An Improved Transfer Learning-Based Model with Data Augmentation for Brain Tumor Detection

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Abstract—Current advances in deep learning have brought various breakthroughs in processing medical data. However, dealing with a limited number of medical datasets remains a challenge in deep learning and often leads to overfitting. To solve this research gap, here we show a new approach to improve the performance of a transfer learning-based model for brain tumor detection from 253 brain magnetic resonance imaging (MRI) sample images. The concept of transfer learning has been applied using a pre-trained InceptionV3 combined with data augmentation. Modified layers using dropout and regularization have been additionally utilized to deal with overfitting. The proposed method shows an increase in accuracy of 6.430%, a precision of 5.531%, a recall of 10.545%, and an F1-score of 8.040% compared to the baseline method. We show that our proposed method has been able to effectively enhance performance and reduce overfitting, even with a small number of datasets. Moreover, our proposed method outperforms state-of-the-art brain tumor detection.

Keywords—*Brain tumor detection, data augmentation, dropout, inceptionV3, regularization, transfer learning.*

I. Introduction

The advances in deep learning are anticipated to be utilized in the healthcare sector. With the advent of deep learning concepts, recent advances in computer-aided medical diagnosis have resulted in improved performance. In particular, convolutional neural networks (CNNs) are commonly utilized for analyzing medical images in brain tumor research [1]–[3].

The classification of brain tumors is an essential task in computer-aided diagnosis for medical purposes. However, there has been a limitation in constructing a computer-aided medical diagnosis employing CNN. The CNN model should be trained on a large dataset, including several possible variations, to obtain more accurate predictions. Several CNN architectures have been developed to handle a wide range of classes. Nevertheless, these designs are robust on large datasets but overfit on smaller ones [4].

Dealing with small numbers of medical datasets is the main problem. We have previously observed that obtaining numerous labeled medical images appropriate for machine learning-based disease detection has been challenging [5]–[7]. On the other hand, using pre-trained CNN models on large datasets, such as ImageNet, is conceivable [8]. A mixture of pre-trained CNN features can be utilized to improve computer-aided diagnostic performance.

Some researchers have implemented the concept of a transfer learning-based model, which transfers the features and weights from a pre-trained model to a new model with less training data. A transfer learning-based MobileNetV2 has been utilized to detect brain tumors from magnetic resonance imaging (MRI) scans [9]. The results showed an accuracy of 0.855, a precision of 0.764, a recall of 0.500, and an F1-score of 0.604. However, the study did not utilize data augmentation to expand the training data. As a result, there was a significant gap between the training accuracy and the validation accuracy.

The ResNet-50 model has been utilized to automate the detection and classification of brain tumors on MRI scans [10]. The lack of datasets for imaging brain tumors has been explained through the joining and processing of datasets from multiple sources. The image underwent noise removal, cropping, and extraction for tumor recognition. The proposed approach showed an accuracy of 0.800, a precision of 0.800, a recall of 0.800, and an F1-score of 0.800. Despite conducting data preprocessing, the performance results remained low.

A method for distinguishing brain tumors in MRI images has been proposed using ResNet-50 and VGG-16 [11]. The proposed approach using ResNet-50 showed an accuracy of 0.950 and an F1-score of 0.952 while using VGG-16 showed an accuracy of 0.900 and an F1-score of 0.909. Nevertheless, the gap between the training and validation accuracy curves indicated that the results were overfitting. Despite its simple architecture, VGG-16 has a high computational cost for network evaluation [12].

Since Inception has a substantially lower computational cost than VGG or its superior predecessors [13], in this study we apply an InceptionV3 transfer learning-based model for detecting brain tumors. The advantage of InceptionV3 is often used to apply knowledge gained from generic tasks to specific domains with limited labeled data.

This study aims to enhance the model performance of InceptionV3 architecture and reduce overfitting. Data augmentation

and modified layers using regularization and dropout are additionally utilized. We then conduct a comprehensive evaluation and validate our results with state-of-the-art methods. The paper outlines the main contributions as follows: The proposed method exhibits outperforming performance when compared to other state-of-the-art methods on the same dataset. It also delivers good performance even with a smaller number of training datasets. Additionally, this study explores the indication of overfitting that occurs when training data is limited and how it impacts classification performance.

II. Materials and Methods

A. Dataset Description

In this paper, we used a public dataset of brain MRI images obtained from the Kaggle website [14] for brain tumor detection. This is due to MRI providing higher soft tissue contrast in brain imaging compared to computed tomography (CT) [15]. The dataset consists of 253 MRI images, containing 155 samples of brain tumors and 98 samples of normal brain. The samples of brain tumors are set to class "Yes," while the samples of the normal brain are set to class "No". The sample of the tumor is marked within the red rectangle. The samples of brain MRI images for each class are presented in Fig. 1.

