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Brain Tumor Automatic Detection from MRI Images Using Transfer Learning Model with Deep Convolutional Neural Network

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ABSTRACT

Brain tumor detection successfully in early-stage plays important role in improving patient treatment and survival. Evaluating magnetic resonance imaging (MRI) images manually is a very difficult task due to the numerous numbers of images produced in the clinic routinely. So, there is a need for using a computer-aided diagnosis (CAD) system for early detection and classification of brain tumors as normal and abnormal. The paper aims to design and evaluate the convolution neural network (CNN) Transfer Learning state-of-the-art performance proposed for image classification over the recent years. Five different modifications have been applied to five different famous CNN to know the most effective modification. Five-layer modifications with parameter tuning are applied for each architecture providing a new CNN architecture for brain tumor detection. Most brain tumor datasets have a small number of images to train the deep learning structure. Therefore, two datasets are used in the evaluation to ensure the effectiveness of the proposed structures. Firstly, a standard dataset from the RIDER Neuro MRI database including 349 brain MRI images with 109 normal images and 240 abnormal images. Secondly, a collection of 120 brain MRI images including 60 abnormal images and 60 normal images. The results show that the proposed CNN Transfer Learning with MRI's can learn significant biomarkers of brain tumor, however, the best accuracy, specificity, and sensitivity gained is 100% for all of them.

Keywords: *Brain Tumor, CNN Transfer Learning, Deep Learning, CNN, Tumor Classification*.

1 INTRODUCTION

Brain tumor is proven to be a life-threatening and fatal disease [4]. In 2018, The American Cancer Society declared that there are 23,880 new instances with a brain tumor and 16,830 deaths in the United States alone [6]. Moreover, in recent decades, the number of died instances from brain tumors has increased in advanced nations by 300% as declared by the National Brain Tumor Foundation (NBTF) [7]. Accordingly, early diagnosis and treatment will lead to better results.

There are different brain imaging techniques that scan the structure and the function of the brain such as Electroencephalography (EEG), Position emission tomography (PET) and Magnetic resonance imaging (MRI). MRI provides better contrast to soft tissues than other techniques as it can present in detail and can distinguish between tissues in the brain. MRI images are considered safe for patients against harmful effects because it does not use any ionizing radiation during the examination [10].

The radiologist comprehensively needs to manual analyze and evaluate a massive amount of MRI images in a short time which needs considerable effort and time. To assist the radiologist and doctors in proper diagnosis, computer-aided diagnosis (CAD) systems have been implemented [14]. CAD systems process digital images of typical appearances and focus completely on clear sections, such as the possibility of tumors, and then support the decision made by the specialist [14].

Machine learning (ML) needs data sets that have high quality and clear characteristics to be trained. To achieve the goal accurately and appropriately from ML, it must take time for the algorithms to learn and develop. ML can be mistaken a lot even though it is independent. Mistakes that occur from ML lead to another set of errors that are difficult to detect later for long periods. Moreover, when the source of the problem is discovered, this takes time, as well as time to correct it. Traditional ML algorithms for classification go through several stages such as preprocessing, feature extraction, feature reduction, and classification [11].

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The artificial intelligence tools are represented in machine learning and deep learning. Nonetheless, The performance difference between deep learning and traditional machine learning makes the first more powerful. Deep learning has enormous neural networks that are trained many times for large data. This performance depends on supervised learning or on labeled data. The deep term refers to a large number of layers and the complex connections between layers. But there are some common drawbacks of deep learning such as it is complexity mechanized, requires a huge number of data to be enough for computations and training process of good algorithms and enhanced techniques. But these disadvantaged remains not confusing and continue improvements in training [22].

Recently, transfer learning becomes a supportive technique that depends on strong pre-trained CNN models to deal and solve various pattern problems [23]. Transfer learning is considered as a new model which transfer knowledge of pre-trained deep CNN model [24]. This technique tries to transfer the features which is learned from previous tasks and then apply those learned features to different objective tasks. The pros of transfer learning when compared to traditional deep learning is that: (i) a pre-trained model is used as an initial stage; (ii) a pre-trained model can be fine-tuned simpler and quicker than initializing a deep neural network from scratch[26]. In our study, different fine-tuning models are examined for each discussed pre-trained network to rate performances of brain tumor detection for each transferred architecture.

In this paper, we implement a special adjustment to the pre-trained network which can be combined structure modifications and tuning the parameters. Five pre-trained networks are selected in this paper named AlexNet, Vgg16, GoogLeNet, Resnet50, and Inceptionv3. Five different structure modifications are applied to those networks providing 25 new structures. Those structures are compared to each other to get the best structure which compared to literature.

The remaining part of this manuscript is arranged as follows: Section 2 presents an overview of classical ML and Deep Learning algorithms in the literature. Section 3 provides the detailed methodology. Section 4 is about testing environment used in this paper. The results and discussion are explained in section 5. Finally, the conclusion and future work are given in section 6.

2 Literature

For the last years, many types of research identify whether the MRI images are normal or abnormal. Javed et al.[1] used some texture features, invariant moments, and support vector machine (SVM) with multiclass. This technique classifies between normal and more than one class of abnormal images. The Database has 48 normal and 25 images abnormal for each abnormal class. Zacharaki et al. [2] presented a procedure to make the classification of various high and low glioma grades depending on SVMs and KNN. He attained an accuracy of 85% for the SVM classification system.

