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Hyber Selective Ensemble Methodology Based on Deep Transfer Learning For Brain Diagnosis Detection

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Abstract: Machine Learning models initiate to have a great effect on the diagnosis of numerous diseases. In the biomedical field, Convolutional neural networks (CNNs) display a potential role for computer-aided diagnosis (CAD) by extracting features directly from the image data instead of the features based on analytically methods or handcrafts features. However, CNNs have many challenges to train medical images from scratch as small sample sizes and variations in tumor presentations. Additionally, it needs more hardware for processing. Alternatively, transfer learning can extract from medical images tumor information through CNNs originally pre-trained for nonmedical images, which cover the shortage of a small dataset.
The proposed model introduces several pre-trained models such as Xception, VGG16, VGG19, ResNet50, MobileNet, MobileNetV2, and InceptionResNetV2 to create a selective ensemble model from them which achieves 97.77accuracy on brain tumor type classification.

Keywords: CNN Architectures Ensemble Learning, Transfer learning, Machine Learning, Artificial Neural Network, Convolutional Neural Network, Deep residual Network Cancer Classification.

1 Introduction

Biomedical image analysis centers are analyzing biomedical images to provide better health care and facilitate biomedical research, with special emphasis on efforts related to the applications of image processing, computer vision, machine learning, and statistical analysis. Medical image analysis is critical to the advance of imaging-based biomedical research [1].
Brain tumor classification from MRIs is the most challenging and upcoming field. Computer-Aided Diagnose (CAD) system is an automatic tool, it can help and support radiologists and medical experts to determine the correct therapy at the right stage for tumor-infected [2]. Our approach will try to improve a computational model to be a step toward automated cancer diagnoses [3].

Our proposed model contrasts a very powerful tool to represent low-level and high-level image information completely in feature extraction and classification phases. This tool is Deep networking, but, it requires a large training dataset for self-learning [4]. The medical imaging datasets are very small; thus, it is a challenging training task to apply train CNN from scratch on the small dataset [5-6].

The proposed classification technique in this paper has two different training strategies. The first approach is full pre-learning models and the second approach is the hyper selective ensemble pre-learning model.
The two approaches are based on pre-learning models which are training on the ImageNet dataset. These models are fine-tuned to use on the brain tumor dataset. The best results came from three selective models based on fine-tuning a pre-trained which achieved a recognition rate of 97.77%.

The rest of this study is organized as follows: Section 2 displays the related work. Section 3 presents a review background on Convolution Neural Network architecture. Section 4 defines the proposed model. Section 5 illustrates the results and the performance analysis, and finally, Section 5 concludes our work.

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2 Related work

In [28], the authors create a new model called Global Average Pooling Residual Network (G-ResNet) for brain tumor detection. The proposed model has the following properties: (1) Establishing CNN architecture in the field of deep learning named ResNet34 to classify brain tumor images. (2) Avoiding overfitting and reducing the number of parameters (3) The feature vectors of different layers are concatenated to fuse the low-level and high-level features of the network. (4) A new loss function is defined, which is the sum of the cross-entropy loss and the interval loss. This model achieves 95.00% classification accuracy.

In [7], the authors developed Capsule Networks (CapsNets) which overcome these weaknesses. The main contribution is to improve CapsNets with an increase to keep the image resolution and improve classification accuracy. They introduce a less trainable CapsNet architecture for classification, which takes the segmented brain tumor regions as inputs within the structure and focused to increase the capabilities of the CapsNets. The proposed model introduced CapsNets consist of multiple convolutional layers which achieved 95.54%.

In [8], to detect and mark the area of brain tumor occurrence with Region Proposal Network (RPN) authors used Faster R-CNN deep learning algorithm. The base layer for the proposed algorithm is VGG-16 architecture. Classification and Detection results of the algorithm show that it achieves an average precision of 89.45% for meningioma, 68.18% for pituitary, and 75.18% for glioma tumors.

In [9], the authors design Convolutional Capsule Network (ConvCaps) architecture to solve the brain tumor classification problem. The architecture has four properties which are: (1) It accepts the input images without scaling them. (2) The spatial relationship components are preserved on the image. (3) Extracting low-level features by adding multiple convolutional layers in the front of the capsule layer. (4) The brain tumor image region is fed as an extra input to increase the network's attention. The experimental results accuracy achieves 93.5%.

In [4], the authors introduce pre-trained a block-wise fine-tuning strategy of the deep CNN model. It achieves an average accuracy of 94.82% with minimal pre-processing.

In [10], it presents a new architecture of CNN for brain tumor classification. It is evaluated by an augmented image database. In this model, the 10-fold cross-validation method was obtained at 96.56% accuracy.