B. Data Augmentation

Data augmentation is the method for creating additional training data by generating modified versions of the original image data [16]. This study utilizes data augmentation techniques to decrease overfitting and enhance model generalization. The diversity of a dataset is increased by applying various transformations to the original samples so that the model does not encounter the same samples again during training. It is a useful technique for deep learning models with fewer image datasets. The data augmentation used in this study includes rescaling, rotating, shifting, shearing, zooming, and flipping [3].

C. Transfer Learning with InceptionV3 Architecture

Transfer learning can be particularly effective when a large and diverse dataset is lacking. In this case, a model trained from scratch would most likely remember the training data rapidly but would struggle to generalize to new data. Transfer

Fig. 1. The samples of brain MRI images for different classes.

learning is used to enhance the likelihood of training an accurate and robust model on a small dataset.

InceptionV3 is a pre-trained model on the ImageNet dataset, comprising 14 million images with 1000 distinct classes [12]. This allows us to leverage the transfer learning capabilities of InceptionV3, which is particularly beneficial when working with limited data resources. The architecture of InceptionV3 enables a deeper network, comprising a stack of interconnected inception modules. Each inception module includes a convolutional layer, activation layer, batch normalization layer, and pooling layer, which are meant to extract various information from the input image [17]. The output of each layer is integrated into a single output sequence as the input for the subsequent sections to further integrate the results and pass across the network. The proposed method of pre-trained InceptionV3 is given in Fig. 2 [18].

D. Flatten and Dense Layer

Flatten is utilized for the multidimensional output of one layer and flattens it into a one-dimensional array. The resulting feature vector will be connected to the final classification layer. The dense layers take the feature vector as input and learn which features will contribute to a specific classification. The features extracted from the fully connected layer are passed to the classifier to generate our prediction.

E. Dropout and Regularization

Dropout is an approach in neural networks to deal with overfitting during training since neighboring neurons often end up with similar weights. This approach has been discussed as a well-known regularization to increase neural network performance in various application domains, such as image classification, machine translation, and image segmentation [16]. This approach was primarily used for fully connected models, in which all neurons in one layer are linked to all neurons in the following layer.

Dropout is useful when it comes to regularizing neural networks by adding noise to hidden units. L1 and L2 regularization are two techniques used to prevent overfitting. L1 regularization constrains the sum of the absolute values of the weights, meanwhile, L2 regularization constrains the sum of the squares of the weights [19]. Both techniques encourage the model to train smaller weight values, which can help prevent overfitting. This study utilizes L2 regularization for its ability to handle multicollinearity well and provide smoother solutions.

F. The Proposed Method

The proposed method's framework is illustrated in Fig. 3 with three scenarios to compare the results, i.e., scenario 1, scenario 2, and scenario 3, as described in Table. I. The medical images should be prepared to match the structure and shape of the color images utilized for training the network. Medical images typically have one grayscale channel. Then, the grayscale images are stacked together to create 3-channel pseudo-color images with dimensions of (224, 224, 3), which
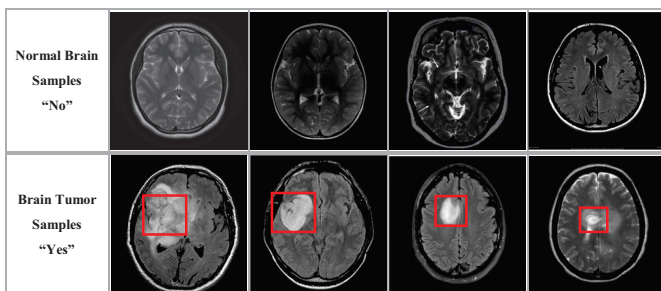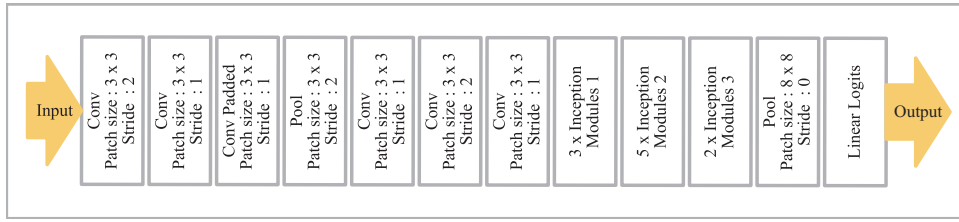
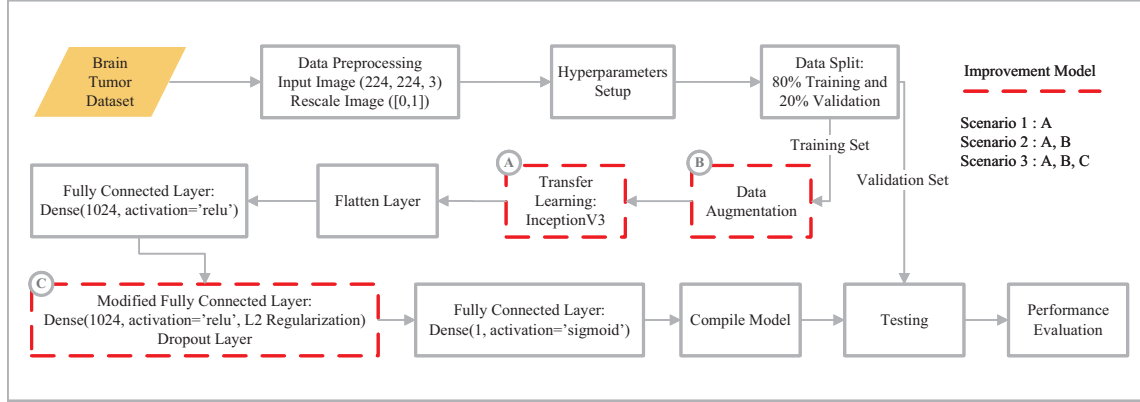Fig. 2.   InceptionV3 architecture block.

