Predicting Brain Tumor using Transfer Deep Learning

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ABSTRACT
Brain tumor is an abnormal collection or accumulation of cells in the brain that can be life-threatening due to their ability to invade and metastasize to nearby tissues. Accurate diagnosis of this dangerous disease can save lives. Deep learning applications have shown significant improvements in recent years.Therefore, improvements within the model architecture perform better approximations in the monitored configuration. Tumor classification using deep learning techniques has made great strides by providing reliable datasets. In this paper transfer models such as the MobileNet, VGG19, InceptionResNetV2, Inception, and DenseNet201 model is applied to predict brain tumors. The proposed models use three different optimizers, Adam, SGD, and RMSprop. Simulation results show that the pre-trained MobileNet model with RMSprop optimizer outperformed all compared models.It achieved 0.995 accuracy, 0.99 sensitivity, and 1.00 specificity, while at the same time having the lowest computational time.

Keywords
Brain Tumor, Transfer Learning, Deep Learning, Computer Vision, MRI

1. INTRODUCTION
According to the global health organization`s statistics, cancer is considered the second leading reason behind human fatalities across the world. Among different types of cancers, the tumor is seen as one of the deadliest, because of its aggressive nature, heterogeneous characteristics, and low relative survival rate. [1] A brain tumor can drastically influence the standard of life, for both patients and their families. The key thing about treating brain cancer and increasing its survivability rate is early diagnosis and properly determining its type. A tumor can have differing kinds (e.g., Meningioma, Pituitary, and Glioma) looking at several factors like the form, texture, and placement of the tumor. Determining the correct tumor type is very important as it can have a significant impact on treatment choices and can predict patient survival. Diagnosis of brain tumors usually includes resonance imaging and biopsy. MRI is recommended because it is non-invasive. However, in some cases, MRI alone is not enough to identify the type of tumor that requires a biopsy. The risks associated with biopsy are high and do not guarantee accurate results. Technicians who perform these steps will have a positive impact on the results and will introduce human error issues. We need a computerized system to help doctors make the right decisions. In recent years, much research has been done on this using various machine learning techniques. Prior to the advent of deep learning, feature selection techniques such as PCA and DWT were used, followed by classifiers such as SVM and ANN. Currently, the first focus is to use neural networks to achieve better results. [2] The prognosis of a brain tumor depends on many factors, including the location of the tumor, the histological subtype of the tumor, and the margin of the tumor. State-of-the-art imaging techniques such as MRI can be used for multiple diagnostic purposes. They can be used to study tumor progression and to identify tumor sites used for surgical prior planning. MR imaging is also used to study anatomy, physiology, and metabolic activity of lesions along with their hemodynamics. Therefore, MR images remain the primary diagnostic modality of brain tumors. [3] Cancer detection, especially early detection, can make a difference in treatment. Early detection is very important because early-stage lesions are likely to heal. Therefore, early intervention can mean the difference between life and death. Deep learning techniques help automate the process of detecting and classifying brain lesions. Also, prioritizing only malignant lesions can reduce the burden on the radiologist to read many images. This ultimately improves overall efficiency and reduces diagnostic errors6. Recent studies have shown that deep learning methods in the field of radiology have already achieved comparable superhuman performance in some diseases [4].

The rest of this paper is structured as follows: Section 2 devoted for related work. Section 3 presents approaches that describe transfer models; Section 4 reflects on the implementation of models; Section 5 presents on the experiential results; while Section 6 points out the core conclusions of the proposed model and highlights the future work.

2. RELATED WORK
Due to the deadly nature of brain tumors, much research has been done to automate their detection and classification. With advances in machine learning, neural networks are gaining attention in developing models for diagnosing brain tumors. Transfer learning techniques can be applied to these models and can be used for other similar diagnoses [5]. This paper attempts to discusses some techniques developed for the classification of brain tumors. Further research and improvement of the technique in this regard is still needed to enable the system developed in to be deployed for physician use.

Muhammad Sjad et. al [6] announced a new multigrade brain tumor classification system based on a convolutional neural network (CNN). Tumor area is segmented using InputCascade CNN. The pre-trained VGG19CNN architecture is optimized for tumor grade classification. The original and expanded data achieved 87% and 90% accuracy, demonstrating the impact of the data expansion, respectively.

Amin Kabir Anaraki et. al [7] proposed the idea of further developing a CNN architecture for tumor classification using genetic algorithms. This study uses a gadolinium-enhanced T1 image with a size of 128x128 pixels. Simple techniques such as rotation, scaling, and mirroring are applied to increase the size of the dataset. GA is implemented to select parameters such as the number of convolution layers and maximum pooling layers, the number of filters and their size. The accuracy achieved was 90.9% and 94.2% for glioma staging and tumor staging, respectively.