3 Common Convolutional Architectures

Robust deep learning is used in tasks such as image recognition, image segmentation, object detection, and other computer vision tasks [11]. All Convolutional Neural Networks (CNN's) work on a template matching method to complete a specific task [12]. CNN's extract essential features from the input image through a progression of convoluting layers with pooling layers, channels (Kernels), fully connected layers (FC), and a, additionally to SoftMax function which is applied to classify the image [13]. Convolution Layers are made up of several filters, and each filter extracts various kinds of features. Multiple activation maps are combined by stacking to the target output. Each convolution layer has a set of parameters, which contains several filters, stride, filter size, and activation function [12]. A convolution layer is often combined with a pooling layer, either average pooling, or max-pooling to be more efficient. Recently, deep learning has great progress and deep convolution neural networks (CNNs) play a vital role in the image classification task.

ILSVRC refers to the ImageNet Large Scale Visual Recognition Challenge, ImageNet is a project designed manually way to label and categorize images. This dataset is divided into ~1.2 million for training 50,000 images for validation and 100,000 images for testing [14]. 1,000 image categories represent object classes that we encounter in our day-to-day lives.

Various architectures models based on ImageNet dataset in training, validation, and testing phases. The next subsection will introduce the architecture of some models which will be used and tested in our proposal. The architecture of each model is described in table 1.

3.1 VGG

It was proposed by Oxford University's Visual Geometry Group [15]. It is designed to use small filters of size 3-by-3 in all of the convolutional layers through the network leads to better performance. The multiple small filters in VGG architecture imitate the effect of larger filters. VGG architectures are widely used. The usage of VGG16 and VGG19 constitute 16 and 19 convolutional layers, respectively. There are two major weaknesses with VGG: (1) It is *very slow* to train. (2) The network architecture weights are quite large in terms of disk and bandwidth.

3.2 GoogLeNet or Inception

GoogleNet architecture is the winner of ILSVRC 2014 which is proposed by Szegedy et al [16]. GoogleNet is the advance of the inception module, which is a small network inside a bigger one. Furthermore, it applies dimensionality reduction by using 1-by-1 convolutional layers. It is 22 layers deep with 9 inception modules. It eliminated a large number of parameters by using average pooling instead of fully connected layers at the top of the convolutional layers. The GoogLeNet versions have been released. The most recent architecture available is InceptionV3. Inception V1 (GoogleNet), is improved in terms of batch representational, computational complexity, and bottleneck normalization and it resulted in Inception V2 and V3[16]. inception". The Xception model contains thirty-six layers deep, without the fully connected layers in the end [18].

3.3 Xception

Xception was presented in 2016 and it stands for "extreme. The convolutional layers are structured into 14 modules in which only the first and last ones do not contain residual connections. Xception is like MobileNet in depth-wise separable layers and it is unlike inceptionV3 because the output of specific layers is summed with the output from previous layers.

Table 1: CNN architectures.

<table>
<tr><td>VGG16</td><td>Model: "sequential_5"
Layer (type) Output Shape Param #
vgg16 (Model) (None, 4, 4, 512) 14714688
flatten_5 (Flatten) (None, 8192) 0
dense_9 (Dense) (None, 512) 4194816
dense_10 (Dense) (None, 3) 1539
Total params: 18,911,043
Trainable params: 18,911,043
Non-trainable params: 0</td></tr>
<tr><td>VGG19</td><td>Model: "sequential_2"
Layer (type) Output Shape Param #
vgg19 (Model) (None, 4, 4, 512) 20024384
flatten_2 (Flatten) (None, 8192) 0
dense_3 (Dense) (None, 512) 4194816
dense_4 (Dense) (None, 3) 1539
Total params: 24,220,739
Trainable params: 24,220,739
Non-trainable params: 0</td></tr>
<tr><td>Xception</td><td>Model: "sequential_3"
Layer (type) Output Shape Param #
xception (Model) (None, 4, 4, 2048) 20861480
flatten_3 (Flatten) (None, 32768) 0
dense_5 (Dense) (None, 512) 16777728
dense_6 (Dense) (None, 3) 1539
Total params: 37,640,747
Trainable params: 37,586,219
Non-trainable params: 54,528</td></tr>
<tr><td>ResNet50</td><td>Model: "sequential_1"
Layer (type) Output Shape Param #
resnet50 (Model) (None, 4, 4, 2048) 23587712
flatten_1 (Flatten) (None, 32768) 0
dense_1 (Dense) (None, 512) 16777728
dense_2 (Dense) (None, 3) 1539
Total params: 40,366,979
Trainable params: 40,313,859
Non-trainable params: 53,120</td></tr>
<tr><td>MobileNet</td><td>Model: "sequential_3"
Layer (type) Output Shape Param #
mobilenet_1.00_128 (Model) (None, 4, 4, 1024) 3228864
flatten_3 (Flatten) (None, 16384) 0
dense_5 (Dense) (None, 512) 8389120
dense_6 (Dense) (None, 3) 1539
Total params: 11,619,523
Trainable params: 11,597,635
Non-trainable params: 21,888</td></tr>
<tr><td>MobileNetV2</td><td>Model: "sequential_2"
Layer (type) Output Shape Param #
mobilenetv2_1.00_128 (Model) (None, 4, 4, 1280) 2257984
flatten_2 (Flatten) (None, 20480) 0
dense_3 (Dense) (None, 512) 10486272
dense_4 (Dense) (None, 3) 1539
Total params: 12,745,795
Trainable params: 12,711,683
Non-trainable params: 34,112</td></tr>
<tr><td>InceptionResNetV2</td><td>Model: "sequential_1"
Layer (type) Output Shape Param #
inception_resnet_v2 (Model) (None, 2, 2, 1536) 54336736
flatten_1 (Flatten) (None, 6144) 0
dense_1 (Dense) (None, 512) 3146240
dense_2 (Dense) (None, 3) 1539
Total params: 57,484,515
Trainable params: 57,423,971
Non-trainable params: 60,544</td></tr>
</table>

