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Refined Convolutional Neural Networks Automated System for Brain Masses Detection using CT/MRI Diagnostic Scans

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Abstract: A brain mass/tumor is considered to be a very fatal illness, exhibiting a diverse array of impacts on individuals' general well-being. A neoplasm with abnormal cell proliferation, typically located inside or close to the cerebral region, is commonly known as a brain mass. Brain masses can manifest as either benign or malignant neoplasms. Medical practitioners employ many diagnostic methods to ascertain the nature of a patient's brain tumor, distinguishing between benign and malignant tumors. Radiology images are currently viewed most often using deep learning techniques. Imaging methods include CT, MRI, PET, and ultrasound. CT and MRI scans are the most popular imaging, each with advantages and disadvantages. This paper has created an automatic system for detecting brain masses using CT and MRI scans. This is because these two types of X-rays each have their own advantages, and a radiologist would benefit from this method. The input image is subjected to testing by the system. If the image is identified as a CT-scan image, it uses the recommended Convolutional Neural Network (CNN) architecture to carry out diagnosis. Based on the achieved accuracy, F1-score, precision, and recall values of 98.01%, 98%, 99.7%, and 98.84%, respectively, the CNN architecture has proven to function exceptionally well. Alternatively, Reset101, a pre-trained convolutional neural network, can be used to diagnose the image in question if it is an MRI scan. The test results give 99.8%, 99.9%, 99.2%, and 99.55% for accuracy, precision, recall, and F1-score, respectively.

Keywords: Brain tumors, CT imaging, MRI scans, Pre-trained deep learning networks, ResNet-101, VGG-16.

1 Introduction

The brain is an intricate organ that regulates every bodily function, including thought, memory, emotion, touch, motor skills, vision, breathing, temperature, and hunger. The central nervous system, or CNS, is made up of the brain and the spinal cord that branches off of it. The average adult brain weighs approximately 3 pounds, with the remaining 40% made up of salt, water, protein, and carbs [1]. The brain is not a muscle, it is made up of nerves, comprising glial cells and neurons, as well as blood vessels. The most intricate and intriguing organ in the human body is the brain [2]. A brain tumor is a specific type of intracranial lesion that is located within the head and usually results in an increase in intracranial pressure. Any portion of the brain can be affected by masses, and depending on which part(s) is/are concerned, there are the following symptoms [3];

*Seizures,
*Difficulty with language,
*Mood changes,
*Change of personality,
*Changes in vision, hearing, and sensation,
*Difficulty with muscle movement,
*Difficulty with coordination control.

One of the most dangerous and incurable diseases is brain cancer [4] .While they shed cells to invade other sections of the brain and develop new tumors that are too small to be detected by standard imaging techniques, tumors may be embedded in areas of the brain that are crucial for controlling the body's vital functions [5]. Brain

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tumors have become more common during the past few years. Unfortunately, many of these tumors will only be discovered after developing symptoms. A little tumor can be removed considerably more quickly and safely than a huge one. Advanced image-guided technology and computer-assisted surgery planning have grown more prevalent in brain surgery [6].

A tumor is defined as an abnormal growth of tissue. A brain tumor is an abnormal mass of tissue where the normal cell-regulating systems don't seem to be able to stop the uncontrollably growing and multiplying cells. Benign tumors and malignant tumors are the two main types of brain tumors [7].

Machine learning (ML) as a subset of artificial intelligence (AI), was applied in diagnostic imaging in the 1980s [8]. Imaging characteristics and settings are predefined using professional experience. Tumor regions can be used to compute the shapes, areas, and histograms of picture pixels. Typically, data entries are divided into testing and training categories. ML is the method used to teach the features. Examples of algorithms include convolutional neural networks (CNN), support vector machines (SVM), principal component analysis (PCA), and others [9]. After training, the algorithm must recognize the features and categories of a testing image. ML has the drawback of requiring users to select picture class features. Some factors may be missing. Deep learning (DL) systems are now the most popular way to look at images from radiology. This includes many imaging methods, like CT, MRI, PET, ultrasound, and more, as well as many tasks, like finding tumors, dividing them into groups, predicting diseases, and more [10]. Using CT has several advantages, such as accurate detection of calcification, bleeding, and bone detail; further advantages include reduced expenses, faster imaging times, and broad accessibility. These circumstances include patients who are too small to fit in an MRI scanner, claustrophobic, have metallic or electrical implants, or are unable to stay for the entire test due to age, pain, or a medical condition [11].

In this work, a system has been developed that uses CT scans and MRI scans to detect brain masses. This is because these two forms of medical imaging each have their own characteristics (advantages and disadvantages), and a radiologist would benefit from this method to functionalize the convenient scan. Section 2 is devoted to the related previous work, and the work background is presented in Section 3. While Section 4 is devoted to description of the proposed system. The Experimental results and discussion are illustrated in Section 5, and the work conclusions are explored in Section 6.