El-Dahshan et al. [3] proposed a system to classify brain tissues as normal and abnormal images. He used a Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) for feature extraction and selection. Artificial neural network (ANN) and k-nearest neighbors (KNN) are used for classification, he obtained an accuracy of 97% and 98% respectively. Cheng et al. [5] performed a method to augment the classification of brain tumors by augmenting the tumor zone by image expansion and then by splitting into subzones. He used to extract features; Gray Level Co-occurrence Matrix (GLCM) and Bag of Words (BOW). Finally achieved the best accuracy of 91.28% by using ring form partition. M. K. Abd-Ellah et al. [30] detect brain tumor through MRI with machine learning model. The model used DWT and PCA for feature extraction and reduction. Then, SVM is applied for the classification.

Deep learning has made important strides in the field of machine learning and newly showed a noteworthy performance. In 2019, Deepak et al.[8] selected a pre-trained deep neural network and applied the concept of transfer learning for brain tumor classification. They focused on the last three layers of the GoogLeNet and applied the modification. Then they trained this modified network and did the test by using the Softmax classifier. They also tried 2 other classifier models that are SVM and KNN. Here, they used the GoogLeNet as a feature extractor. They achieved a mean classification accuracy of 98%.

In 2019, Swati et al.[31] concentrated on the power of deep learning about low-level and high-level features extraction. They used pre-trained VGG19 and adapt the idea of transfer learning with block wise fine-tuning to transfer the learning from original images to medical images especially the MRI images. Accuracy of 94.82 is obtained. Shahzadi et al. [12] proposed a cascade model consists of the CNN with long short term memory (LSTM) network which is another form of recurrent neural network (RNN) to classify the gliomas images into high and low grades. They relied on some deep networks as AlexNet, Vgg16 and ResNet with LSTM and stated an accuracy of 71%, 71% and 84% respectively.

In the research introduced by [17], the image classification of the brain CT was applied by using a deep neural network (DNN). They used a gray-level co-occurrence matrix (GLCM) to be a feature extractor for the classification done by DNN. They obtained an average accuracy of 83%. Gao et al. [18] proposed an integrated 2D and 3D architectures of CNN to classify CT brain images. Each network contained seven layers. The average classification accuracy of 87.6% was achieved. Yan Xu et al. used deep convolutional activation features to classify and segment the brain tumor. The accuracy of 97.5% for this system classification was attained [21].

M. Toğaçar et al. proposed a new CNN named BrainMRNet to classify brain MR images. This module consisted of image preprocessing and augmentation, attention modules, convolutional layers with hypercolumn technique and dense layer before the classification stage. The accuracy of this model was obtained. Posteriorly, Kaur et al.[25] replaced last 3 layers for 8 pre-trained CNN such as: AlexNet, GoogLeNet, ResNet50, ResNet101, Vgg16, Vgg19, Inceptionv3 and InceptionResNetV2. They performed the training and testing by dividing the MRI datasets into 60% training and 40% testing. They achieved an accuracy of 94% and 95.92% from clinical, and benchmark Figshare repository datasets.

TABLE 1. An overview of techniques for brain tumor classification.

Authors	Features Extraction	Classification	Dataset	Ac (%)	Limitations
[1]	texture features and invariant moments	SVM	123	-	- Not suitable for low contrast images.
[2]	Gabor texture features.	KNN and SVM	102	85%	- Small dataset. - Poor resulted accuracy.
[3]	DWT and PCA	ANN and KNN	70	98%	- Few images are used. - High computational complexity, cost, and needs large storage.
[5]	Intensity histogram, GLCM and BOW	ring form partition.	3064.	91.28 %	- High computational complexity.
[9]	DWT and PCA	Several kernels of SVM.	349	66.96	- Small dataset. - High computational cost and needs large storage.
[8]	Deep learning	Softmax, SVM and KNN	3064	98%	- Dealing with a few number of layers for the GoogLeNet.
[11]	Deep learning	Softmax	3064	94.8%	- High computational complexity.
[12]	Deep learning	Softmax and LSTM	120	84%	- Have poor accuracy. - Small dataset.
[17]	GLCM	Deep neural network	10	83%	- Dataset is very small. - Poor resulted accuracy.
[18]	Deep learning and hand- crafted features.	Softmax and SVM	285	87.6%	-Poor resulted accuracy.
[19]	Deep learning	SVM	45	97.5%	- Not suitable for new training dataset.
[20]	BrainMRNet model	BrainMRNet model	253	96 %	- Time consuming. - High computational complexity.
[13]	Deep learning	Softmax	253	95%	- Time consuming.
[15]	Deep learning	Softmax	253	97.2%	- Time consuming. - High computational complexity.
[25]	Deep learning	Softmax	160	95.9%	- Time consuming. - High computational complexity.
[16]	Deep learning	Softmax	3064	98.6%	- Proposed method only classifies some brain tumors (meningioma, glioma, and pituitary) and does not detect it.
[27]	Deep learning	ECOC-SVM.	349	99.5%	- High computational cost, complexity and optimization.
[28]	Deep learning	Softmax	349	97.79	- High computational complexity.
[29]	Deep learning	Softmax	1800	97.4%	- High computational complexity.

96.05% [20]. Thereafter, Saxena et al.[13] applied pre-trained vgg16, ResNet50 and Inceptionv3 networks to detect brain tumor cells as cancerous or noncancerous, based on transfer learning strategy. They performed pre-processing and augmentation techniques on the datasets. Best accuracy of 95% was obtained from ResNet50 network.