3.4 ResNet

ResNet is a short name for Residual. ResNet architectures are proposed by He et al. [17] from Microsoft and won the 2015 ILSVRC. In residual learning, it tries to extract the residual instead of extracting the features. Residuals can be known as the inference of highlights gained from the impact of that layer. Residual layers skip connections to solve the problem of vanishing gradient that may result in stopping the weights in the network to additional update. It has been verified that training through ResNet architectures is more effective than training regular deep CNN's.

3.5 MobileNet

MobileNet architecture proposed by Google to run on mobiles and embedded systems or devices which need low computational power [20]. Depth wise separable convolutions are used in MobileNet architecture in comparison to regular CNNs having comparable depth. The depthwise separable convolution depends on both spatial dimensions and the number of channels. Depth wise splits the kernel into two small kernels one for depth-wise and the other for pointwise. This splitting drastically reduces the number of trainable parameters and computational cost significantly.

3.6 MobileNetV2

It is a powerful network for the next generation of mobile vision applications [21]. MobileNetV2 is an important development over MobileNetV1.

MobileNetV2 based upon the ideas from MobileNetV1 [1], used depthwise separable convolution as efficient building blocks. Though, V2 displays two new features to its architecture: (1) linear bottlenecks between the layers. (2) Shortcut connections between the bottlenecks.

The bottlenecks encode the model's intermediate inputs and outputs although the inner layer in this architecture encapsulates the model's ability to transform from lower-level to higher-level descriptors. Finally, shortcuts enable faster training and better accuracy.

3.7 Inception-ResNetV2

It is a combined architecture proposed by Szegedy et al. [19] in 2016. It uses the idea of residual layers and inception blocks together. To avoid the problem of degradation which occurs by deep networks, residual connections are used and to reduce the training time also. This architecture contains 164 layers based on 20 inception-resnet blocks.

4 Hyper-parameters of CNN

In the machine learning field, a hyper-parameter is a parameter value is used to control the learning process such as batch size, loss function, and optimization algorithm [12]. It also is the effects of classification accuracy and learning time. These hyper-parameters are described below to illustrate each one and its effect.

4.1 Categorical Cross-Entropy

It measures the performance of the classification model whose output is a probability between 0 and 1 for each class [23]. The classifier takes the top probability as it is the winner class. Cross entropy increases as the predicted probability entropy loss.

$$loss(y_i) = -\sum_{i=0}^{outofsize} y_i * log\, \hat{y_i} \qquad (1)$$

where $y\hat{}_i$ is the *ith* scalar value in the model output, y_i is the corresponding target value, and the output size is the number of scalar values in the model output.

4.2 Adam

It is derived from adaptive moment estimation [24]. It is an optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iterative which is the foundation stone in the training process.

Stochastic gradient descent maintains a single learning rate called alpha for all weight updates and the learning rate does not change during training.