2 Related Previous Work

This section provides an overview of prior endeavors aimed at detecting brain tumors. MRI scan images have been extensively employed in these investigations; a selection of such studies will be provided. CNN was trained by Abiwinanda et al. [12] to differentiate between common brain tumors like gliomas, meningiomas, and pituitaries, hence 98.51% and 84.19%, respectively, represent their best training and validation accuracy. On the same dataset, more intricate region-based segmentation techniques produced accuracy ranging from 71.39 to 94.68%. To categorize brain tumors in T1-weighted contrast-enhanced MRI, Das et al. [13] used a CNN model. Two crucial processes comprise the proposed system. Utilizing a variety of techniques, first preprocess the images and then use CNN to arrange them. For the investigation, a dataset of 3064 images of pituitary, meningioma, and glioma tumors was employed. 94.39% testing accuracy, 93.33% precision, and 93% recall were achieved by our CNN model.

A new correlation learning method (CLM) for deep neural networks was presented by Woźniak et al. [14], fusing CNN with traditional architecture. CNN uses the support neural network to determine which pooling and convolution files are best. The principal neural classifier learns new information faster and more efficiently as a result. With their CLM model, they achieve 96% accuracy, 95% precision, and 95% recall. Brain tumors were diagnosed with MRI images by Çinar et al. [15], as they used the ResNet50 design, adding eight new levels and removing the final five ResNet50 layers. Accuracy with that model is 97.2%. Additionally, the models from GoogleNet, InceptionV3, AlexNet, ResNet50, and Densenet201 produced passable results. Other investigations indicate that the new method works well and can be applied to computer-aided systems for brain tumor detection.

A CNN architecture was presented by Badža et al. [16] to classify three types of brain tumors. The network was evaluated on T1-weighted contrast-enhanced magnetic resonance imaging, and it is less complex than pre-trained networks. The generalization of the network was examined using an enriched image database, subject-wise cross-validation, and a 10-fold technique. For record-wise cross-validation on the improved data set, the 10-fold cross-validation approach produced the best accuracy (96.56%). Because of its great generalization and quick execution, radiologists might use the new CNN architecture as a decision-support tool for medical diagnosis.

Brain tumors were extracted from 2D MRIs by Shah et al. [17] using convolutional neural networks, fuzzy C-means clustering, and classical classifiers. A real-time dataset with different tumor sizes, locations, morphologies, and picture intensities was used in the experimental inquiry. Scikit-learn employed conventional classifiers such as Naïve Bayes, MLP, KNN, SVM, Logistic Regression, and Random Forest. They then used TensorFlow and Keras to create CNN, which outperforms conventional ones in terms of performance. Impressively, their CNN reached 97.87% accuracy. Fuzzy C-means clustering algorithm was the first technique put forth to remove brain tumors from 2D brain MRIs. Conventional classifiers and convolutional neural networks came next. A real-time dataset with a variety of tumor sizes, locations, forms, and image intensities was used for the experimental investigation. We used six classic classifiers in the traditional classifier section: Support Vector Machine, Random Forest, Logistic Regression, K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), and Naïve Bayes, all of which were built using scikit-learn. After that, as CNN performs better than the conventional methods, we switched to using Keras and TensorFlow to construct it. CNN achieved an impressive accuracy of 97.87% in their work [17].

A fully automatic model for brain tumor segmentation and classification utilizing a Deep Convolutional Neural Network with a multi-scale approach was presented by Diaz-Pernas et al. [18]. Meningioma, glioma, and pituitary tumor MRI images can all be analyzed by the suggested neurological model. The effectiveness of this approach is contrasted with previously reported DL and classical ML approaches on a publicly accessible MRI image dataset consisting of 3064 slices from 233 patients. The tumor classification accuracy of the suggested method, when compared to other methods using the same database, was higher at 0.973.

Using hybrid CNNs based on MRI scans, AlTahhan et al. [19] presented an improved automatic classification system for brain cancers. They used a dataset of 2880 T1-weighted contrast-enhanced MRI brain scans, which includes a class of no tumors and three classes of brain tumors: gliomas, meningiomas, and pituitary tumors. By utilizing two hybrid networks, AlexNet-SVM and AlexNet-KNN, they were able to enhance the performance of the CNN's fine-tuning algorithm, AlexNet. They obtained validity and accuracy of 96.9% and 98.6%, respectively. Their suggested method would speed up clinical diagnosis by automatically identifying and categorizing brain cancers using MRI scans.

To identify a tumor, Siar et al. [20] used CNN; here was where the images were first observed. Images were classified using the SoftMax fully linked plate, which has a 98.67 percent classification accuracy. Additionally, CNN's precision when using the Decision Tree (DT) classifier is 94.24 percent, and when using the Radial Basis Function (RBF) classifier, it is 97.34 percent. Several investigations have been conducted using CT scans; these studies will be included below.