In 2020, Çinar et al.[15] used Resnet50 architecture to diagnose the tumor in the MRI images. They removed the last 5 layers of the Resnet50 and put other 8 layers. They also dealt with some pre-trained deep networks as AlexNet, GoogLeNet, DenseNet201 and Inceptionv3 for training and test the images. Best accuracy of 97.2% was

In another work, Rehman et al.[16] applied the classification of brain tumor by using 3 deep networks AlexNet, Vgg16 and GoogLeNet. Transfer learning is executed to extract most relevant features. They used pre-processing and augmentation to enhance and increase the database. The classification is done by two ways, which are Softmax and SVM classifier. Preferable accuracy of 98.69% was attained from fine-tuned Vgg16. M. K. Abd-Ellah et al. presented a deep CNN model for brain tumor detection. The model extract features by CNN network and classify the extracted features by Error-correcting output coding-SVM (ECOC-SVM) [27]. M. K. Abd-Ellah et al. designed deep CNN architecture to detect brain tumor through MRI images [28]. They improved their model by designing a new CNN architecture for brain tumor detection and classification. The presented network used two parallel branches with two different filter size that extract both global and local features [29]. Different classification techniques are compared in Table 1 in terms of feature extraction, classification, Dataset, and performance.

description of the pre-trained networks employed in our experiment is provided in Table 2. Those networks have been modified in five different ways. We start by modifying a number of layers each time for each network and see the effect on the accuracy. The detailed of each network modifications are provided in Fig 1 which includes designing new 5 transferred models for each deep CNN. This is done by replacing one layer in the first model and then replacing an additional layer in the second model, until reaching the last model, which contains five replaced layers. Then every model has trained and predicted by using softmax and classification layers. Finally the best model has accepted.

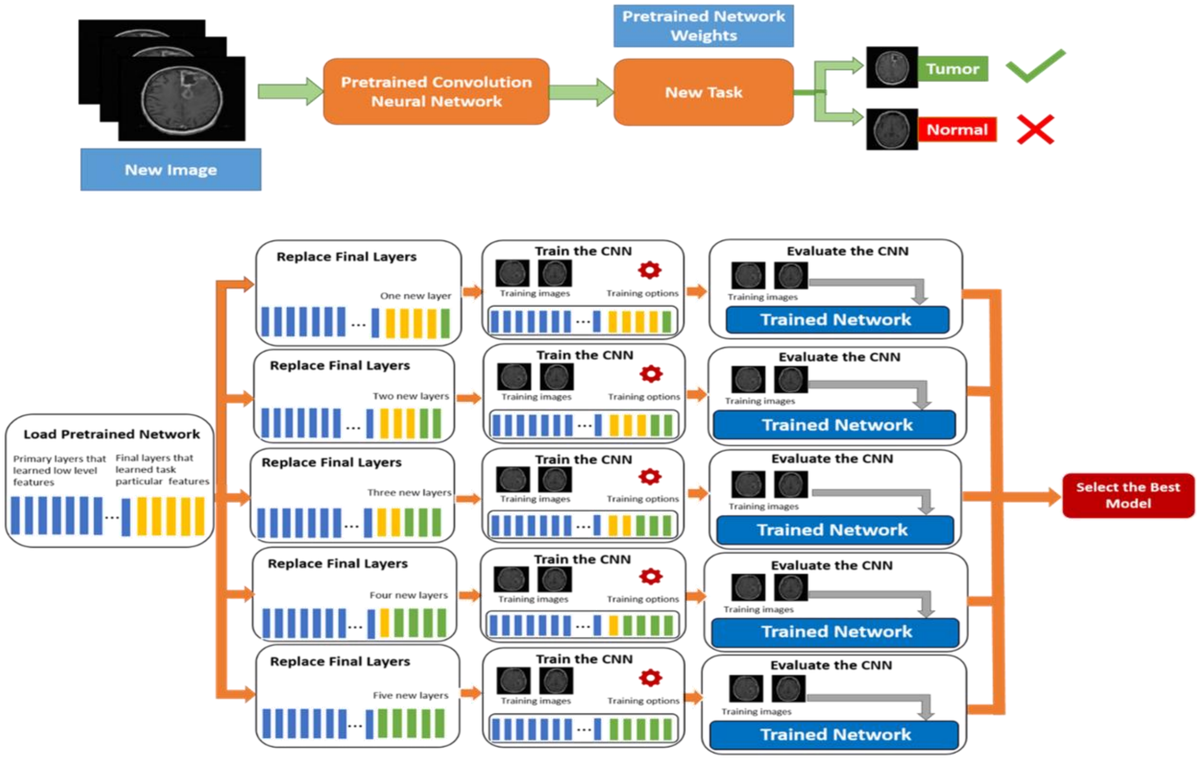

Fig 1. Flow chart of the proposed system. Upper part includes the main task of classification depending on transfer learning. Down part includes the applicable mechanism for the transferred layers in each model.

3 METHODOLOGY

The paper strategy suggests a more advanced systems, wherein special adjustments are implemented to the pre-trained network, to obtain the best results. Those adjustments may combine structure modifications and tuning the parameters. So, just distinct information gained from the prior task is maintained, whilst extra trainable parameters are included in the system. The new parameters need to be trained on a massive number of images to obtain advantageously. A brief

TABLE 2. The pretrained CNN and their parameters for transfer learning

Layer name	DEPTH	PARAMETER	IMAGE INPUT SIZE
AlexNet	8	61M	227-by-227
Vgg16	16	138M	224-by-224
GoogLeNet	22	7M	224-by-224
Resnet50	50	25.6M	224-by-224
Inceptionv3	48	23.9M	299-by-299

3.1 Pre-processing

Before starting the proposed structure, a pre-processing step is obtained. To get a better performance in lower time and more unpretentious calculations of the network, the original image dimensions must be decreased by downing-size the images [32]. First database (349 samples) has original gray images with size of 256×256×1 pixels, where second database (120 samples) has original gray images with size of 512×512×1 pixels. The original images of both database are downed size into 227×227×1 for (AlexNet), 224×224×1 for (Vgg16, GoogLeNet and Resnet50) and 299×299×1 for Inceptionv3. Then the resulted gray images are converted to RGB images to be compatible with input layer of each deep network.