Adam optimizer computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients. The equations for Adam are given by Equations 2, 3, and 4.

$$M_{i,t} = \frac{\beta_1 . M_{t-1,i} + (1-\beta_1) . \frac{\partial f}{\partial \theta_{t,i}}}{1-\beta_1^t} \qquad (2)$$

$$V_{i,t} = \frac{\beta_2 . V_{t-1,i} + (1-\beta_2) . (\frac{\partial f}{\partial \theta_{t,i}})^2}{1-\beta_2^t} \qquad (3)$$

$$\theta_{t+1,i} = \theta_{t,i} - \eta \frac{M_{t,i}}{\varepsilon + \sqrt{V_{t,i}}} \qquad (4)$$

Where η is the global learning rate and ε is numerical stability. $\beta 1$ and $\beta 2$ are exponential decay rates for moving averages, advised to set $\beta1 = 0.9$ and$\beta2 = 0.99$.

4.3 Rectified linear unit (ReLU)

$$g(a)=max(0,a) \qquad (5)$$

It is an activation function which is used in this work, it is the most popular activation function in-deep learning, it is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train [25].

4.4 Softmax

$$g(a) = \frac{e^{a_i}}{\sum_j e^{a_j}} \qquad (6)$$

The most common use of the softmax function in applied machine learning is in its use as an activation function in a neural network model [26]. Specifically, the network is configured to output N values, one for each class in the classification task, and the softmax function is used to normalize the outputs, converting them from weighted sum values into probabilities that sum to one. Each value in the output of the softmax function is interpreted as the probability of membership for each class.

5 The proposed methodology

Transfer learning is a machine learning technique when a model designed for a specific task is reused as the starting point for a model on a new task [4-10]. It will decrease the computational resources and also processing time by the convolution network weights are initialized. Transfer learning leads to a very fast learning rate and high accuracy. Fig.1 shows the benefits of transfer learning.

5.1 Pre-training CNN models

In this paper, we consider seven CNN architectures Xception, InceptionResNetV2, MobileNetV2, MobileNet, VGG-16, VGG19, and ResNet50. These models were trained and optimized using Adam which a learning reduction algorithm was implemented which reduced the learning rates of the models every time validation loss increased. Categorical cross-entropy is used as a loss function to classify the three classes.

The pre-trained models take an input image of dimensions 128 x 128 x 3. Images were passed in a batch of 64; the input image then goes through pointwise and depth-wise convolution various times. The two last layers of all the models were kept trainable while all other layers were un-trainable. It means that the features extracted from the above process are fed into two dense layers of dimension 512 x 1 and 3 x 1.

The above process is repeated in numerous epochs of forwarding propagation and backward propagation. The 10 epochs of forwarding and backward propagation make the model optimized for brain tumor classification. Fig. 2 describes the sequence of the layers which is applied to each pre-training model.

The average time for each model is used for training and the produced learning model built on the brain tumor dataset is showing in fig. 3.

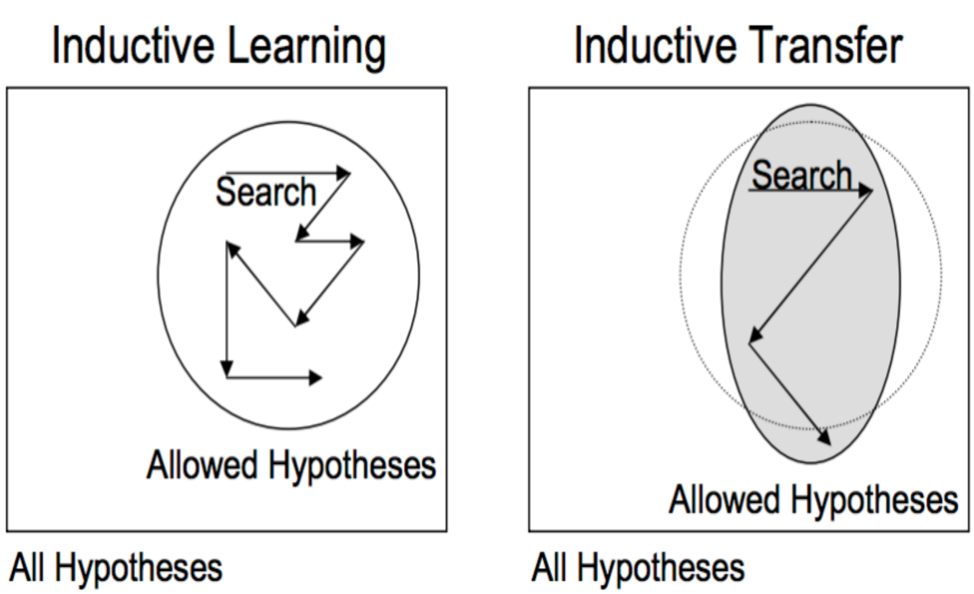

Fig. 1: Learning rate from scratch and transfer learning.

