A fine tune robust transfer learning based approach for brain tumor detection using VGG-16

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ABSTRACT

Brain tumor recognition by magnetic resonance imaging (MRI) is crucial because it improves survival rates and allows them to plan treatments accordingly. An accumulation of abnormal cells known as a brain tumor can spread to nearby tissues and endanger the patient. Magnetic resonance imagery is the primary imaging technique which determines the extent of brain tumors. Deep learning techniques rapidly grew in computer vision due to ample data for model training and improved designs on applications. MRI has shown promising results when using deep learning approaches to identify and classify brain tumors. This study uses MRI data and a convolutional neural network (CNN) to create a reliable transfer learning model that classifies tumors under four classes. Brain tumors' unwanted parts are excised, the quality is improved, and the cancer is coloured. By eliminating artefacts, decreasing noise, and boosting the image. The number of MRI images has increased using two augmentation techniques. A number of CNN architectures, including VGG19, VGG16, MobileNet, InceptionV3, and MobileNetV2 analyzed the augmented dataset. Where VGG-16 provides the accuracy of highest level. The best model underwent a hyperparameter ablation investigation, which led to the suggested hyper-tuned VGG16 obtaining 99.21% test and validation accuracy and 99.01% test accuracy.

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1. INTRODUCTION

The brain tumor is one of the highly critical and serious disorders. A brain tumor occurs when unchecked, unregulated cell proliferation occurs in the brain. On the other hand, meningioma, glioma, and pituitary tumors are frequent brain tumors. Identifying, categorizing, and analyzing brain cancers early on is essential to treat the tumor effectively. The benign tumors most frequently found in the thin crusts protecting the brain and spinal cord are meningiomas. A high-grade glioma, in contrast, is an aggressive brain tumor with a two-year survival rate. Pituitary tumors are the result of the brain cells' atypical proliferation. The pituitary gland of the brain is where pituitary tumors grow. When it comes to deaths involving tumor in the central nervous system, brain tumors ranks 10^{th} in case of most frequent reasons of death in both women and men [1]. Reports estimate that, in case of brain tumor development of all the cancer types in the world 40% of them are caused by metastasis rather than death [2]. In an effort to raise public awareness and educate the public about tumors concerning the brain, the 8^{th} of June was declared world brain tumor day in 2000 [3]. In the brain, a brain tumor occurs when abnormal cells grow unnecessarily. Corresponding to the World Health

Organization (WHO), brain tumors can be classified into four groups depending on their molecular characteristics and histopathology in 2016 [3], [4]. Patients with advanced brain cancer have an extremely poor chance of survival [5].

As a result, accurate and timely grading and diagnosis of cancer improve prognosis and treatment options. It is possible to reduce mortality from brain tumors if it is perceived and treated at an initial phase. Tumor grade and diagnosis are determined by neurological examinations, imaging, and biopsies [3], [6]. Before and after treatment, doctors use magnetic resonance imaging (MRI) to determine the tumor's shape. So, when the condition gets worse, surgical resections can be scheduled and followed [7]. A successful prognosis depends on the early classification of brain tumor grade [6]. Anticipated to its non-invasive contrast enhancement nature, MRI is the preferred imagery process for diagnosing gliomas [7]. Radiologists use the conventional method to diagnose tumors, which is inefficient and labour-intensive. In computer aided medical diagnosis (CAMD), AI and deep learning have made great steps, enabling medical picture interpretation by doctors in a few seconds [8]. The effectiveness of deep learning is greatly influenced by the amount and quality of a dataset. Highly enhanced annotations are needed for images while using deep learning techniques.

The challenge of cataloguing enormous amounts of medical images is that it is both time-and expertise-intensive [9]. The lack of expert annotations and image data has hampered deep learning for medical imagery [9]. The above-mentioned difficulties have been addressed in a number of different ways. When there are limited domain samples to train on, a transfer learning approach may be advantageous. A pre-trained network is usually refined using large, labelled datasets. System junction speed is increased while computational complexity is decreased by applying learned information to the target dataset [10]. This study aims to identify and categorize brain tumors hooked on glioma, meningioma, no tumor, and pituitary at an early stage, thereby reducing the danger of death by supplementary experts in more effective as well as efficient medication. It is crucial to remove noise and artefacts to accomplish excellent execution from a convolutional neural network (CNN) model. Furthermore, interpretation may be challenging due to the similarities between tumor-affected areas and impermeable brain tissue. In order to improve the visibility tumorous lesions contrast and brightness levels of MRI images need to be balanced. This study uses a fully automated and trustworthy deep learning model, the fine-tuned and hyper-tuned VGG16 built on ablation study and transfer learning, to predict brain tumors in MRI images.

