Brain Tumor Classification Using Convolutional Neural Network and Deep Transfer Learning Approach with MR Imaging

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October 5, 2022

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***Abstract*—Brain tumors are one of the leading causes of death worldwide. It is a challenge to solve brain tumor segmentation and classification using only traditional medical image processing. a difficult and complex task In fact, medical research suggests that manual classification with human help may result in inaccurate prognosis and diagnosis. This is primarily owing to the similarities and contrasts between normal tissues and malignancies. Recently, deep learning approaches have demonstrated promising outcomes. The purpose of this study is to develop an effective strategy for identifying brain tumors using MRI that is based on transfer learning. This article employs the Convolutional Neural Network (CNN) and popular deep learning models to classify a brain tumor diagnosis system. Using pre-trained models such as Efficientb0, DenseNet121, and Densenet169. For the prediction of a brain tumor, the accuracy is achieved at 93% through CNN. Deep learning models have achieved accuracy efficientb0 of 48%, DenseNet121 96%, and DenseNet169 98% these models are Ensemble, and a 98 % accuracy level is attained Experimental findings suggest that an Ensemble of deep characteristics can significantly increase performance.**

***Keywords*— Deep learning, Convolutional neural network, magnetic resonance imaging, Brain tumor, Efficientb0, DenseNet, Ensemble Learning, Transfer Learning.**

I. INTRODUCTION

Brain tumors are abnormally growing clusters of brain tissue that can severely impair the central nervous system. Moreover, the mass of tumor cells can disrupt the normal functions of the brain. It should also be mentioned that many types of tumors cause the brain cells to enlarge over time, resulting in the death of brain cells[1]. However, early detection of brain tumors can dramatically increase treatment options and patient survival rates. In practical practice, classification of tumors using a large number of MRI scans is time-consuming and labor-intensive, whereas benign tumors are slow-growing and less dangerous/Using magnetic resonance imaging (MRI) for medical purposes produces high-quality images. Scientists frequently use this imaging technique to detect brain abnormalities. displaying the progression of tumors over time. MRI images play a vital part in the realm of automatic medical analysis [2]. They enhance visualization of the many brain structures, offering specific details on its Researchers have created various detection methods and classification-detecting a brain tumor using MRI scans. These techniques range from conventional medical image processing to machine learning techniques. Deep learning (DL), a subfield of machine learning, can learn without human supervision from unstructured and unlabeled data. A range of complex problems demanding extremely high precision and depending on hierarchical feature extraction and data-driven self-learning has shown encouraging outcomes in recent years using DL techniques and models. In a wide range of applications, deep learning has been used to classify patterns, detect objects, recognize speech, and make decisions[3]. The need for a huge amount of training data is the biggest problem for DL. In healthcare, for example, there isn't a lot of medical data available to the public that scientists can use to train deep learning models. This is mostly because people are worried about the privacy and security of their data. Because of this, transfer learning has been used a lot in the medical field to make up for the lack of data. Transfer learning is when a deep learning model that was trained for one task is used to start working on another problem. This is usually done when there isn't enough training data[4]. Transfer learning is used in this study to develop a deep learning model for categorizing MRI images with brain malignancies. The suggested model is built on three deep that have already been trained:

- In this work, we present a fully automatic system for brain tumor classification that makes use of CNN additionally, we use pre-trained models to extract deep features from brain MR images.
- Three distinct pre-trained models and an ensemble of these pre-trained and CNN models on a dataset of brain MRI images with 2 classifications (normal/tumor).
- This research classifies normal and abnormal brain tumors using densenet121, and densenet169 with transfer learning on Kaggle datasets MRI improves tumor identification, categorization, and growth rate prediction.

The remainder of the paper is structured as follows: Section II elaborates on related work. Detailed models for the segmentation and classification of a brain tumor utilizing transfer learning are discussed in section III. In Section IV, the models that have been proposed are discussed and their outcomes are deliberated. Finally, in section V, the conclusion with regards to future work is discussed.