TABLE 3. Architecture Of AlexNet

Layer	Layer function	Output shape	Learnable parameters
1	Image Input	[227, 227, 3]	0
2	Convolution	[55, 55, 96]	34,944
3	ReLU	[55, 55, 96]	0
4	Cross Channel Normalization	[55, 55, 96]	0
5	Max Pooling	[27, 27, 96]	0
6	Grouped Convolution	[27, 27, 256]	307,456
7	ReLU	[27, 27, 256]	0
8	Cross Channel Normalization	[27, 27, 256]	0
9	Max Pooling	[13, 13, 256]	0
10	Convolution	[13, 13, 384]	885,120
11	ReLU	[13, 13, 384]	0
12	Convolution	[13, 13, 384]	663,936
13	ReLU	[13, 13, 384]	0
14	Convolution	[13, 13, 256]	442,624
15	ReLU	[13, 13, 256]	0
16	Max Pooling	[6, 6, 256]	0
17	4096 fully Connected	[1, 1, 4096]	37,752,832
18	ReLU	[1, 1, 4096]	0
19	Dropout	[1, 1, 4096]	0
20	4096 fully Connected	[1, 1, 4096]	16,781,312
21	ReLU	[1, 1, 4096]	0
22	Dropout	[1, 1, 4096]	0
23	1000 fully Connected	[1, 1, 1000]	4,097,000
24	Softmax	[1, 1, 1000]	0
25	Classification Output	-	0

3.2 CNNs Transfer learning

Transfer learning transfer the collected knowledge from the dataset by CNN to resolve another related task, including a new dataset, that contains an insufficient number of samples to train the network from the scratch.

3.2.1 Transferred AlexNet Models

Five models depend on the employment of a famous deep learning-based CNN named AlexNet. The utilized parameters are tabulated in Table 3 that contains 25 layers. The first layer in all models is the input layer which has a fixed size of 227-by-227-by-3 pixels that is an RGB image. Each model has a number of changed layers. Accordingly, number of parameters of each model has also changed from the original number of parameters (61M). The brief explanation of all models' layer modifications is tabulated in Table 4. The unchanged layers are a portion of the pre-trained AlexNet network which trained with another dataset named ImageNet.

3.2.2 Transferred Vgg16 Models

Five models depend on the employment of a famous deep learning-based CNN named Vgg16. The first layer in all models is the input layer which has a fixed size of 224-by-224-by-3 pixels that is an RGB image. Each model has a number of changed layers. Accordingly, the total parameters value of each model has also changed from the original value of total parameters (138M). The brief explanation of all models' layer modifications is tabulated in Table 5.

TABLE 5. The transferred VGG16 models and their output.

Model	Layer	Old	New	Shape	Parameter
Model 1	39	1000 FC	2 FC	[1, 1, 2]	134.3 M
Model 2	38	Dropout	ReLU	[1, 1, 30]	134.3 M
	39	1000 FC	2 FC	[1, 1, 2]	
Model 3	37	Relu	FC	[1, 1, 30]	134.4 M
	38	Dropout	ReLU	[1, 1, 30]	
	39	1000 FC	2 FC	[1, 1, 2]	
Model 4	36	4096 FC	CONV	[1, 1, 8]	118.5 M
	37	Relu	FC	[1, 1, 30]	
	38	Dropout	ReLU	[1, 1, 30]	
	39	1000 FC	2 FC	[1, 1, 2]	
Model 5	35	Dropout	BN	[1, 1, 4096]	118.5 M
	36	4096 FC	CONV	[1, 1, 8]	
	37	Relu	FC	[1, 1, 30]	
	38	Dropout	ReLU	[1, 1, 30]	
	39	1000 FC	2 FC	[1, 1, 2]	

3.2.3 Transferred GoogLeNet Models

Five models depend on the employment of a famous deep learning-based CNN named GoogLeNet. The first layer in all models is the input layer which has a fixed size of 224-by-224-by-3 pixels that is an RGB image. Each model has a number of changed layers. Accordingly, the total parameters value of each model has also changed from the original value of total parameters (7M). The brief explanation of all models' layer modifications is tabulated in Table 6.

TABLE 6. The transferred GOOGLENET models and their output.

Model	Layer	Old	New	Shape	Parameter
					M
					M
					.7 M
					.6 M
					.6 M
	141	Dropout	ReLU	[1, 1, 30]	
	142	1000 FC	2 FC	[1, 1, 2]	

TABLE 4. The transferred AlexNet models and their output.