Seere and Karibasappa [11] provided an approach to distinguish between diseased and normal tissues of the brain. The system proposed a segmentation according to thresholds and watersheds; after that, using an SVM classifier, it achieved an accuracy of classification of 85.32% overall [11]. The created model effectively discriminated between diseased and normal brain slices using a method known as the k-fold-cross with an overall classification accuracy of 92.14% [12].

An algorithm for classifying brain tumors was proposed by Ullah *et al*. [13] and his research associates, based on brain MRIs obtained from Radiology Department of Bahawal Victoria Hospital (RD-BVH). Extracting the intensity, texture features and shape from brain MRI slices led to an accuracy of 97%. Anaraki *et al*. [14] introduced a method for classifying brain tumors using CNNs and genetic algorithms. As proposed by Biswas and Islam [15], the suggested technique for building networks, known as "Levenberg-Marquardt," provides 97.83% specificity, 94.58% sensitivity, and 95.4% accuracy. MRI images can be used to identify and classify brain cancers using a faster CNN that is region based developed by Avşar and Salçin [16]. The accurate prediction of the model was 91.66%.

There is also a method in [17] for classifying MRI brain cancer based on grayscale, symmetry, and texture features. Three optimizers, namely ADAM, SGDM, and RMSprop, are suggested by Precious *et al.* [18], from which detection rate of 98.1%, 92.5%, and 83.0% is acquired. To represent model experts, Papageorgiou *et al*. [19] developed the fuzzy cognitive map (FCM). The addition of an activation Hebbian methodology enhanced the classification abilities of the FCM ranking method. A hundred examples and medical resources were used to validate the suggested technique. A wavelet transform of two-dimension was used by Schmeelk [20] to work with images having 2 dimensions. The two transform techniques were applied on divided elements were thoroughly compared by the authors.

2. METHOD

To find the best transfer learning model for categorization, this study analyzed five models, transfer learning model: MobileNetV2, InceptionV3, VGG16, MobileNet, and VGG19, there are a total of five pre-trained networks which are developed on training examples and testing data. The diagram in Figure 1 represents a process of preparing and analyzing a brain tumor MRI image dataset. The first step involves processing the dataset with various techniques to improve the visual quality. This includes the removal of speckle noise using a median filter, the removal of artifacts with morphological closing, and brightness adjustment using contrast limited adaptive histogram equalization (CLAHE). The next step involves balancing the dataset using data augmentation techniques, which helps in addressing the problem of class imbalance. The final step is to train and evaluate transfer learning algorithms using the processed dataset, out of which VGG16 performs the best. This model is then finely tuned using an ablation study to get the maximum performance. Finally, the performance of the finely tuned transfer learning model is analyzed to evaluate its effectiveness. This process helps in understanding the strengths and weaknesses of the model and identifying areas for further improvement.