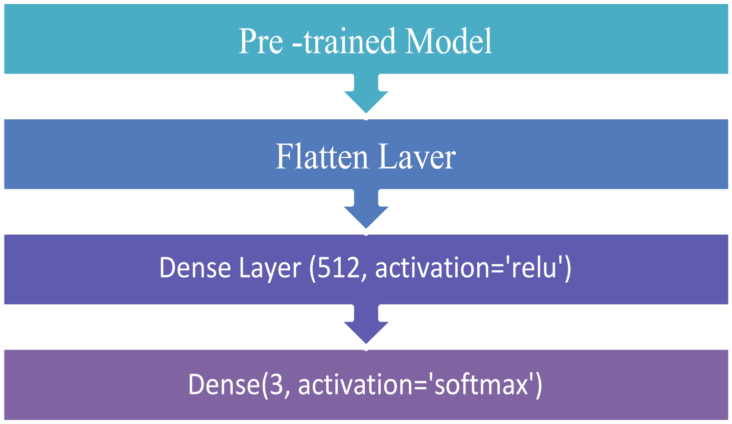

Fig. 2: Pre-trained model architecture.

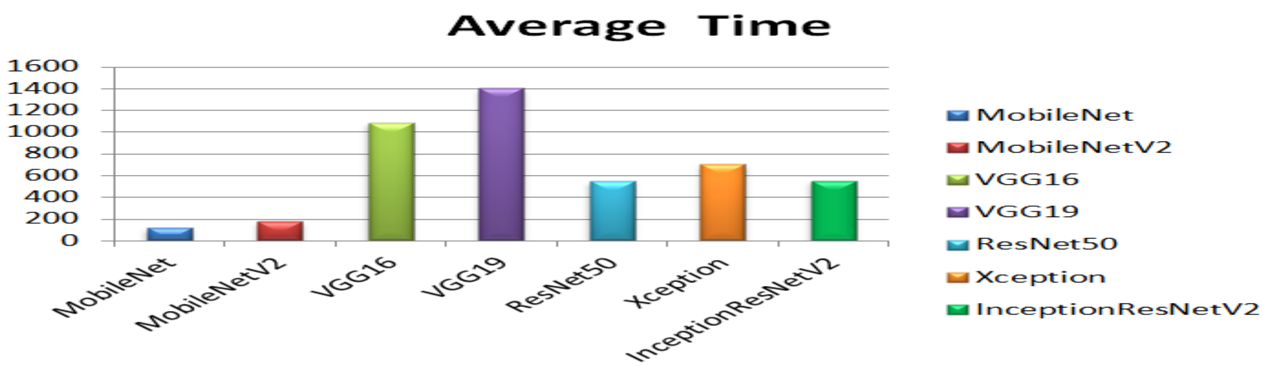

Fig. 3: Pre-trained model architecture.

Fig.4 is extracted from table.1 to illustrate the importance of transfer learning. The number of trainable parameters is a huge number that is already initialized; it means that small training time and computer resources are saved.

After training the seven models are saved on a hard disc to be evaluated and reused in the next section. Fig.5 illustrates each model size in megabytes. Inception-ResNetV2 has the largest size despite MobileNet V1 and V2 having the lowest size MobileNet is designed for a mobile device.

5.2 Ensemble transfer learning

Ensemble learning is a form of sequential learning method. This method works by adjusting the weight of an observation based on the last classification training. The final output is calculated by various transfer learning classifier models and then the averages result is taken by a weighted average technique. Fig. 6 displays the sequential method which is tracked by the ensemble model upon training data.

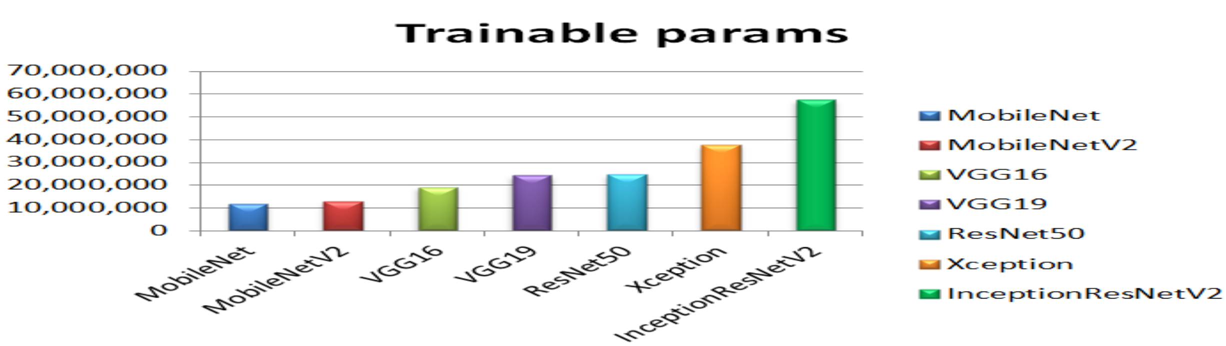

Fig. 4: the number of trainable parameters.