Model	Layer	Old	New	Shape	Parameter
Model 1	23	1000 FC	2 FC	[1, 1, 2]	56.9 M
Model 2	22	Dropout	ReLU	[1, 1, 30]	56.9 M
	23	1000 FC	2 FC	[1, 1, 2]	
Model 3	21	Relu	FC	[1, 1, 30]	57 M
	22	Dropout	ReLU	[1, 1, 30]	
	23	1000 FC	2 FC	[1, 1, 2]	
Model 4	20	4096 FC	CONV	[1, 1, 8]	40.4 M
	21	Relu	FC	[1, 1, 30]	
	22	Dropout	ReLU	[1, 1, 30]	
	23	1000 FC	2 FC	[1, 1, 2]	
Model 5	19	Dropout	BN	[1, 1, 4096]	40.4 M
	20	4096 FC	CONV	[1, 1, 8]	
	21	Relu	FC	[1, 1, 30]	
	22	Dropout	ReLU	[1, 1, 30]	
	23	1000 FC	2 FC	[1, 1, 2]	

Model 4	21	Fully Connected	[1, 1, 30]
	22	ReLU	[1, 1, 30]
	23	Fully Connected	[1, 1, 2]
Model 5	19	Batch Normalization	[1, 1, 4096]
	20	Convolution	[1, 1, 8]
	21	Fully Connected	[1, 1, 30]
	22	ReLU	[1, 1, 30]
	23	Fully Connected	[1, 1, 2]

3.2.4 Transferred Resnet50 Models

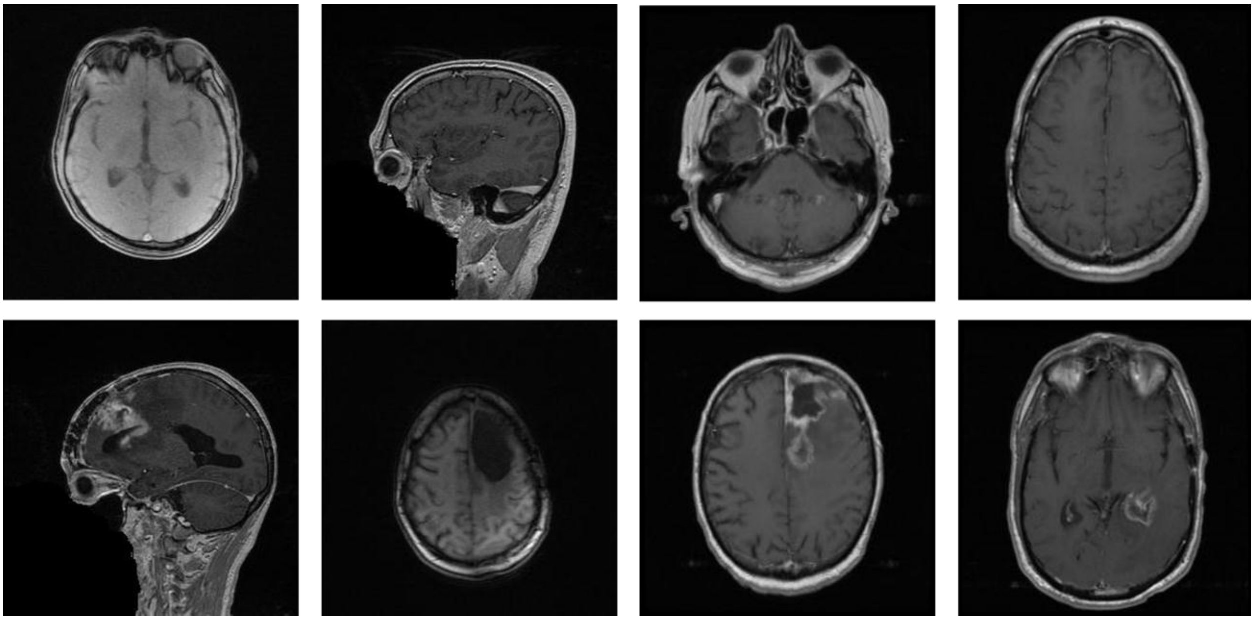

Fig2. Sampled images from the Two datasets. The normal images are in the first row, while abnormal images are in the second raw. The first two-columns from the left belongs to the first dataset (RIDER dataset), while the other two-column from the right belongs to the second dataset.

TABLE 7. The transferred RESNET50 models and their output.

Model	Layer	Old	new	Shape	Parameter
Model 1	175	1000 FC	2 FC	[1, 1, 2]	23.5 M
Model 2	174	Average Pooling	ReLU	[1, 1, 30]	23.7 M
	175	1000 FC	2 FC	[1, 1, 2]	
Model 3	173	ReLU	FC	[1, 1, 30]	25.5 M
	174	Average Pooling	ReLU	[1, 1, 30]	
	175	1000 FC	2 FC	[1, 1, 2]	
Model 4	172	Addition	Concatenate	[1, 1, 8]	27.5 M
	173	ReLU	FC	[1, 1, 30]	
	174	Average Pooling	ReLU	[1, 1, 30]	
	175	1000 FC	2 FC	[1, 1, 2]	
Model 5	171	BN	CONV	[1, 1, 4096]	26.1 M
	172	Addition	Concatenate	[1, 1, 8]	
	173	ReLU	FC	[1, 1, 30]	
	174	Average Pooling	ReLU	[1, 1, 30]	
	175	1000 FC	2 FC	[1, 1, 2]	

TABLE 8. The transferred INCEPTIONV3 models and their output.