Deepak et. Al [8] adopted the concept of transfer learning for feature extraction of the classification system. As a pretreatment, the MRI image was normalized and reduced to 224x224 pixels. The pre-trained GoogLeNet has been modified to learn function from brain MRI. The extracted features are tested on the SVM and ANN classifier models along with the GoogLeNetsoftmax layer. Deep Transfer Learned (standalone) model, SVM and ANN classification accuracy is 92.3%, 97.8%, and 98%, respectively.

Vimal Kurup, et. Al [9] used CapsNet to investigate the impact of pretreatment techniques on the classification of brain tumors. Rotation and patch extraction are the pretreatment steps used. CapsNet is applied to the original dataset and provides 87 ° accuracy. Applying the same architecture to the preprocessed data gives an accuracy of 92.6, demonstrating that the accuracy increases as the data is preprocessed.

Zar Nawab Khan Swati et. al [10] used a pre-trained deep CNN model, we propose a block-by-block fine-tuning strategy based on transfer learning. A 5-directional cross-validation is used to evaluate performance. The accuracy of the proposed method is 94.82%.

Nyoman Abiwinanda et. Al [11] tried to identify the best CNN architecture for brain tumor classification. Five CNN architectures with different numbers of convolutional layers and fully connected layers are being studied. The CNN architecture, which consists of two convolutional layers with 32 filters, activation (ReLu) and Maxpool, followed by a fully-connected layer with 64 neurons, has 84.19% verification accuracy.

Polly et. Al [12] proposed a cod system for the detection and classification of HGG and LGG tumors. Otsu binarization is applied to convert images to binary files. The segmented image then undergoes feature extraction using the discrete wavelet transform. This not only extracts features, but also reduces noise. Tested with 100 images, the accuracy of this system is 99%.

Heba Mohsen et. Al [13] considered a deep neural network for classifying 66 brain MRI datasets into four classes. The classifiers used are DNN with seven hidden layers, ANN with k = 1 and k = 3, Linear Discriminant Analysis (LDA) and SMOSVM. DNN offers the highest accuracy of any technology at 98.4%.

Garima Singh et. Al [14] proposed a brain tumor classification system using a normalized histogram and segmentation using a K-means clustering algorithm. SVMs have proven to be more efficient at 91.49% than at 87.23% for Naive Bayes. Images in which tumors were detected were segmented using the K-Means algorithm.

Parnian Afshar et.al [15] proposed a CapsNet architecture for brain tumor classification. The proposed architecture provides 90.89% accuracy.

Table 1 The related work summary

Work	Model	Accuracy
Sjad et. Al [6]	Pre – trained VGG – 19	90%
Kabir Anaraki et. Al [7]	CNN	94.2%
Deepak et. Al [8]	KNN	97.8%
Vimal Kurup, et. Al [9]	CapsNet	92.6%
Khan Swati et. Al [10]	Pre – trained deep CNN	94.82%
Abiwinanda et. Al [11]	CNN	84.19%
F. P. Polly et. Al [12]	SVM	99%
Heba Mohsen et. Al [13]	Deep Neural Network	98.4%
Garima Singh et. Al [14]	SVM	91.49%
Parnian Afshar et.al [15]	CapsNet	90.89%

3. APPROACH

3.1 Image Processing

As shown in Fig. 1, the dataset is consisting of raw images and need preprocessing.

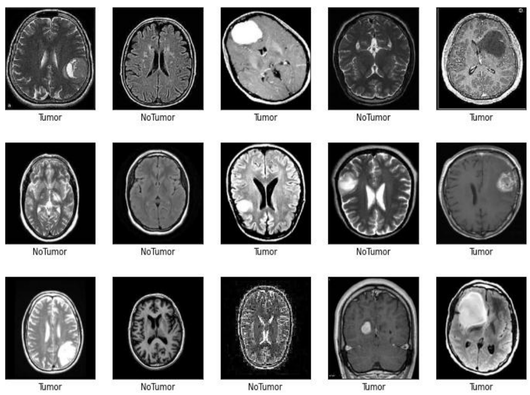


Fig 1. The dataset raw images

As shown in Fig. 2, the dataset images after applying image processing with histogram equalization. This technique usually enhances the overall contrast of many images, especially when the image is represented by a narrow range of intensity values. This adjustment allows you to use the entire range of intensities evenly and better distribute the intensities on the histogram. As a result, areas with low local contrast can have high contrast.

