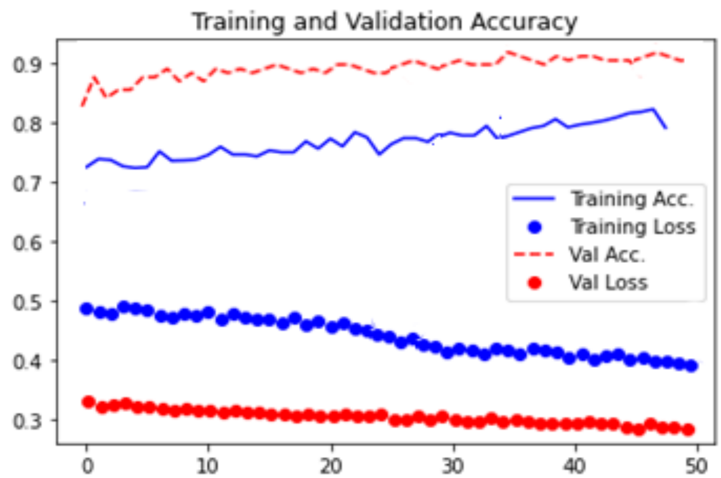


Fig. 3: The training performance based ResNet-50 model.

5.3. Experiment 3: Using pre-train MobileNet-V2 model

Compared to MobileNet-V1, there were two new modules added to MobileNet-V2, namely, an inverted residual module and a linear bottleneck module. The idea of depthwise separable convolution provided the foundation for MobileNet. By convolving in the depth dimension, the fundamental 2D convolution processes all input channels directly to generate a single output channel. Converging each input channel with its appropriate filter channel is what the depthwise convolution does. Once the filtered output channels have been generated, they are stacked once again. Filtering the stacked channels' outputs with a 1×1 convolution, also known as pointwise convolution, creates a single channel that may be independently manipulated in terms of depth (Indraswari et al., 2022).

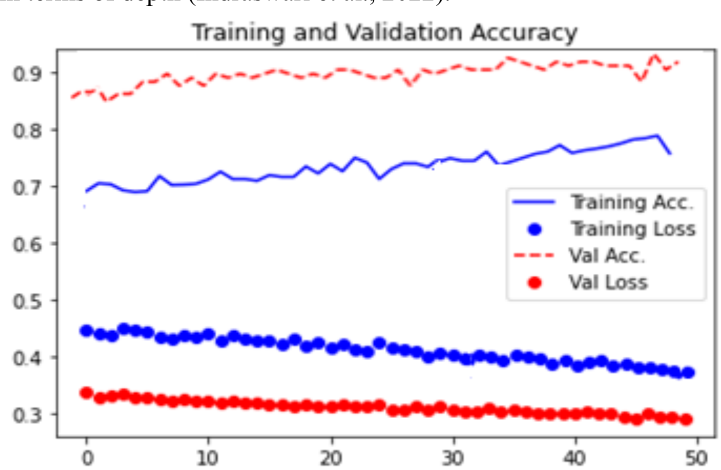


Fig. 4: The training performance based MobilNet-V2 model.

An improved version of MobilenetV1 is MobileNet-V2. This increases its effectiveness and potency. Because of the simplified and smaller models, MobileNet-V2 models run more quickly (Web 3). We initially trained two more layers using MobileNet-V2, which had already been pre-trained by ImageNet as a fixed feature extractor, based on the transfer learning theory, and then we adjusted it by making select layers trainable rather than all of them. Figure 4 depicts the training performance in terms of accuracy and loss during the training period.

Table 3 shows the test results of the proposed model for the three pre-trained models: MobileNet-V2, ResNet-50, and VGG-16. One can easily say that the proposed system has higher accuracy using MobileNet-V2, where the accuracy is 97.6%, and values of precision, recall, and F1-score are 96%, 95%, and 96% respectively. MobileNet-V2 yielded also the best F1-score. In addition, we can say that MobileNet-V2 model has an extra feature: it has less parameters than the other two models, which minimizes the model's complexity and makes it faster in medical diagnosis.

Table 3: CT brain diagnoses test results based on three pre-train models.

Pre- train model	Accuracy %	Precision %	Recall %	F1-score %	Total parameters
VGG-16	93	94	97	95	138,357,544
ResNet-50	96.5	96	94	95	25,636,712
MobileNet-V2	**97.6**	**96**	**95**	**96**	3,538,984

6 Conclusions and Future Work

Brain tumors are one of the worst diseases, having much further effects on human health. CT images has advantages such as effective calcification, bleeding, and bone detail identification, as well as lower costs, shorter imaging times, and universal availability. Patients who are too huge for an MRI scanner, patients who are claustrophobic, patients who have metallic or electrical implants, and patients who are unable to sit motionless for the duration of the test due to age, pain, or a medical condition are examples of these scenarios. The neuroradiologists may face problems in brain tumor diagnosis especially with CT scans. So, the proposed CAD system is suggested to aid them especially in the emergency cases where the CT machine is available. Affordable dataset is collected for brain CT scans from Mansoura University Hospital. Three pre-trained models are tested for feature extraction: VGG-16, ResNet-50, and MobileNet-V2. By comparing the results, the MobileNet-V2 model, with the lowest number of parameters, produced better results. Its accuracy is 97.6%, while its precision, recall, and F1-score values are 96%, 95%, and 96%, respectively. Hence, we recommend the proposed approach for brain tumor diagnosis using CT scans due to its high accuracy, low cost, and plentiful resources at the hospitals. In the future work, we will work on more slices of brain images with the help of attention algorithm in order to improve the performance and accuracy.

Ethical Approval

This study was performed using medical imaging dataset that approved by the ethical committee at Faculty of Science, Mansoura University No. Sci-Phy-M-2022-84.

Informed Consent

No informed consent was needed in this study.

Conflict of Interests

The author has not any conflict of interests with the information presented within this article.

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