Model	Layer	Old	new	Shape	Parameter
Model 1	314	1000 FC	2 FC	[1, 1, 2]	21.8 M
Model 2	313	Average Pooling	ReLU	[1, 1, 30]	22.1 M
	314	1000 FC	2 FC	[1, 1, 2]	
Model 3	307	BN	CONV	[1, 1, 30]	23 M
	313	Average Pooling	ReLU	[1, 1, 30]	
	314	1000 FC	2 FC	[1, 1, 2]	
Model 4	300	BN	CONV	[1, 1, 8]	26.7 M
	307	BN	CONV	[1, 1, 30]	
	313	Average Pooling	ReLU	[1, 1, 30]	
	314	1000 FC	2 FC	[1, 1, 2]	
Model 5	299	BN	CONV	[1, 1, 4096]	28 M
	300	BN	CONV	[1, 1, 8]	
	307	BN	CONV	[1, 1, 30]	
	313	Average Pooling	ReLU	[1, 1, 30]	
	314	1000 FC	2 FC	[1, 1, 2]	

Five models depend on the employment of a famous deep learning-based CNN named Resnet50. The first layer in all models is the input layer which has a fixed size of 224-by-224-by-3 pixels that is an RGB image. Each model has a number of changed layers. Accordingly, the total parameters value of each model has also changed from the original value of total parameters (25.6M). The brief explanation of all models' layer modifications is tabulated in Table 7.

3.2.5 Transferred Inceptionv3 Models

Five models depend on the employment of a famous deep learning-based CNN named Inceptionv3. The first layer in all models is the input layer which has a fixed size of 299-by-299-by-3 pixels that is an RGB image. Each model has a number of changed layers. Accordingly, the total parameters value of each model has also changed from the original value of total parameters (23.9M). The brief explanation of all models' layer modifications is tabulated in Table 8.

4 TESTING ENVIRONMENT

4.1 Machine tool

The specifications of the device in which the work was carried out included the following: processor of intel(R) Core (TM) i7-4500U CPU @ 1.80GHz 2.40GHz. Intel(R) HD Graphics Family. RAM of 8 GB and operating system of 64 bit. The software of the proposed system computations was implemented on Matlab R2019a.

4.2 Dataset

The first database was acquired from a standard dataset named RIDER Neuro MRI database. It was acquired from 19 patients with T1-weighted and T2-weighted MRIs which includes 349 brain MRI images with 109 normal images and 240 abnormal images. The second database was acquired from Brain-Tumor-Progression. All image sets are in DICOM format and contain T1-weighted (pre-contrast and post-contrast agent), acquired from 20 patients with 6 slices. The second dataset was divided into two parts training sets (70%) and test sets (30%). Sampled MRI images from the datasets are presented in Fig 2. Details are shown in Table 9. The two datasets are published in TCIA (The Cancer Imaging Archive) with the last updated version in 2020 [33].

Table 9. Training and testing data

Dataset	Training data		Testing data		Total
	Tumor	Normal	Tumor	Normal	
Dataset 1	77	45	163	64	349
Dataset 2	42	42	18	18	120

5 EXPERIMENTAL RESULTS AND DISSCUSSION

5.1 Evaluation metric

To summarize the prediction results, Sensitivity, Specificity, and Accuracy have been calculated from confusion matrix's parameters in equations:

$$\text{Specificity (Sp)} = \frac{TN}{TN + FP} \tag{5}$$

$$\text{Sensitivity (SV)} = \frac{TP}{TP + FN} \tag{6}$$

$$\text{Accuracy (Acc)} = \frac{TP+TN}{P+N} \tag{7}$$

Where, true negative (TN) is number of normal predicted samples and they are also actually normal.

Table 10. Tested hyper-parameters

Parameter	Number
Convolutional layer	1, 2, 3
ReLU layer	1, 2
Batch normalization layer	1, 2
concatenation layer	1
Fully connected layer	1, 2, 3
Mini-batch size	8, 16, 32
Maximum epochs	5, 7, 40, 60, 80, 100, 140, 160
Initial learning rate	0.01, 0.001, 0.0001
Learning frequency	1, 2, 3, 8

True positive (TP) is number of tumors predicted samples and they are also actually tumor. False negative (FN) is the number of normal predicted samples while they are actually tumor. False positive is the number of tumor samples while they are actually

TABLE 11. Comparison of all proposed transfer learning models with the two datasets. The highest performance of the models has been fulfilled by using the bolding architectures.

Network Name	DATASET 1								DATASET 2
	Model	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity	Accuracy
AlexNet	**Model 1**	**63**	**163**	**1**	**0**	**99.56%**	**100.00%**	**99.39%**	97.22%
	Model 2	60	163	4	0	98.24%	100.00%	97.60%	91.67%
	Model 3	61	161	3	2	97.80%	96.83%	98.17%	**100%**
	Model 4	63	162	1	1	99.12%	98.44%	99.39%	**100%**
	Model 5	47	150	17	13	86.78%	78.33%	89.82%	91.67%
Vgg16	Model 1	64	59	0	104	54.19%	38.10%	100.00%	91.67%
	Model 2	60	113	4	50	76.21%	54.55%	96.58%	88.89%
	Model 3	62	97	2	66	70.04%	48.44%	97.98%	86.11%
	Model 4	**45**	**162**	**19**	**1**	**91.19%**	**97.83%**	**89.50%**	**97.22%**
	Model 5	54	134	10	29	82.82%	65.06%	93.06%	69.44%
GoogLeNet	**Model 1**	61	137	3	26	87.22%	70.11%	97.86%	**97.22%**
	Model 2	**59**	**156**	**5**	**7**	**94.71%**	**89.39%**	**96.89%**	**94.44%**
	Model 3	0	163	64	0	71.81%	NAN	71.81%	88.89%
	Model 4	0	163	64	0	71.81%	NAN	71.81%	94.44%
	Model 5	12	163	52	0	77.09%	100.00%	75.81%	94.44%
Resnet50	**Model 1**	**44**	**161**	**20**	**2**	**90.31%**	**95.65%**	**88.95%**	**91.67%**
	Model 2	56	148	8	15	89.87%	78.87%	94.87%	91.67%
	Model 3	0	163	64	0	71.81%	NAN	71.81%	94.44%
	Model 4	0	163	64	0	71.81%	NAN	71.81%	91.67%
	Model 5	0	163	64	0	71.81%	NAN	71.81%	**97.22%**
Inceptionv3	Model 1	42	158	22	5	88.11%	89.36%	87.78%	80.56%
	Model 2	64	125	0	38	83.26%	62.75%	100.00%	83.33%
	Model 3	62	108	2	55	74.89%	52.99%	98.18%	86.11%
	Model 4	**54**	**155**	**10**	**8**	**92.07%**	**87.10%**	**93.94%**	**86.11%**
	Model 5	61	141	3	22	88.99%	73.49%	97.92%	**94.44%**