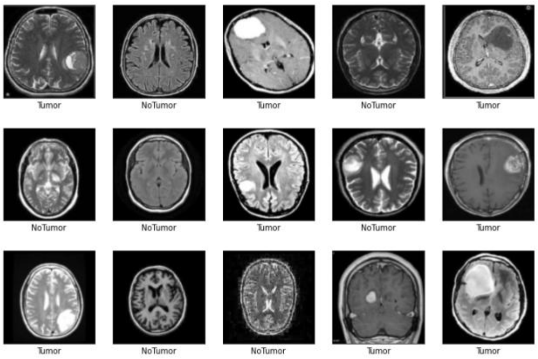


Fig. 2 Images after image processing

3.2 Deep Transfer Learning Model Steps

As shown in Fig. 3, the proposed Transfer model building steps are:

1. Data Loading: Loading images from directories as class for each directory.
2. Apply histogram equalization: Appling image processing using sci-lit images API.
3. Split Data: Splitting data to train, test and validate sets.
4. Load keras Application: using tf.keras.applications to load required application.
5. Load Transfer Model: Downloading the base model from keras API.
6. Train and evaluate the model: using of sci-kit learn metrics API to evaluate the results of training.

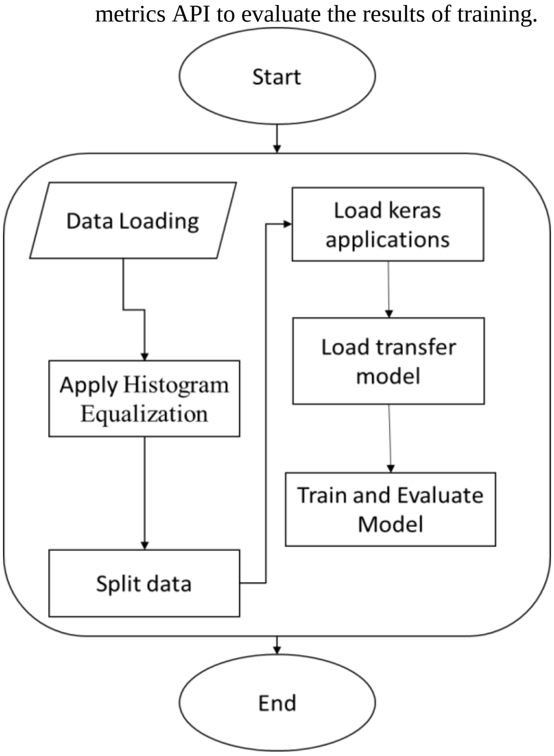


Fig. 3 Transfer learning approach

4. EXPERIMENTAL RESULTS

The deep transfer learning models are applied and tested with Br35H Dataset [16].

As shown in table 2, it presented the accuracy comparison between different transfer learning models optimized with three different optimizers. One can notice that MobileNet optimized with RMSprop achieved the best accuracy with 99.5%. Also, Fig.3 shows the comparison of accuracies.

Table 2 The accuracy comparison between models optimized with 3 different optimizers

Model/optimizer	**Adam**	**RMSprop**	**SGD**
MobileNet	98.83	**99.5**	97.83
VGG19	97.33	96.33	80.67
InceptionResNetV2	98.17	98.17	95.50
Inception	99.00	98.67	97.00
DenseNet201	99.00	99.33	97.50

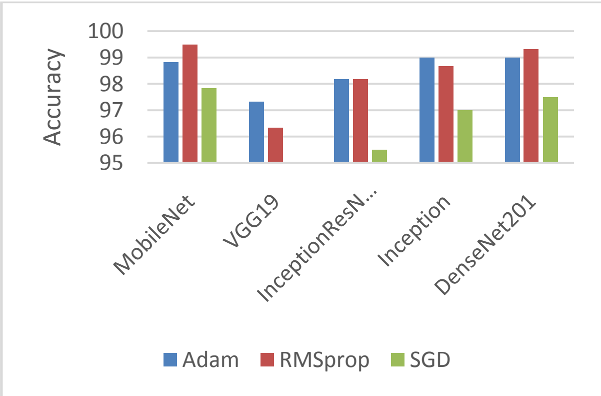


Fig.3 The accuracy comparison between models optimized with 3 different optimizers

As shown in table 3, it presented the Sensitivity comparison between different models optimized with three different optimizers. MobileNetand DenseNet201achieved the highest Sensitivity with 99.33. Also, Fig.4 shows the sensitivity comparison between different models.

Table 3 The Sensitivity comparison between models optimized with 3 different optimizers.