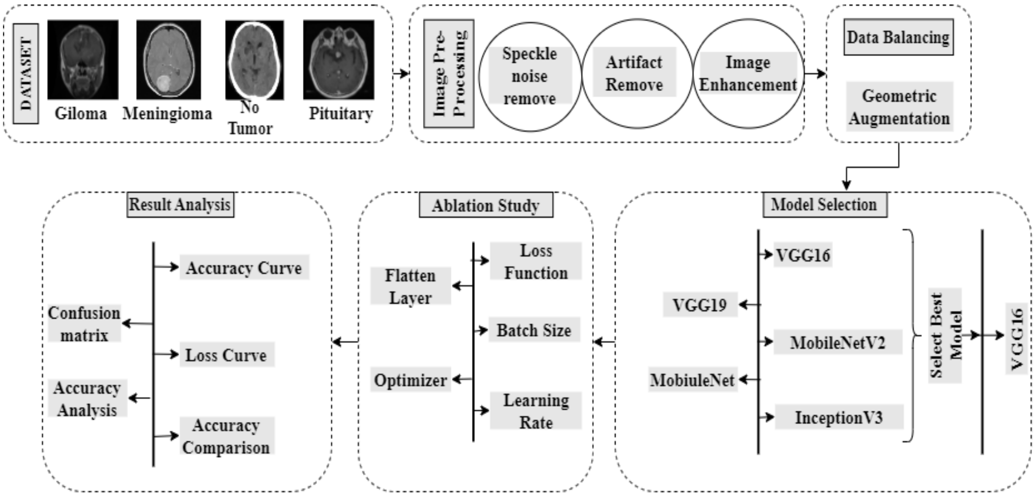

Figure 1. Workflow of the entire classification

2.1. Dataset description and training approach

A total of 3264 MRI scans from the brain tumor MRI dataset were examined for this study. A total of four classes makes up the dataset, pituitary, meningioma, glioma, and no tumor. The class of pituitary contains 951 images, meningioma contains 937 images, glioma holds 926 images, and no tumor class has the lowest of images which is 500. The grayscale system for each image in the datasets is 224×224 pixels. The dataset has been collected from openly accessible website Kaggle. Three different splitting ratios are commonly used (90:10, 80:20, and 70:30). In a study conducted recently it was found that 20% of data was used for testing the final outcome [21]. The dataset has been collected from openly accessible website Kaggle. The maximum number of epochs for training the models is 100, with a batch size of 16. The best model's weights were saved during training using Keras' "callback" function relying on a minimum loss value. At a learning rate of 0.001, Adam has been employed for optimization. For multiclass situations, categorical cross-entropy is the default loss function [22]. 'SoftMax' activation is used to predict the likelihood for individual class. SoftMax always has an aggregate of 1, as they normalize all values ranging from 0 and 1.

2.2. Image pre-processing

The images from the dataset are full of artifacts and noises. Consequently, the goal of this research is to apply image processing to increase the model's accuracy. Since pictures are frequently damaged by noises and artifacts, the processing of images is the preliminary step in training deep learning models. Morphological closing is utilized first to get rid of artifacts from these images, and then a median filter is applied for noise removal.

The image in Figure 2 depicts a brain tumor MRI dataset that is undergoing several image preprocessing techniques. The first technique being applied is a median filter, which is used to remove speckle noise from the images. This is followed by the use of morphological closing, which is used to remove artifacts from the images [23]. The image is then upgraded using CLAHE, which improves the image's brightness and sharpness.

This technique helps to make the features of the brain tumor more visible and distinguishable [24]. The enhancement of local contrast enhances the legibility of medical images [25]. To enhance the quality of brain tumor MRI images and prepare them for analysis by machine learning algorithms, certain preprocessing approaches must be applied. The resulting images will have reduced noise, artifacts, and enhanced features that will aid in spotting the precise position of brain tumors in the processed imaginings.

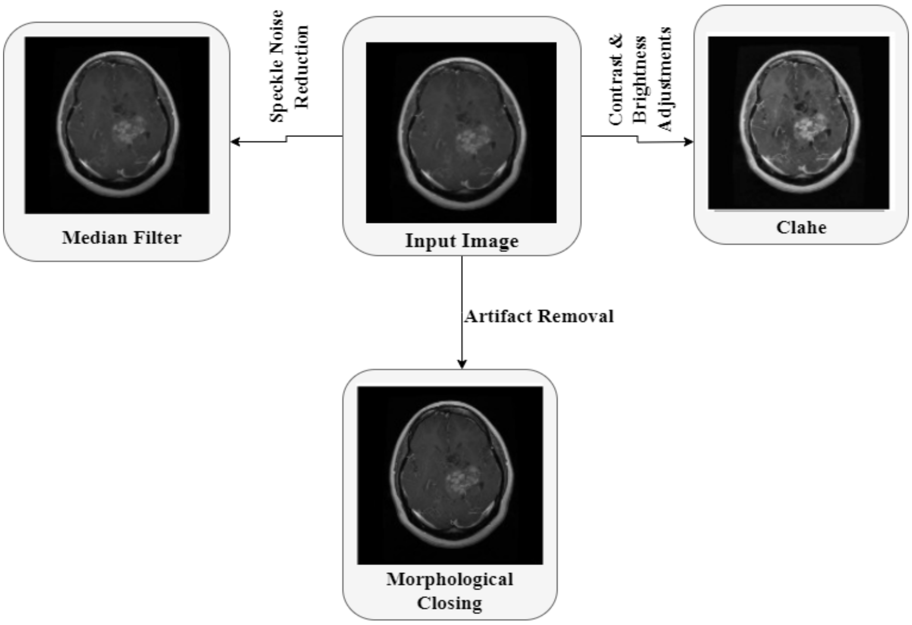

Figure 2. Applied image pre-processing techniques

2.3. Verification

Numerous methods of numerical evaluation, including mean square error (MSE), structured similarity index method (SSIM), and peak signal to noise ratio (PSNR), MSE is unquestionably the most fundamental and frequently utilized error term. The difference between the image's truncated and raw versions is shown as the squared cumulative error. The relationship between the error and MSE value is inverse. The PSNR which determines how well an image is compressed or reconstructed, rises. According to the SSIM, preprocessing algorithms lower image quality.