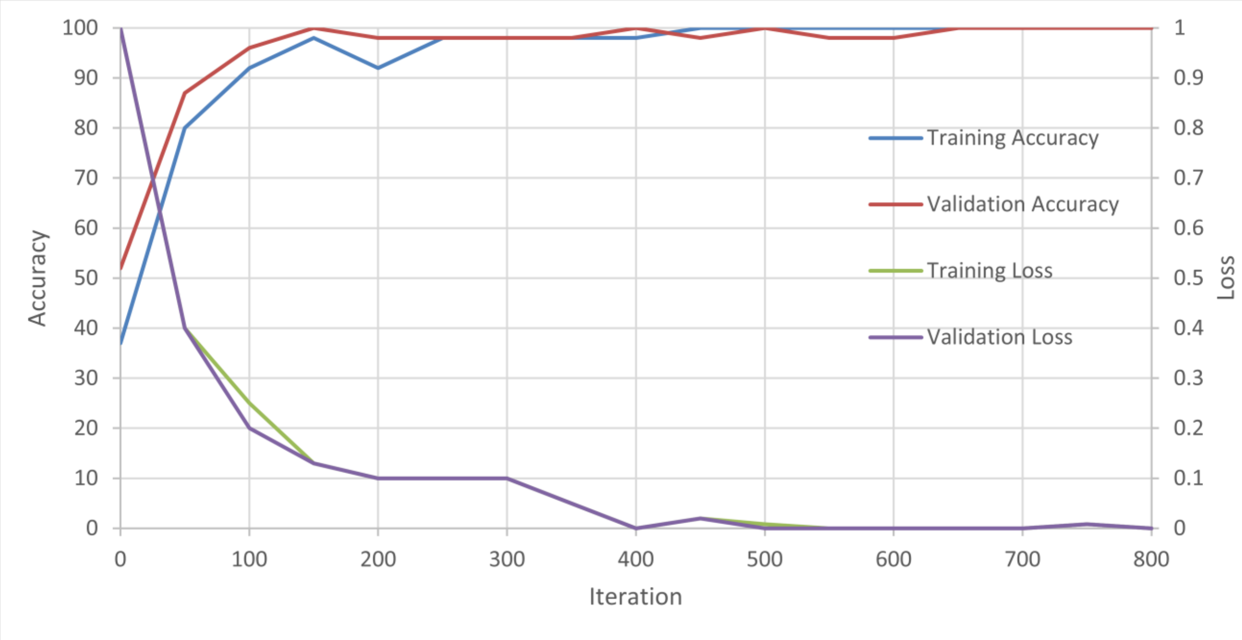

Fig 3. Training and testing progress for the best proposed transfer learning Model.

normal. N is the number of normal cases while P is the number of tumor cases.

5.2 Hyper-parameter optimization

The tuning is an essential step in selecting a group of hyper-parameters for a learning algorithm. The optimized hyper-parameters have a great impact on network performance. In this section, the various architectures parameters in each proposed model are presented. Table 10 shows a different number of layers and hyper-parameters that were tested before reaching the effective performance for each model of all CNNs.

5.3 Results

Table 11 shows a comparison between all proposed transfer learning models for each deep CNN network. Confusion matrix parameters, Accuracy, Sensitivity, and Specificity are obtained for the first datasets while the accuracy is attained for the second datasets. As shown, there are different results that appear the effectiveness of the models, while the best models have resulted from AlexNet. These models are model 3 and model 4, which have the same best Accuracy, Sensitivity, and Specificity of 100%.

Table 12 shows a comparison between our proposed system and the other state-of-the-arts who's applied different machine learning and deep learning architectures for brain tumor classification presented in the literature. In addition, table 13 displays a detailed comparison between our work and other previous works that have the same first database. We must always be mindful that a false negative in this data is deciding that patients with a tumor are told that they may not want to pursue further treatment, allowing the tumor to progress quietly. Further, A false positive is deciding that a tumor-free patient is told that warrants further invasive tests and/or treatment. The best model can be clarified as the model that gets false-negative

Table 12. Comparison between proposed system and other related works.