II. RELATED WORK

Brain Tumor classification, and detection, from MR images, require medical image segmentation, which is crucial for timely treatment planning. Classification methods for MRI brain tumors are numerous MRI (Magnetic resource imaging) is the basic method of medical imaging for brain tumor analysis. The conventional machine learning techniques categorize the brain tumor based on some handicraft property or radiologist choice. In this paper, the brain MRI images are going to classify the benign and malignant tumors by using ensemble modeling using the SVM & CNN classifier [5]. And also managing the threshold-based segmentation in terms of detecting the brain tumor, results in distorted boundaries and edges.

A deep learning model for brain tumor diagnosis was developed using Resnet-50 and TL. Their experimental results are 95 % accurate. To achieve fivefold cross-validation, researchers used block-wise-based transfer learning. accuracy of 94 %A benchmark dataset based on magnetic resonance imaging with T1-weighted contrast was used to test their method (CEMRI)[6]. The Google Net architecture is used to classify brain magnetic resonance imaging images. They were able to get a classification accuracy of 98 %. A support vector machine-based technique is used as a classifier[7].CNN is used for classification and feature extraction. They use two fully connected layers and two convolutional layers. They used Transfer Learning to classify brain cancers using nine deep learning models, and their accuracy was 97.39 percent (TL)[7].

They used deep learning mode to explore MR data. The proposed system showed a 98.71 % accuracy in magnetic resonance image classification.The study had a tiny sample size, the results were impressive. The CNN architecture was 100 percent accurate. VGG was also 96 percent accurate, ResNet50 was 89 percent accurate, and InceptionV3 was 89 percent accurate. 75 percent accuracy [8]. According to CNN, architecture is built to perform much faster and with a higher level of precision a level of accuracy of 98.24 percent. CNN is a recommended multi-scale brain tumor MRI image analysis. They used the MRI image dataset to evaluate the proposed model and discovered that it had a classification accuracy of 97.3 percent[9]. The CNN model has used two convolutional layers and two fully connected layers for feature extraction and classification of brain Tumor. They were 97% percent accurate in classifying brain Tumors [10]. To classify normal and pathological brain MRI data, the researchers used a transfer learning method with a convolutional neural network ResNet34 model[20]. To increase the number of photos and attain 100% accuracy, they adopted a strategy for enhancing data pictures of brain tumors are normal or not [11].

The Gray Wolf Optimizer (GWO) optimization approach was integrated with the ANN model. They used GWO-ANN to get a classification accuracy of 98.91 percent. They demonstrated a deep CNN network that has been trained with ResNet-50 and brain MR data[12]. Using the data enhancement method, the suggested model achieved 97.48 percent accuracy. A Capsnet CNN model with 90.89 percent accuracy was suggested using a brain MRI dataset[13]. Three different convolutional neural network classifiers are put together to make an ensemble model that achieved 98%[14]. Transfer learning can be used to classify brain cancers, according to the study [15]. The four different designs for CNN DenseNet-2, VGG-16, VGG-19, and ResNet-50 were selected as used to categorize things. FigureShare was utilized in this study. in which 3064 MRI scans of three brains were used sorts of tumors A public test bed was used to refine the generated model. Figshare dataset that can be accessed the findings showed that facilitated the sharing of knowledge The ResNet-50 model was successfully developed.99.02 percent of the time.

In 2020, the researchers resumed their efforts using the same dataset to improve the accuracy with which brain cancers were classified. Two convolution layers for feature extraction and two completely coupled layers for classification were proposed for a basic CNN [16]. This CNN properly classified brain cancers 97.39 percent of the time. According to the available data, a study was conducted that successfully categorizes different types of brain tumors. They used KNN, ANN, RF, and LDA as classifiers. By combining the KNN model and the NLBP feature extraction technique, they achieved 95.56 percent accuracy[17]. The earlier ways to transfer learning have drawbacks, such as being intrusive, complex, and prone to sampling errors, which need to be addressed when working with a brain on the identification and classification of tumors. Generally speaking, these approaches suffer from a lack of study regarding their reliability and efficiency. system. Because of this, we have established the concept of transfer learning. models for determining the classification of brain tumors. Deep learning, a relatively novel and potent classification technique, was utilized to classify images, and faster region-based CNN (faster R-CNN) was employed to classify tumor kinds.