2.4. Ablation study

In CNN-based applications, different hyperparameters and layers are altered or removed to evaluate the model's performance and stability. In this study, hyperparameter ablation is used to generate strong and well-tuned networks. In this research, there are 5 case study has experimented on the MRI-augmented dataset.

3. RESULTS AND DISCUSSION

3.1. Result of transfer learning models

Table 1 illustrates the outcome of five transfer learning models for a particular task. The table presents six metrics for each model, including test accuracy, validation (Val) accuracy, train accuracy, train loss, test loss, and val loss. The five transfer learning models presented in the table are VGG-16, VGG-19, MobileNet, MobileNet V2, and InceptionV3. From the table, we can see that VGG-16 has the highest train accuracy (97.77%), test accuracy (96.13%), and val accuracy (96.83%) among the five models, indicating that it performs the best on the given task. On the other hand, InceptionV3 has the lowest train accuracy (78.76%), test accuracy (77.81%), and val accuracy (77.86%), suggesting that it performs the worst among the five models.

Table 1. Results of five transfer learning model

Model	Train accuracy (%)	Test accuracy (%)	Val accuracy (%)	Train loss	Test loss	Val loss
VGG-16	**97.77**	**96.13**	**96.83**	**0.18**	**0.19**	**0.12**
VGG-19	97.45	96.07	96.64	0.21	0.23	0.23
MobileNet	95.98	95.23	95.23	0.17	0.29	0.28
MobileNet V2	96.21	95.78	95.78	0.21	0.31	0.32
InceptionV3	78.76	77.81	77.86	0.4	0.4	0.41

3.2. Result of ablation study

Modifying certain design elements can enhance classification accuracy and improve overall reliability. To explore these improvements, five ablation investigations were conducted, where different components were modified in the VGG16 model. These alterations were aimed at creating a finely tuned model with enhanced performance.

3.2.1. Case study 1: flatten layer alterations

In Table 2 it has been demonstrated that using the flattened layer yields the best accuracy. Furthermore, pooling methods like global maximum and average do not offer better performance. While global average pooling and global maximum works 95.19% and 95.22% precision, accordingly, flattening the layer yields 96.13% accuracy.

Table 2. Altering flatten layers

Case study 01				
Configuration no.	Flatten layer types	Epochs × training times (s)	Test accuracy (%)	Findings
1	**Flatten**	**97×5**	**96.13**	**Maximum accuracy**
2	Global max pooling	61×4	95.22	Modest accuracy
3	Global average pooling	67×5	95.19	Modest accuracy

3.3.2. Case study 2: changing the batch size

Table 3 shows the results of a case study on the effect of batch size on the test accuracy of a machine learning model. The table presents four configurations with different batch sizes, epochs, training times, and test accuracies. Configuration no. 2, provides the maximum accuracy of 96.93%, where the batch size is 32 and the model is trained for 43 epochs with a training time of 4 seconds. The table suggests that choosing the optimal batch size is crucial for achieving the highest accuracy.

Table 3. Altering the batch size

Case study 02				
Configuration no.	Batch size	Epochs × training times (s)	Test accuracy (%)	Finding
1	16	97×5	96.13	Modest accuracy
2	**32**	**43×4**	**96.93**	**Highest accuracy**
3	64	82×5	93.92	Modest accuracy
4	128	27×5	93.45	Modest accuracy

3.2.3. Case study 3: changing learning rate

Table 4 illustrates the results using different learning rates on increasing the model’s accuracy. The highest accuracy of 99.21% is achieved in configuration no. 2, where the model is trained with a learning rate of 0.001 for 97 epochs with a training time of 5 seconds. In this case, a learning rate of 0.001 resulted in the highest accuracy, while other learning rates resulted in accuracy drops or improvement.