Model/optimizer	**Adam**	**RMSprop**	**SGD**
MobileNet	99.00	99.33	97.00
VGG19	96.00	93.67	83.67
InceptionResNetV2	96.67	97.00	93.33
Inception	99.00	98.67	95.67
DenseNet201	99.00	99.33	97.33

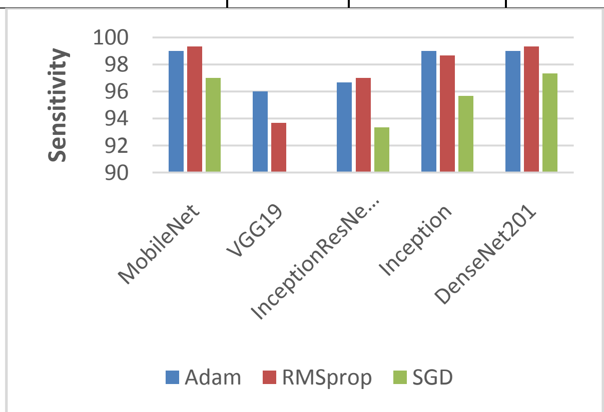
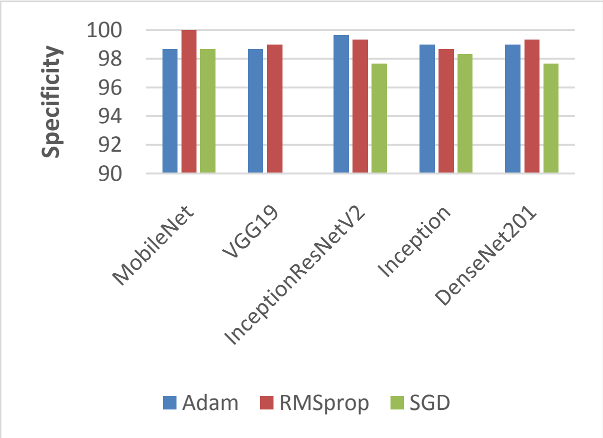


Fig.4 The sensitivity comparison between models optimized with 3 different optimizers

As shown in table 4, it presented the Specificity comparison between models optimized with three different optimizers. Also, Fig.5 shows the Specificity comparison between different models.

Table 4 The Specificity comparison between models optimized with 3 different optimizers

Model/optimizer	**Adam**	**RMSprop**	**SGD**
MobileNet	98.67	**100.0**	98.67
VGG19	98.67	99.00	77.67
InceptionResNetV2	99.67	99.33	97.67
Inception	99.00	98.67	98.33
DenseNet201	99.00	99.33	97.67



Tables from 5 to 8 present the different performance evaluation metrics for all compared models. One can notice that MobileNet outperform all compared models.

Table 5 The comparison between MobileNet optimized with 3 different optimizers

Metric	**MobileNet-Adam**	**MobileNet-RMSprop**	**MobileNet-SGD**
Accuracy	98.83	**99.5**	97.83
Balanced Accuracy	98.83	**99.5**	97.83
Precision	98.67	**100**	98.64
Recall	99	**99**	97
Specificity	98.67	**100**	98.67
F1-Score	98.84	**99.5**	97.82

Table 6 The comparison between VGG19 optimized with 3 different optimizers.

Metric	**VGG19-Adam**	**VGG19-RMSprop**	**VGG19-SGD**
Accuracy	**97.33**	96.33	80.67
Balanced Accuracy	**97.33**	96.33	80.67
Precision	98.63	**98.94**	78.93
Recall	**96**	93.67	83.67
Specificity	98.67	**99**	77.67
F1-Score	**97.3**	96.23	81.23

Table 7 The comparison between Inceptionoptimized with 3 different optimizers.

Metric	**Inception-Adam**	**Inception-RMSprop**	**Inception-SGD**
Accuracy	**99**	98.67	97
Balanced Accuracy	**99**	98.67	97
Precision	**99**	98.67	98.29
Recall	**99**	98.67	95.67
Specificity	**99**	98.67	98.67
F1-Score	**99.5**	98.67	96.96

Table 8 The comparison between DenseNet201optimized with 3 different optimizers.

Metric	**DenseNet201-Adam**	**DenseNet201-RMS**	**DenseNet201-SGD**
Accuracy	99	**99.33**	97.5
Balanced Accuracy	99	**99.33**	97.5
Precision	99	**99.3**	97.66
Recall	99	**99.33**	97.33
Specificity	99	**99.33**	97.67
F1-Score	99	**99.33**	97.5

5. CONCLUSION AND FUTURE WORK

In this paper different deep transfer learning methods were used to classify the brain tumors. In some medical imaging scenarios, the small dataset makes it difficult to use deep learning and training CNN from scratch with a small data set. To solve this problem, we propose a block-by-block fine-tuning strategy supported by transfer learning as the MobileNet model, VGG19 model, InceptionResNetV2 model, Inception model, and DenseNet201 model. The proposed model does not use hand-crafted features, requires minimal pre-processing, and has the highest effective accuracy of 99.5%, 99% sensitivity, and 100%for RMSprop-optimized MobileNet models. It is more common to achieve specificity. In future work swarm intelligence and federated learning models will be used to optimized the used models [17-26].

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