TABLE I. Literature Review

Sr#	Author	Transfer Learning Models	Dataset	Accuracy
1	Pravitasari	The model number is UNet-VGG16.	152 MR images were taken at the RSUD.	96%
2	Guy-Fernand	Using a method known as selective attention,	Figshare has 3064 MR images.	95%
3	Alaraimi	VGG16, Google Net, AlexNet,	3064 magnetic resonance images (MR) from the Figshare collection	98%
4	Agerwal	VGG-16 model	270 MR pictures taken from a publicly available dataset	96%
5	Naser	VGG-16 model U-Net model,	110 MR pictures of LGG from TCIA	92%
6	Swati	VGG-19 model	3064 MR pictures of the dataset on Figshare	96%
7	Soumik	InceptionV3 model	3064 magnetic resonance images (MR) from the Figshare collection	99%
8	Polat	DenseNet-2, VGG-19, VGG-16, ResNet-50	MR images totaling 3004 from the Figshare dataset	99.2%

III. Proposed System

Transfer learning-based classification is the goal of this approach. those with a brain tumor and those that don't for those without. In the beginning, a variety of preprocessing procedures are used.MRI scans for image enhancement and augmentation. A total of 245 MRI pictures are included in the original dataset there were 146 cancerous samples and 99 healthy ones. Magnetic resonance imaging (MRI)Images are gathered from a variety of sources. The following are some of the however, it's worth noticing. To build a larger MRI, this collection has been expanded data set for learning. There are three pre-trained CNN architectures employed. To put the proposed model to the test. As you'll see below, in this investigation, the most important preprocessing stages were the classification model based on transfer learning has been suggested.
suggested.

A. Data Pre-processing step

Data pre-processing For deep convolutional neural networks, the size of the datasets required to train them is critical. Using Keras TensorFlow's Image Data Generator tool, the original image dataset is supplemented with random alterations (rotations, height and width shifts, brightness changes, etc.) to increase the number of MRI images for training the proposed system. Data augmentation settings are chosen in such a way that the suggested classifier will never see the same image more than once. As a result, the model can better generalize and avoid overfitting[18]. The number of photos in the original collection is increased from 245 to 1470 Data augmentation is shown in Table I, which shows the number of photos in each class, Tumor, and Non-tumor.

B. Data augmentation

The performance of deep convolutional neural networks is heavily influenced by the number of datasets used in their training. MRI images are added to the original dataset to train the proposed system with more MRI images. (rotations, changes in height and width, brightness) transformations use Keras' ImageDataGenerator tool to alter TensorFlow. The factors that were used to enhance the data to ensure that the proposed classifier will be able to accurately identify. There will never be two identical images in your life. The model gets a boost from this procedure immproves generalisation and reduces the likelihood of overfitting. The number of images in the original dataset has been increased from 245 to 1470.Table 2 lists the number of images in each of the two categories Tumor and Non-tumor after data augmentation.

TABLE II. Number of Images of brain tumorand non-Tumor.

Class	Number of images
Tumor	876
Non-Tumor	594
Total	1470

C. Rezing and Crope

Using a technique, the first step in this step is to remove the brain from the image background[19] The goal of this method is to use OpenCV to find the extreme points of a bounding box. It's important to note that because the MRI images used in this study came from various locations, their sizes vary. The images are re-sized to 64x64x1 in order to make them more consistent.

D. Data Spiliting

Data used in this study is broken down into subsets proposed method will be evaluated in three stages: training, validation, and testing. a model of in-depth learning. Using the first subset, the model can be fit. This represents 80% of the total data set. The rest is gone. both verifying and testing the system are evenly distributed the remaining 20% will be used for validation).