DL networks were employed by Venugopalan et al. [21] to categorize CT brain data. They studied the significance and effect of using DL approaches to give more data for the early detection of Alzheimer's disease (AD) and used CNN to classify CT brain scans. CT images are classified into three categories: AD, lesion (such as a tumor), and normal aging. From there, a complex CNN architecture is built by fusing 2D and 3D CNN networks. With an average of 87.6%, this intricate CNN architecture offers classification accuracy rates of 85.2%, 95.3%, and 80% for the classes of AD, regular, and lesion, respectively.

For CT brain scans, Dawood et al. [11] used pre-trained models, such as MobileNet-V2, ResNet-50, and VGG-16. Despite having the fewest parameters, MobileNet-V2 model outperformed the other models in terms of results. With comparable values of 96%, 95%, and 96% for precision, recall, and F1-score, it yielded an accuracy result of 97.6%. Moreover, Table 1 explores some previous research related to the classification techniques and the corresponding accuracy achieved.

3 Background

3.1 AI role in medical imaging

The capacity of a machine to imitate intelligent human behavior is known as artificial intelligence, or AI. In research on diagnostic and therapeutic medical imaging, artificial intelligence is the most talked about topic. From 100–150 per year in 2007–2008 to 1000–1100 per year in 2017–2018, AI was used in diagnostic imaging papers. Researchers have utilized AI to recognize complex imaging patterns and quantify radiographic features automatically. Radiation oncology uses AI for tumor delineation and therapy evaluation on several image modalities. Radionics extracts many picture properties [28]. High-throughput radiation image extraction is a popular medical imaging research topic. AI is crucial to processing massive amounts of medical photos and exposing illness traits that are unseen to the human eye.

AI is important in radiology as AI-based ML was used in diagnostic imaging in the 1980s [29], whereas 12 users predefined imaging parameters and features using professional experience. The forms, areas, and histograms of picture pixels in tumor regions can be calculated. Usually, certain data items are used for training and the rest for testing. Select a ML algorithm to teach features. Algorithms include PCA, SVM, CNN, and others. For a testing image, the trained algorithm must recognize attributes and label it. A problem with ML is that users must choose features that classify a picture. This may exclude some factors.

To diagnose lung tumors, the user must split the tumor area as structure features. Manual feature selection has always been inconsistent due to patient and user variance. Users don't need to input features for DL. Deep learning learns from more data than its name implies. Use deep artificial neural network models [30]. Multiple layers of DL extract more complicated features from photos. It helps identify traits and separate abstractions from raw picture input. It deconstructs abstractions and identifies performance-enhancing features. The idea of DL is decades old. Due to the large number of medical images and advances in hardware like GPUs, DL became viable

Table 1: Summary of classification accuracy obtained by other models

Author	Methods	Dataset	Accuracy
Wu et al. [22]	Deep CNN and SVM	BraTS2014 and BraTS2016	SVM 87.05% and CNN 86.69%
Islam and Zhang [23]	Deep CNN and SVM	OASIS dataset	93.18% accuracy, 94% precision, 93% recall and 92% f1-score
Suhara and Mary [24]	Deep CNN and Google Net	Fig share	SVM classifier 0.97% and DCNN 92.3%
Yang et al. [25]	Discrete wavelet transforms (DWT)	GE Healthcare	Clustering accuracy of 94.8% and a balanced error rate of 7.8%
Demirhan et al. [26]	Wavelets, Neural Networks and self-organizing map (SOM)	IBSR2015 and BRATS2012	WM 91%, GM87%, edema 77%, tumor 61% and CSF 96%
Hussein et al. [27]	Artificial Neural Networks	Adaptive & filter	Enhancement filter Recurrent Network (RNN), Design 76.47, Elman Network 88.24

only in the last decade. One challenge with ML is consumer understanding. GPU started to fail as ML grew more critical. This issue was addressed by Google's Tensor Flow AI system's tensor processing unit (TPU), an AI accelerator integrated circuit. TPU is designed for neural network ML but can be utilized in medical imaging.

The AI medical terms listed below are important.

– Mathematical image processing enhances clarity. Computer vision processes images for identification and interpretation [31].
– Artificial neural networks (ANNs) use nonlinear statistical data modelling to build complicated input-output interactions [32]. This method mimics the human brain by absorbing input and creating decision-making neural networks. ANNs produce output by feeding input into one set of algorithms and output into another.
– Computers can learn from experience and adapt their data processing to new information through ML [33]. A simple if-then decision-making tree or DL algorithms could mimic how the brain processes information and develop neural network decision-making patterns. An algorithm analyzes data (images, Excel charts, etc.) using a predetermined artificial neural network in DL [34]. The algorithm is taught with training data to answer queries. The training data collection must accurately represent the problem for reliable outcomes [35].
– CNNs analyze data using DL and hidden layers. CNNs have multiple hidden layers and intricate convolutional layer interactions [36].
– DL reprocesses various data sets for multiple evaluations [37]. The previous layer's results inform each layer's evaluation. concealed layers compute with concealed inputs and outputs [38]. A polyp-hunting colonoscopy picture will be multiplied. Each photo will be filtered and scanned. Color, edge, and marking filters' scores will be applied to subsequent layers. This approach adds layers as needed [39].
– Detection is the primary focus of researchers in AI medical diagnostic imaging. In the 1980s, scientists initiated the development of computer-aided detection (CAD) systems. Mammography, CT, and MRI were the domains in which conventional ML algorithms were implemented. Although considerable effort was devoted to research in this field, the actual clinical applications showed little promise [40]. Multiple sizable trials have reached the consensus that CAD has, at best, provided no benefit. And has at worst, decreased the accuracy of radiology, leading to increased rates of recall and biopsy.