Method	Image	ACC %	Classification method
Zacharaki et al.[2]	102	85	SVM and KNN
El-Dahshan et al.[3]	70	98	ANN and KNN
Cheng et al.[5]	3064	91	SVM and KNN
Deepak et al.[8]	3064	98	SVM and KNN
Swati et al.[11]	3064	94.82	CNN
Shahzadi et al.[12]	120	84	CNN and LSTM
Saxena et al.[13]	253	95	CNN
Çinar et al.[15]	253	97.2	CNN
Rehman et al.[16]	3064	98.69	CNN
Da et al. [17]	10	83.0	DNN
Gao et al. [18]	285	87.6	2D, 3D CNNs
Yan Xu et al. [21]	45	97.50	CNNs
Toğaçar et al. [20]	253	96.05	BrainMRNet
Kaur et al.[25]	74 160	94 95.92	Pre-trained CNN
Proposed system	349 120	**99.56** **100**	Pre-trained CNN

Table 13. Comparison between proposed system to previous work used with the same database as a unified benchmark.

Method	Image	Sp %	Sv %	Acc %	Classification method
[9]	349	25.0%	83.43%	66.96%	SVM
[27]	349	100.0%	99.38%	99.5%	ECOC-SVM
[28]	349	97.54%	98.43%	97.79%	Softmax
Proposed Method	**349**	**99.39%**	**100%**	**99.56%**	**Softmax**

equal to zero and Sensitivity equal to 100%, which shows the proposed model's superiority over other literature models.

The result of the best-proposed model is compared with other related works that pretend the power of the proposed deep CNN structure, where our method has overcome some faults that were present in literature as computational complexity and hand-crafted features. Our proposed system is considered accurate due to the appropriate transferred layers that learned the optimized features. Moreover, the best resulted models (model 3 and 4 of AlexNet) have reduced weights (57 M, 40.4 M) than pre-trained AlexNet model (61M). This means that the network capacity is simpler in computations and runtime.

Figure 3 shows the outcomes of accuracy and loss rates for training and testing progress of our best proposed fine-tuned model 3 of the AlexNet. This figure gives us some important notes: The training and testing loss both reach the minimum value at the end, which is very close to zero. Likewise, the training and testing accuracy both reach the maximum value at the end of iterations. Although the data set is small, we find the best accuracy and loss rate and this is the benefit of using Transfer Learning. The mini-batch size is set to 16 and the number of iterations at 800.

5.4 Discussion

In this paper, a procedure for brain tumor classification is proposed by modifying convolution neural network models based on the transfer learning algorithm with magnetic resonance images. The proposed transfer learning system can train a deep CNN for more than one dataset. Large collection of parameters is used to adjust the 25 different model systems to reach an effective result for each of the proposed models for the 5 CNNs. Training a fine-tuned CNN readily with a small dataset is challenging as it maybe takes a time to achieve acceptable results for a database without being over conform or under conform. Another important portion is the difference in performance between traditional machine learning and deep transfer learning.

6 CONCLUSION AND FUTURE WORK

In this paper, a detailed study about the classification is discussed for five modifications to five different CNNs. The deep learning model depending on a fine-tuning convolutional neural network to classify brain tissues as normal and abnormal sets. Each proposed model consists of different layers beginning with the input layer until the last output layer. For all proposed models, the softmax layer is used for classification to provide the predicted class. The experimental results of our structures propose an accuracy of 100.00% for the best two AlexNet models. In future work, we will deal with multi-class for brain tumors classification.

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الكشف التلقائي عن أورم المخ من خلال صور التصوير بالرنين المغناطيسي باستخدام نموذج نقل التعلم مع الشبكة العصبية التلافيفية العميقة

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الملخص :

إن الاكتشاف المبكر للورم الدماغي له دور هام في تحسين علاج المريض و ابقائه على قيد الحياة. يعد تقييم صور التصوير بالرنين المغناطيسي (MRI) يدويا مهمة صعبة للغاية بسبب أعداد الصور الكثيرة التي يتم تصويرها للمرضى في المستشفيات بشكل روتيني. ولذلك، فإن هناك حاجة لاستخدام نظام التشخيص بمساعدة الكمبيوتر (CAD) للكشف المبكر عن أورام المخ وتصنيفها على أنها طبيعية وغير طبيعية. يهدف البحث إلى تصميم وتقييم نظام Transfer Learning المطبق على الشبكة العصبية الالتفافية (CNN) الحديثة والمقترحة على مدار السنوات الأخيرة. تم تطبيق خمسة تعديلات مختلفة على خمسة شبكات CNN مشهورة وعالمية لمعرفة التعديل الأكثر فعالية. يتم تطبيق التعديلات على خمسة طبقات مختلفة مع ضبط معايير كل بنية لتقديم شبكة عصبية التفافية جديدة للكشف عن ورم الدماغ. تحتوي معظم بيانات أورام المخ على عدد صغير من الصور لتدريب بنية التعلم العميق. لذلك، يتم استخدام مجموعتي بيانات في التقييم لضمان فعالية التصميم المقترحة. أولاً، مجموعة مكونه من 120 صورة بالرنين المغناطيسي للمخ تتضمن 60 صورة غير طبيعية و 60 صورة طبيعية. ثانيًا، مجموعة صور قياسية من قاعدة بيانات RIDER Neuro MRI تتضمن 349 صورة تصوير بالرنين المغناطيسي للمخ، تحتوى على 109 صورة طبيعية و 240 صورة غير طبيعية. تظهرالنتائج أن نظام CNN Transfer Learning المقترح باستخدام التصوير بالرنين المغناطيسي يمكنه التعرف على المؤشرات الحيوية المهمة لورم الدماغ. كما يظهر أن أفضل دقة ونوعية وحساسية تم الحصول عليها هي 100٪ لكل منهم.