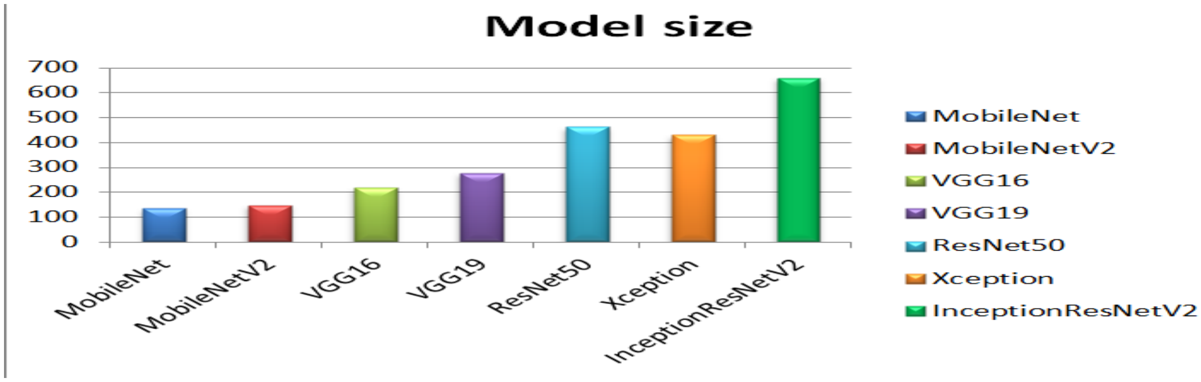

Fig. 5: The Model's size.

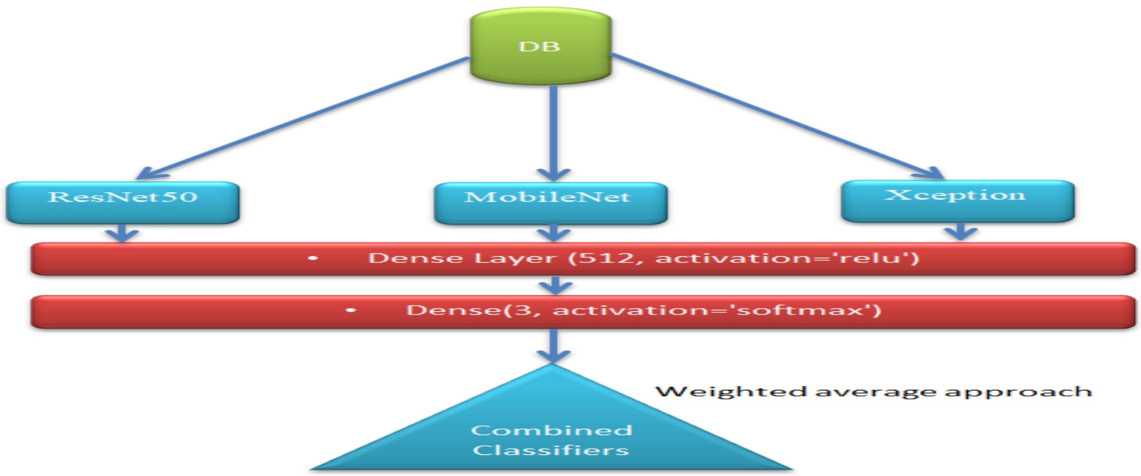

Fig. 6: Ensemble pre-learning model.

6 Experiments and results

For implementing the proposed model and obtaining these results, Python 3.7 Programming language is used, NumPy, Scikit-Learn, and TensorFlow 2.0, and Keras >= 2.0 libraries were installed. The System specifications are 16 GB Ram and Intel(R) CORI 7 CPU @ 2.30 GHz.

6.1 Brain tumor dataset description

The image dataset used in this work is collected from [72]. T1-weighted contrast-enhanced magnetic resonance images (CE-MRI) benchmark dataset. The total number of images is 3064 which consists of three categories (meningioma, glioma, and pituitary). It is based on 233 patients with three kinds of brain tumor: glioma (1426 slices) meningioma, pituitary tumor (930 slices), and (708 slices). The images are gray level images with intensity values ranging from (0 to 255) in Dicom form, its size 256 *256 by type int16. The Dicom form can't be used directly in python but convert it to jpg form and resize each image to 128*128 to be easy to be an input to this model. The brain image dataset is divided into two sets. The training dataset represents 80% of all data and the testing, the dataset represents 20%.