3.2 Image classification using CNN

CNN has been one of the most appealing approaches. They have proven essential in many hard and effective ML applications, such as those that put ImageNet's object identification, picture categorization, and face recognition to the test. Consequently, we employ CNN as our model for these challenging image classification tasks. CNN is utilized in professional and scholarly settings for image classification and segmentation. Image recognition is used in many domains, such as automated photo organization, stock photography, face identification, and many more related industries [42].

Deep artificial neural networks are known as CNNs. CNN was utilized for object detection within scenes, photo search clustering based on similarity, and image classification. It can be used to identify faces, individuals, street signs, malignancies, platypuses, and many other aspects of visual data. The convolutional layer is the core element of CNN. The parameters of the layer are a set of learnable filters, commonly referred to as kernels, each

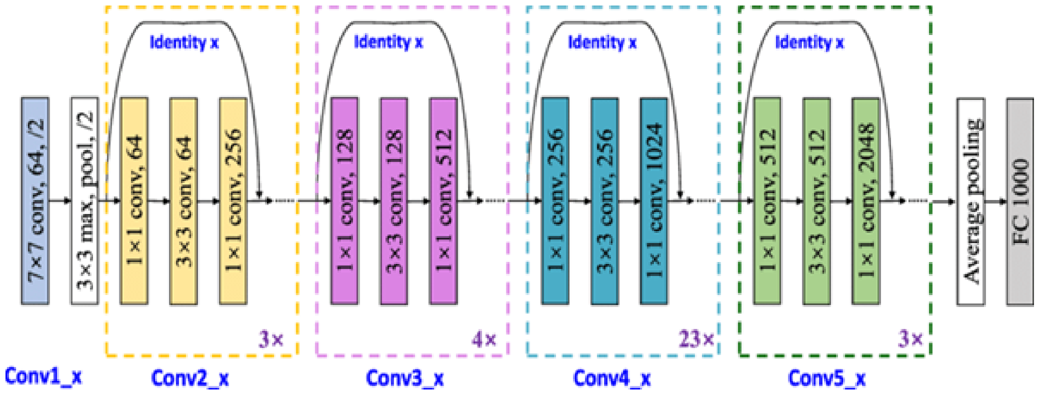

Fig. 1: Pre train CNN ResNet101 [41]

having a small receptive field that extends to the whole depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, which yields a 2-dimensional activation map for that filter and the calculation of the dot product. As a result, the network is made aware of the filters. The filter activates when a specific type of feature is found in the input at a specific spatial position. The activation maps are then sent into a down-sampling layer one patch at a time, like how convolutions work. CNN also has a fully linked layer that classifies output using a single label per node [43].

3.3 Pre-train CNN ResNet-101

ResNet-101 is a CNN with 101 layers deep. A pre-trained version of the network, trained on more than a million photographs, is available in the ImageNet database [44]. The pre-trained network can classify images of 1000 distinct object categories, such as a keyboard, mouse, pencil, and various animals.

A deep learning model called Residual Network (ResNet) is employed in computer vision applications. The architecture of CNN is intended to accommodate thousands or even hundreds of convolutional layers.

ResNet-101: The VGG-19 [45] model served as inspiration for the design of ResNet [46]. It is among the most intricate architectures for ImageNet (the challenge for object identification and image classification) that has been suggested. A CNN typically consists of multiple layers that are trained to carry out different functions and are connected to one another. At the end of its layers, the network learns features at several levels. This model's convolutional layers are mostly 33 filters in size. In order to maintain the temporal complexity for each layer in ResNet, the number of filters in each layer is the same for output feature map sizes of the same size and doubles if the feature map size is half. It directly performs down sampling by convolving layers at a stride of two.

A fully linked layer with SoftMax enabled and a global average pooling layer complete this ResNet. The ResNet Module is shown in Figure 1. To put it simply, residual learning is the process of removing input information that came from that layer. ResNet does this by building shortcut connections to every 33-filter pair. By recycling activations from the previous layer until the layer next to it has learned its weight, layers are avoided in order to prevent the issue of fading gradients. Weights will adjust throughout training to amplify the layer adjacent to it and muffle the layer before it. This network has been found to be easier to train than standard deep convolutional neural networks. It also fixes the accuracy drop problem. A 101-layer residual network called ResNet-101 is an adaptation of the 50-layer ResNet.