E. Convolutional Neural Network

CNN is well-known because it has gotten better at classifying images. CNN uses the data that is given to it to automatically collect features. It is a well-known DL architecture with feedforward connections between each layer. Deep architecture helps these networks learn complex functions that a simple neural network can't learn[20]. CNN is the brains behind computer vision, and it can be used to classify objects, monitor activities, and create medical images. Its preprocessing is simple and small compared to other neural classifiers because it has an internal filter. A typical CNN architecture includes the following components: Convolution (ii), pooling (iii), activation (iv), and a dense layer (v) are all steps in the classification process.

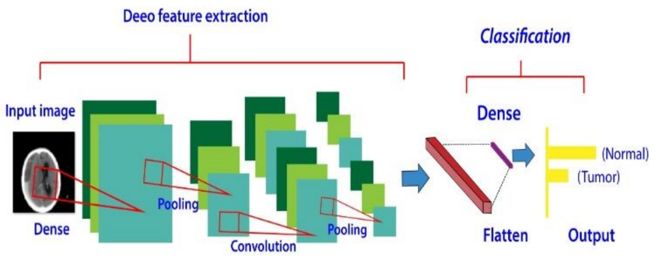

Fig. 1. CNN Structure

F. *Transfer Learning*

Transfer learning (TL) is a deep learning strategy that marries an existing model trained on a large dataset with a new model trained on a different dataset to tackle the same problem. In general, CNN performs better with more data than with less. In CNN situations when the datasets are small, TL can be useful. The field of TL has expanded in recent years, finding applications in object detection, medical imaging, and picture categorization[21] Large Datasets, such as ImageNet, were utilized to train the models so that they can extract useful characteristics. Applications utilizing smaller data sets, such as brain MRI data, are common. One of the benefits of TL is that it shortens the time it takes to complete training. Procedures, avoiding snug fits, training with fewer data, and motivating improved performance. CNN model training is complete. Efficientb0, DenseNet121, and DenseNet169 were utilized in our study.

1) EfficientNetb0

This article introduces a thick CNN model. Pre-trained EfficientNetB0 and dense layers. EfficientB0 has 230 layers and 7 MBConvs. It features a 4-year growth rate, a dense block structure, and firmly linked layers. Each layer uses the previous level's output feature maps as input. EfficientNeb0's dense block approach uses convolution layers the same size as feature maps[22]. By feeding the dense block the feature maps from earlier convolution layers, more feature maps can be created with fewer kernels. Enhanced MRI images fed into a CNN model gave 150, 150 outputs. EfficientNetb0 has alternating drop-out and thick layers. Dense layers are fundamental. It receives the layer below's outputs and sends one from each neuron to the layer above. During training, the drop-out layer reduces network capacity. Which limits the network's efficiency. First, we add a pooling layer, then four dense layers, and three drop-out layers to the model. 0.5 and indicate dropouts. The authors finished by wiring four neurons to a Softmax output layer. Transfer learning (TL) mixes two deep learning models to address the same problem.

2) Densenet121

Pre-trained deep learning models include the Dense Convolution Network (DenseNet121). Each layer feeds into the next. DenseNet121 only employs (L(LC1))/2 direct connections, unlike normal L-layer CNNs. Each layer has a feature map. Each layer uses the previous layer's feature map. Connecting all levels directly allows for maximum data flow DenseNet121 reduces the number of parameters, reduces gradient runaway, increases feature diffusion, and promotes feature reuse. The old CNN. Because the feature map isn't relearned, DenseNet121 uses fewer parameters. DenseNet121 uses regularization to reduce the likelihood of node overlap. Each dense block comprises six, twelve, twenty-four, and sixteen convolution blocks. demonstrates how Densenet121 design affected the model utilized to acquire classification results.

3) DesneNet169

Due to DenseNet169's low parameter count, the low number of layers, and ability to solve the disappearing gradient problem; this model is used. [23]. Procedures for pre-processing database comprise images that are 32 by 32 pixels and have three channels (RGB). SoftMax activation is used to create the output. RELU activation was employed up until the very last frame. The structure contains more parameters than other models and successfully tackles the disappearing gradient problem.DenseNet169 is used for brain cancer classification. These models solve the problem of overfitting and underfitting. 96 percent accuracy was attained with densenet169.