6.2 Accuracy

The model is built on CNN, it is more generic as it does not use any handcrafted features. These models are characterized by high accuracy in classical machine learning.

We target the applications where the available dataset is a small set to train on CNN. Transfer learning is a knowledge learning technique that controls the knowledge learned from a source task to improve learning in a related but different target task.

Two strategies are followed to be applied to the brain tumor classification process. In the first approach, the seven pre-training models are trained on a brain tumor dataset, afterward; they are tested and evaluated by using accuracy metric. In the second approach, we propose the Ensemble of Deep Transfer Learning (EDTL) methodology to improve the classification accuracy when the previous work accuracy is insufficient. Ensemble pre-learning can decrease the risk of selecting a learning algorithm with poor performance by combining prediction results from the three highest learning algorithms' efficiency.

6.3 Training phase

We apply 10 epochs for seven models. Table3 displays the training accuracy in each epoch for each model. After the 4th epoch, it is observed that all models' accuracy exceeds 97% except VGG19. After the first epoch, MobileNet, Xception, and ResNet50 are exceeding 95.5%.

By analyzing the training data, Xception, MobileNet, and ResNet50 will achieve the highest accuracy and VGG19 accuracy will be the worst one. These results are clearly defined in fig.7 which is designed in a line chart to be more visualized.

6.4 Testing phase

The primary purpose of the Testing Phase is to determine whether our approach achieves the target and whether the result is sufficient or not. We test the models over 610 images which represent 20% of the dataset.

In the first strategy, seven models are tested and evaluated. The classification accuracy results of Xception , VGG16, VGG19, ResNet50, MobileNetV2, MobileNet, InceptionResNetV2 were 90.05%, 85.68%,45.36%,88.63%, 95.09%,59.45%, and49.4% respectively. Xception, MobileNet, and ResNet50 achieve high accuracy. Fig8. is an indicator of the next strategy. Table3. Display the pre-training CNN models' accuracy, additionally to our approach.

Table 2: Training accuracy for seven models.

Training Accuracy / Model	1	2	3	4	5	6	7	8	9	10
InceptionResNetV2	45.32%	47.79%	74.74%	94.17%	97.16%	98.32%	98.36%	99.02%	99.60%	99.82%
VGG19	66.42%	70.91%	75.03%	78.78%	81.19%	83.16%	82.83%	85.49%	87.68%	89.21%
ResNet50	88.22%	96.32%	98.54%	99.85%	99.89%	99.74%	99.82%	99.64%	99.64%	99.93%
MobileNetV2	83.45%	94.60%	98.10%	97.67%	98.32%	98.43%	97.16%	98.40%	98.69%	98.87%
MobileNet	88.01%	95.66%	97.48%	96.76%	97.92%	98.65%	98.36%	99.42%	99.42%	99.56%
Xception	85.34%	95.70%	97.16%	95.95%	98.47%	99.74%	99.60%	98.98%	97.52%	99.49%
VGG16	76.96%	92.67%	96.76%	97.85%	97.23%	96.83%	98.76%	98.40%	99.23%	98.72%

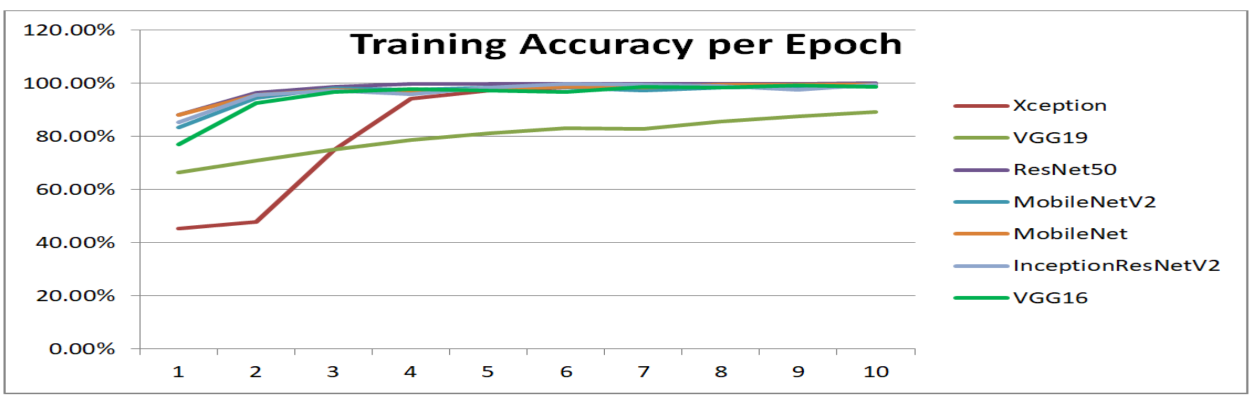

Fig. 7: Training accuracy per each epoch.