Table 4. Altering learning rates

Case study 03				
Configuration no.	Learning rates	Epochs × training times (s)	Test accuracy (%)	Findings
1	0.01	92×55	98.41	Accuracy dropped
2	**0.001**	**97×5**	**99.21**	**Highest accuracy**
3	0.0001	68×57	98.32	Accuracy improved

3.2.4. Case study 4: changing the loss function

The findings of a case study on the impact of various loss functions on a transfer learning model's test accuracy are presented in Table 5. The table presents five configurations with different loss functions, epochs, training times, and test accuracies. The highest test accuracy of 96.93% is achieved in configuration no. 2, where the model is trained with the categorical cross-entropy loss function for 97 epochs with a training time of 5 seconds. In this case, the categorical cross-entropy loss function obtained the highest performance, while other loss functions resulted in accuracy drops or errors.

Table 5. Altering the loss function

Configuration no.	Loss functions	Epochs × training times (s)	Test accuracy (%)	Findings
Case study 04				
1	Binary crossentropys	Error	Error	Error
2	**Categorical crossentropys**	**97×5**	**96.93**	**Maximum accuracy**
3	Mean squared errors	97×5	96.79	Modest accuracy
4	Mean absolute errors	49×4	69.46	Low accuracy
5	Mean squared logarithmic error	46×5	97.78	Modest accuracy

3.2.5. Case study 5: changing optimizers

Table 6 presents the results of utilizing different optimizers on the test accuracy of the VGG-16 model. The Adam optimizer achieved the highest accuracy of 98.41% in configuration no. 1, where the model is trained for 97 epochs with a training time of 5 seconds. In this case, the Adam optimizer outperformed the other optimizers, including Nadam, SGD, and Adamax, which resulted in accuracy drops.

Table 6. Altering optimizers

Configuration no.	Optimizers	Epochs × training times (s)	Test accuracy (%)	Findings
Case study 05				
1	**Adam**	**97×5**	**98.41**	**Maximum accuracy**
2	Nadam	44×5	96.93	Previous dropped
3	SGD	89×5	86.22	Modest accuracy
4	Adamax	75×5	91.59	Modest accuracy

3.3. Performance analysis of best model

The finely tuned VGG-16 model after ablation study was performed achieved a test accuracy of 99.21%. 224×224-pixel images were used while model training, utilizing the optimizer Adam with a batch size of 32 and a learn rate of 0.001 for 90 epochs. The model utilized softmax activation function, and a dropout rate of 0.5, along with a momentum of 0.9. The table suggests that the configuration of the model, including the choice of optimizer, activation function, dropout rate, and other hyperparameters, can significantly affect how accurate the model is.

3.4. Performance analysis and statistical analysis

Table 7 presents statistics and performance evaluation of a machine learning model. The model had a 99.21% accuracy rate. Other evaluation metrics such as false negative rate (FNR), false positive rate (FPR), false discovery rate (FDR), Matthew's correlation coefficient (MCC), and Kappa coefficient (KC) are also provided. The precision, recall, specificity, and F1 score of the model are also shown in the table. The values in the table indicate that the model has high accuracy and performs well on most evaluation metrics

Table 7. Performance evaluation

Accuracy	FPR (%)	FDR (%)	FNR (%)	KC (%)	MCC (%)	Precession	Recall	Specifity	F1 score
99.21	1.55	2.56	2.41	99.04	2.23	97.65	89.108	96.124	96.89

4. CONCLUSION

Substantial, annotated training datasets are required for deep learning systems used in medical imaging to identify tumors. A radiology subspecialty often involves manually annotating images. The advancement of AI in healthcare imaging is hampered by prohibitively expensive charges. Expertise and time are also valuable as the AI field tends to develop very fast. In order to build a competitive classification system with low annotation expense, transfer learning techniques have now been created. Models can recognize and categorize new data using the knowledge they have gathered from large datasets thanks to the transfer learning technique. Using a transfer learning model, this study proposes a system for categorizing brain tumor MRI images more accurately, thereby reducing death rates. In this experimentation, artefacts, and noise are removed from the image using various preprocessing techniques. We experimented with five transfer learning models using the brain tumor MRI dataset. The proposed model attained the best accuracy since the hyperparameters were tuned properly. In the near future, the efficacy of the suggested model can be evaluated using real-time medical data with expanded quantities of unprocessed medical photos. However, this research's suggested model accurately categorizes the four kinds of brain tumors in most tests. Despite a few minor drawbacks, it is possible to guarantee that the proposed well-tuned VGG16 model is precise and enhanced across all diagnosis areas.

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