4) Ensemble learning

Ensemble learning combines numerous characteristics from several models into a single predictive feature to improve performance and avoid using a single feature from a model that does not work well. Depending on the extent of integration, ensemble learning can be separated into the highlighted ensemble and the classifier ensemble. Feature ensemble refers to the process of assembling groups of features that are then fed into a classifier to produce the final output. The process of aggregating sets of classifier outputs, with voting procedures determining the outcome, is known as classifier ensemble. Classification accuracy is expected to improve with deeper integration because the feature set contains more information about the MR images than the classifiers' output sets. "Feature ensemble" is a technique that we use in this project to learn together. Three different pre-trained models are combined into a single sequence in our ensemble module. Some of the most advanced features include EfficientNetb0, DenseNet121, and DenseNet169. Stringing together these features into a single sequence is our feature-level ensemble step. An algorithm that has been pre-trained using aggregated deep features to predict the outcome. To compare with the pre-trained model that only uses the three most important attributes, we created a list of every possible combination and fed it into CNN.

IV. Result and Discussion

We describe the measures used to evaluate the proposed system's performance here. We also compare the proposed system to some current approaches.

A. *Evaluation metric*

The four criteria for evaluating the categorization of repurposed Efficient, Dense Net 0121, and Dense Net 169 models. Accuracy and precision were chosen as the evaluation criteria (Acc),f1-score, precision (Pre), and recall (Rec). The precision as well as the following additional parameters: TN, false positives (FP), and false negatives (FN) FN. Some of the most prevalent evaluation metrics include a tool for gauging one's performance. Indicators of The following are the performance evaluation formulas:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = \frac{2 * Recall * perciscion}{Recall + precision}$$

B. RESULTS

A lot of experiments have been done to test the CNN model to see if it is correct. All of the experimental evaluations have been done in a programming environment for Python that works with GPUs. First, max-min normalization is used to improve the contrast in MRI images during pre-processing. For better accuracy, the proposed CNN model turned on the added tumors. On training data, the proposed model was right 95 percent of the time. and 93 percent accuracy on the testing dataset, which is shown in Figure 2.