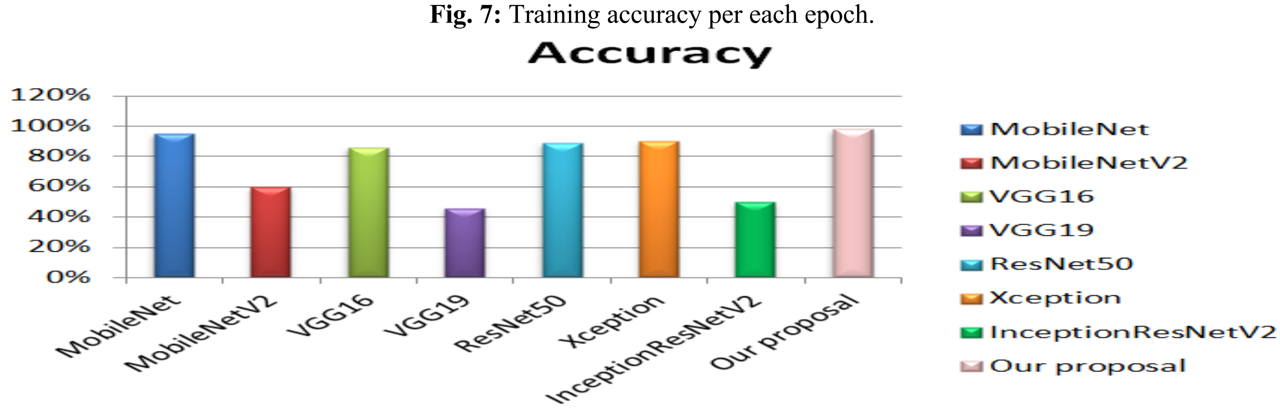

Fig. 8: Results of experiments using different models of CNN and our approach.

The previous results indicate that the selective models combined from Xception, MobileNet, and ResNet50 altogether. The second strategy is based on these three models successfully to achieve the highest accuracy in the classification process.

Our results are compared with the previous work done based upon the same benchmark dataset [27] in Table 4. Authors in [1] [2] [4] [5] [8] have achieved accuracies of 95%, 95.54%, 93.5%, 94.82%, 96.56% respectively. It is found that our proposed model has achieved the state of the art results using the proposed model, achieving a higher accuracy by 1.24% from the previous works [36] and outperformed all previous work.

Table 3: The accuracy of experiments using different models of CNN and our approach.

Model	**Accuracy**
Xception	90.05%
VGG16	85.68%
VGG19	45.36%
ResNet50	88.63%
MobileNet	95.09%
MobileNetV2	59.45%
InceptionResNetV	49.4%
Our Proposal	97.77%

Table 4: Previous works for brain tumor classification based upon the same benchmark dataset.

Author	**Year**	**Method**	**Performance (Accuracy)**
Liu et al [28]	2019	G-ResNet	95.00%
Kwabena et al [7]	2019	CapsNets	95.54%
Cheng et al [9]	2019	ConvCaps	93.50%
Zar et al [4]	2019	Pre-trained DCNN	94.82%
Milica et al [10]	2020	Augmented-CNN	96.56%.
This Work	2020	Ensemble pre-training CNN	97.77%

7 Conclusions

We propose an ensemble transfer learning technique that automatically classifies between brain tumor types of MR images. The proposed method presents a Transfer Learning technique to use the Xception Convolutional Neural Network, MobileNet and ResNet50 pre-trained weights on ImageNet as an initialization for the new model.

Our model was trained and optimized by Adam which an optimization learning algorithm. Categorical cross-entropy is used as a loss function to classify the three classes.

Our approach outperforms baseline models and state-of-the-art previous results work in some performance measures. Moreover, we achieve an accuracy of 97.77% which increases than previous works by 1.21%

In future work, we plan to extend our experiments to explore various deep CNNs architectures and suitable learning strategies, whilst focusing more on the problem of medical images. We would also try using data augmentation techniques, increasing the number of epochs, and increasing the number of dense layers, to make a deep statistical analysis of its performance.

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