3.4 Data augmentation

DL has gained popularity in artificial intelligence research recently for the processing and interpretation of medical images [47]. A specific type of DL method called CNNs is capable of automatically deriving a set of feature detectors from a labelled dataset. This is usually applied across multiple layers, resulting in a ”deep” model [48]. CNNs have demonstrated state-of-the-art performance in medical imaging tasks such as image segmentation (e.g., automatically delineating anatomical structures in radiation therapy) and image classification (e.g., distinguished between benign and malignant tumors in computer-aided diagnosis in radiology) [49]. Physician decision-making, treatment planning and delivery, and operational effectiveness may all be enhanced by DL software for these tasks [50]. To create a DL model, split the main dataset into a training and test set. The data that the DL network consumes during training throughout multiple iterations, or epochs, when the network's parameters are adjusted in an attempt to improve the desired result, is referred to as the training set. After training is complete, the performance of the final model is assessed using the test dataset.

DL techniques usually require enormous amounts of data to train a model to prevent over-fitting, which is a common issue when the model is fitted to a limited training set and produces a model that does not generalize well to new testing data. However, implementing deplaning in medical image analysis is occasionally hampered by a lack of training data because getting well-annotated medical data can be expensive and time-consuming. To mitigate this problem, data augmentation - which may be viewed as a kind of regularization approach to lessen the model's generalization - is often used in DL to expand the amount and variety of the training set. General data augmentation or picture segmentation are two instances of this [51–54]. As far as we are aware, this work offers the first thorough summary of modern data augmentation techniques for typical radiological tasks, such as the classification and segmentation of medical images on CT and MRI, the two main imaging modalities used in radiation oncology.

4 Proposed Automatic System for Brain Tumors Detection using CT/MRI

The system consists of mainly five main stages: image acquisition, data augmentation, feature extraction, image classification, and finally evaluation, that illustrated in Figure 2. It will be listed in detail below.

4.1 Image acquisition

In the proposed system, two different datasets were used, one for CT- scan images and the other for MRI- scans. The CT scan images obtained from Ref. [55], it consists of three classes Aneurysm (168 images), cancer (182 images), and tumor (168 images), while the MRI scans obtained from Ref. [56] , it consists of 253 images of two classes; normal brain (98 images) and abnormal brain (155 images).

Large volumes of data are usually needed to train a model using DL techniques in order to prevent over-fitting, which is a common issue when using these models. As a kind of regularization strategy to lessen the model's generalization, data augmentation is frequently used in DL to increase the size and diversity of the training set to address this issue. General data in this system is augmented using:
rotation range = 20, horizontal flip and width shift range = 0.2,
height shift range = 0.2, and shear range = 0.2, zoom range = 0.2.

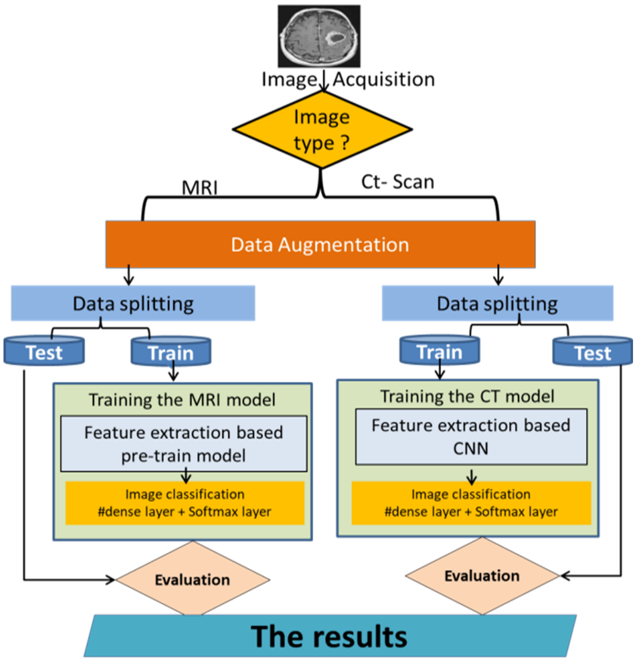

Fig. 2: Automatic Detection of Brain Tumors using CT/MRI Scans

4.2 Architecture of the Feature extraction and classification model

Since the images from CT and MRI scans are different, it was discovered that the feature extraction methods would also differ.

4.2.1 CT-scans classification model

Figure 3 presents the proposed architecture for CT–scan image classification after feature extraction. In the feature extraction phase, 7 CNN layers followed by the ReLU function are used to extract the CT-image features. The first layer convolutional with a filter size $(f \times f)$ is 4×4, the number of filters is 64 with ReLU, then followed by max- the pooling layer with pooling size 2×2. The next two layers are convolutional with filter size $(f \times f)$ is 4×4, the number of filters is 48, each with ReLU function and followed by max- pooling layer with pooling size (2×2). The next two layers are convolutional with filter size $(f \times f)$ is 4×4, the number of filters is 24, each with ReLU function and followed by max- pooling layer with pooling size 2×2. The extracted feature vector is flatted with a flattened layer to be ready for the classification stage. Three thick layers make up the classification stage, which is followed by the dropout layer and the SoftMax layer. All three dense layers - the first with 512 neurons, the second with 128 neurons, and the third with 32 neurons - have ReLU function.