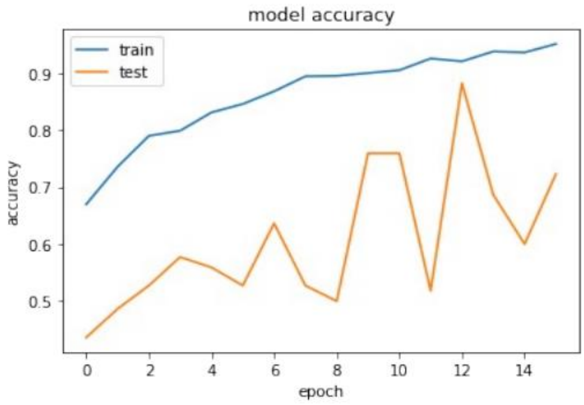

Fig. 2. CNN Accuracy with 16 Epoch

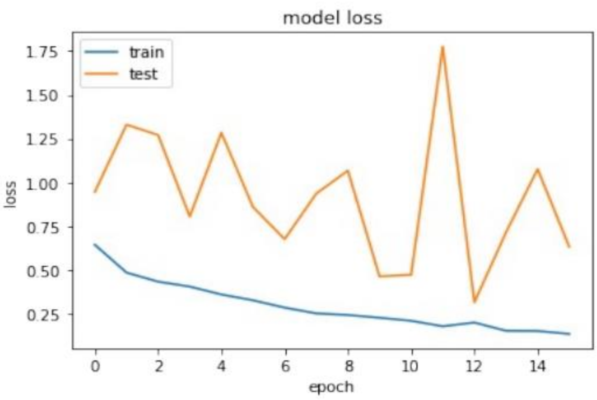

Fig. 3. CNN Model loss with 16 Epoch

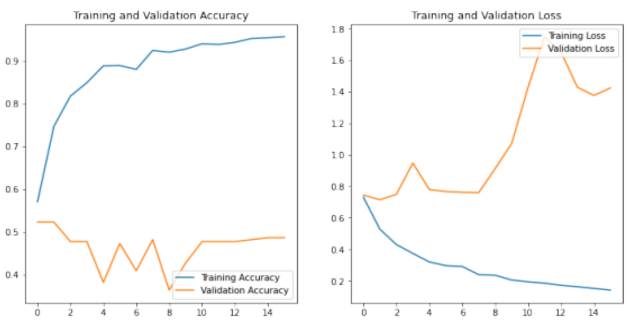

Fig. 4. EfficeNetb0 Model Training and Validation Accuracy with 16 Epoch

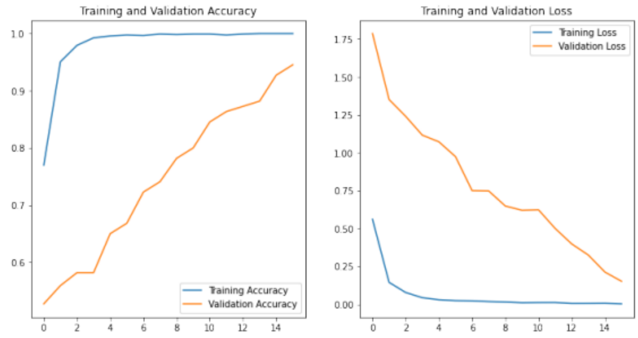

Fig. 5. DenseNet121 Training and Validation Accuracy with 16 Epoch

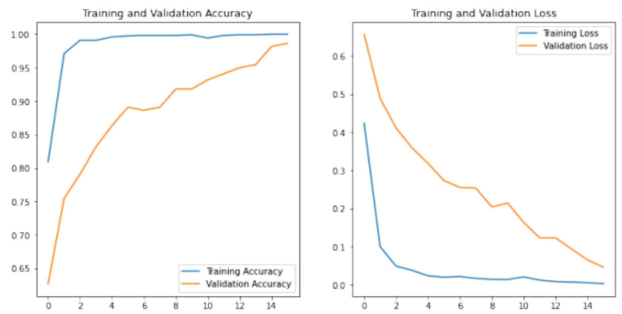

Fig. 6. DenseNet169 Training and Validation Accuracy with 16 Epoch

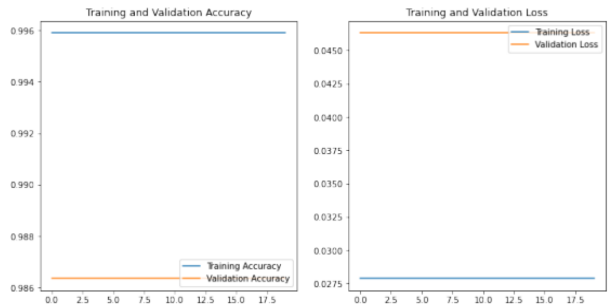

Fig. 7. Ensemble Learning Training and Validation Accuracy with 16 Epoch

C. Conclusion

In this study, we provided a transfer Using three trained models and CNN for brain categorization. MR image datasets and three transfer learning models leveraging two unique optimizers (ADAM and RMSprop) were evaluated. Using three dense layers and a SoftMax layer, these three models categorize data. The proposed deep TL models learn rapidly from Adam and are prevented from becoming overly competent using dropout. We compared the accuracy, recall, precision, and F1 score. DenseNet169's deep transfer learning model produced the greatest results. Three pre-trained models are ensemble and comparison another classifier CNN, through ensemble learning are achieved the highest accuracy According to these data, deep learning models detect brain tumors accurately. In addition, we have the transfer learning approaches that were compared to CNN. Our proposed models for system transfer learning outperform all current methods. We will work on multiclassification in the future. tumor of the brain with extensive transfer learning Datasets for instruction and evaluation.

Acknowledgment

This study has been carried out following Comsats Univesity Islamabad, Sahiwal Campus, Pakistan.

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