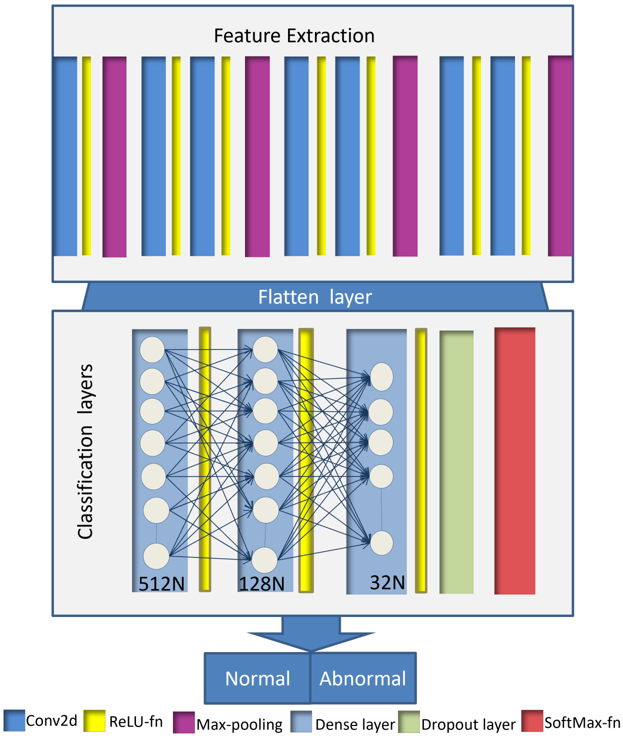

Fig. 3: The proposed architecture for CT scan image classification

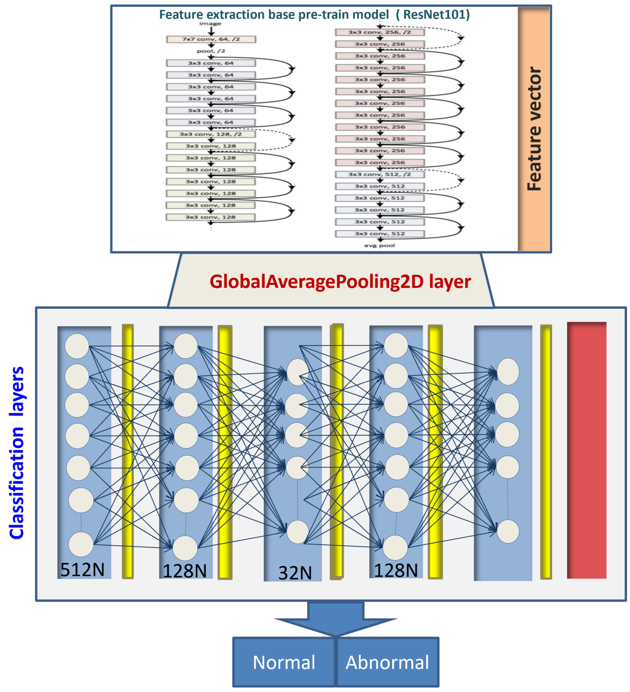

Fig. 4: The proposed architecture for MRI scan image classification

4.2.2 MRI-scans classification model

Figure 4 presents the proposed architecture for MRI–scan image classification after feature extraction. The feature extraction is done with the help of pre-train CNN model called ResNet101, The average-pooling layer with pooling size (2×2) is added after that. Five thick layers make up the classification stage, which is followed by the dropout layer and the SoftMax layer. All the thick layers with ReLU function have 512 neurons in the first layer, 128 neurons in the second, 32 neurons in the third, 128 neurons in the fourth, and 2 neurons in the fifth.

4.3 Evaluation measures

In order to assess the performance of the suggested system, four assessment metrics are commonly utilized in classification problems: accuracy, precision, recall, and F1-score. The ratio of accurate forecasts to all predictions, typically expressed as a percentage and determined by using Eq. (1), is the definition of accuracy. An equation called precision determines how well a model can predict results for a given Eq. (2). Recall is defined as the fraction of successfully identified positive patterns and is computed using Eq. (3). The F1-score in Eq. (4) is the weighted average of precision and recall [19,57].

$$\text{Accuracy}(\%) = \frac{\text{Number of correct prediction}}{\text{Total number of predictions}} \times 100 \quad (1)$$

$$\text{Precision}(\%) = \frac{\text{Particular category predicted correctly}}{\text{All category predictions}} \times 100 \quad (2)$$

$$\text{Recall}(\%) = \frac{\text{Correctly predicted category}}{\text{All real categories}} \times 100 \quad (3)$$

$$\text{F1-score}(\%) = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \times 100 \quad (4)$$

5 Experimental Results and Discussion

Tensor flow and Keras with GPU Google Colab are used for the studies. There are two experiments carried out. Using CT-scan pictures, we applied the suggested model in the first experiment. The suggested model is implemented for the MRI scan images in the second experiment.

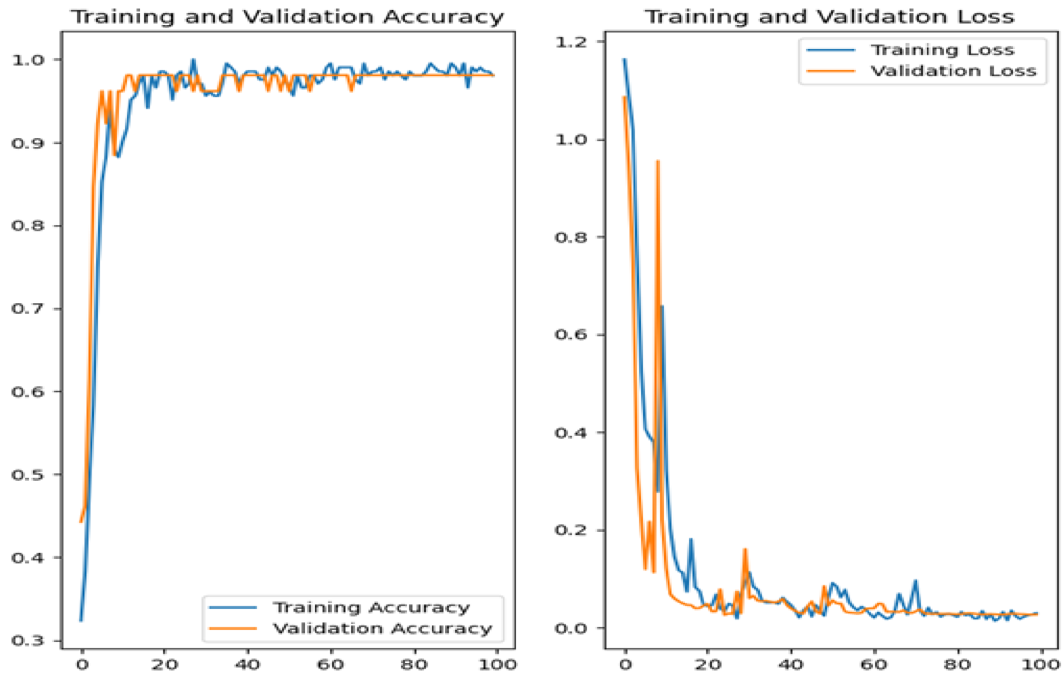

Fig. 5: The CT-scan model performance.

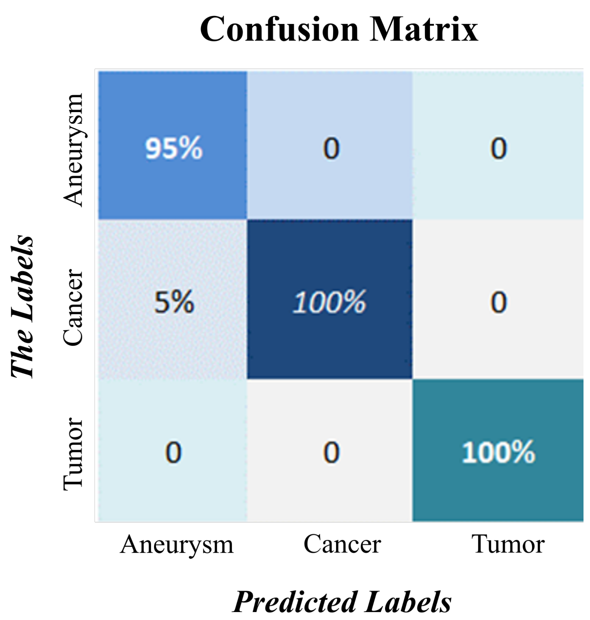

Fig. 6: The CT-scan model confusion matrix.

5.1 Experiment I

The framework of the suggested model in Figure 3 is implemented with learning rate = 1×10-6 in this experiment and drop out = 0.5 and 'adam' optimization function. 5 shows CT-scan model performance through the training process, while the confusion matrix is illustrated in Figure 6; the classification test accuracy is 98.01%. The results above are the result of utilizing the identical structure but with only 5 CNN layers, which achieved an accuracy of 92.8 all through testing.

5.2 Experiment II

The structure of ResNet-101 in this experiment is modified by adding 5 dense layers with ReLU function, and finally a classification with SoftMax activation layer. The hyper-parameters used are learning rate = 1×10-6 and 'adam' optimization function. Figure 7 shows MRI-scan model performance, while the confusion matrix illustrated in Figure 8. The classification test accuracy is 99.8%, while it was only 94.2% by applying VGG16.

The test results of the suggested model for CT and MRI images are displayed in Table 2. The first proposed architecture for CT scans, which has seven CNN layers and an accuracy of 98.01, is employed. The F1-score, precision, and recall values are 98%, 99.7%, and 98.84%, respectively. In contrast, the accuracy, precision, recall, and F1-score of the alternative five-layer architecture

Table 2: The CT /MRI Performance Results

	Model	Accuracy %	Precision %	Recall %	F1-score %
CT scans	Proposed architecture(7 CNN layers)	98.01	98	99.7	98.84
	Proposed architecture(5 CNN layers)	92.8	93.4	92.01	92.70
MRI scans	ResNet-101	99.8	99.9	99.2	99.55
	VGG-16	94.2	95.01	91	92.96

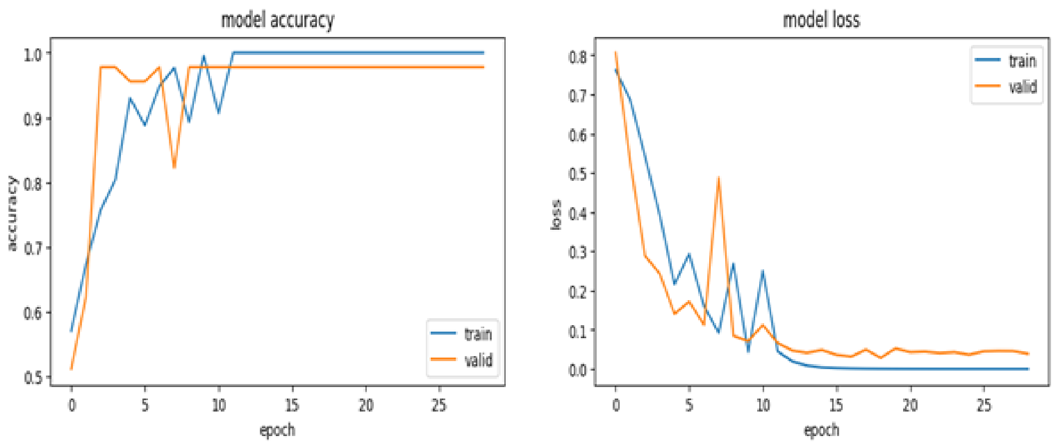

Fig. 7: The MRI -scan model performance.

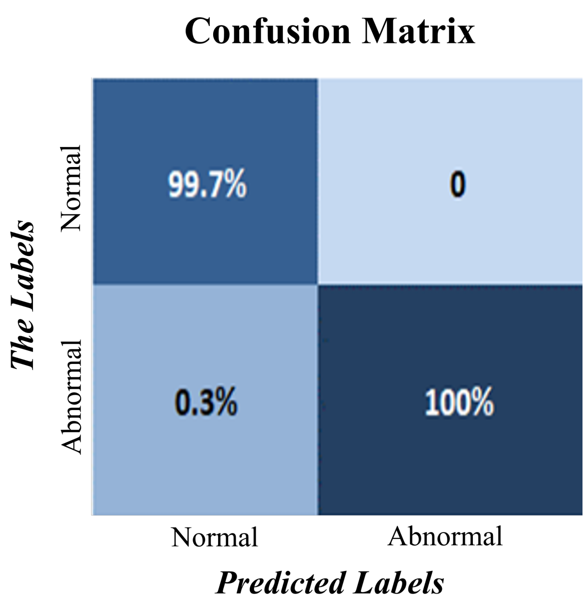

Fig. 8: The MRI-scan model confusion matrix.

were 92.8%, 93.4%, 92.01%, and 92.70%, respectively. The accuracy, precision, recall, and F1-score for the MRI scans are given by the ResNet101 findings as 99.8%, 99.9%, 99.2%, and 99.55%, respectively, but the results of the VGG16 test were 94.2 percent, 95.01%, 91%, and 92.96%, respectively.

6 Conclusion

Brain masses can be either benign or malignant in nature. Many diagnostic approaches are used by radiologists to determine the nature of a patient's brain mass, distinguishing between benign and malignant masses. The CT scan and MRI scan are the most used imaging scans, and each has advantages and disadvantages. This work describes the development of an automatic system for detecting brain tumors using CT and MRI scans. This is since these two sorts of radiologic scans each have their own set of characteristics, and a radiologist would benefit from having this method. The proposed system does test on the input image; if the image is recognized as a CT scan, the suggested CNN architecture is used for diagnosis. The CNN architecture has performed admirably, as seen by accuracy, F1-score, precision, and recall values of 98.01%, 98, 99.7%, and 98.84%, respectively. Alternatively, if the scanned image is an MRI scan, it can be diagnosed using Reset101 as a pre-trained CNN. The results are 99.8%, 99.9%, 99.2%, and 99.55% for accuracy, precision, recall, and F1-score, respectively. The future work will consider other different classification methods and fusion techniques for the sake of precis and quick diagnosis, for better medical treatment and optimizing the healthcare system.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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