Fig. 3.   The framework of the proposed method.

imitate the RGB natural image structure. It has been additionally found that color is not a significant feature for image classification [20].

The image is represented by a three-dimensional array of pixel values, each indicating intensity on a scale of $[0, 255]$. Deep learning models perform better when dealing with floating-point values in the range of $[0, 1]$. To normalize these numbers into the range of $[0, 1]$, the image is rescaled by dividing all the pixel values by 255.

The image data are split into 80% for training and 20% for validation based on the Pareto principle. The Keras library provides the ImageDataGenerator class that simplifies the implementation of image data preprocessing and augmentation [21]. In this study, ImageDataGenerator is used for data rescaling and splitting. Data augmentation is additionally performed by the ImageDataGenerator with the specified settings. The data augmentation is only utilized for the training set. The images are then processed in the InceptionV3 architecture and the convolution operation is performed.

The output of the last InceptionV3 layer is connected to a flattened layer that turns a three-dimensional tensor into a one-dimensional vector. To introduce nonlinearity, the output

TABLE I
THE SCENARIO OF THE PROPOSED METHOD

Scenario	Method
Scenario 1	Transfer learning InceptionV3 baseline (stand-alone)
Scenario 2	Transfer learning InceptionV3 with data augmentation
Scenario 3	Transfer learning InceptionV3 with data augmentation and modified layers using regularization and dropout

of each channel is then processed by a Rectified Linear Unit (ReLU) function. The ReLU activation function solves the gradient vanishing problem in backpropagation [22].

The layer is then connected to a dense layer with 1024 neurons. A modified layer using the L2 regularization of 0.01 was added to the dense layers of the model. Dropout was additionally applied to randomly select a subset of neurons and remove them to hinder overfitting. A dropout of 20% was utilized before the final classification layer. Since the class is binary, the final layer has a size of 1 and utilizes the sigmoid activation function to predict the classes. The model is then compiled with the binary cross-entropy loss function. The performance evaluations are done based on the metrics of accuracy, precision, recall, and F1-score [22].

III. RESULT AND DISCUSSION

A. Experimental Setup

The proposed method was run with TensorFlow and Keras in Python. The implementation was carried out on the Tesla T4 GPU, which is available in the Google Colab environment. We selected the loss function of binary cross-entropy for binary class models and the Adam optimizer with a learning rate of 0.001 to update the weights during training [22]. Testing was done in 50 epochs with a batch size of 20.

B. Evaluation of Transfer Learning Baseline

We performed experiments on scenario 1 as a baseline. Fig. 4 presents the training and validation accuracy of the stand-alone transfer learning model. The findings indicate that validation accuracy continues to lag behind training accuracy.
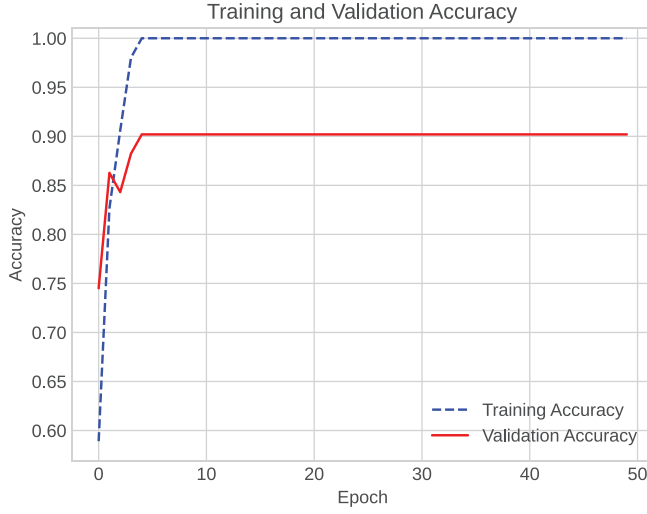
Fig. 4. Training and validation accuracy of the baseline transfer learning model (scenario 1).

This behavior indicates overfitting occurred, causing a gap between the training and validation curve. The model learned specific training images but lacked generalization capability. When tested against the validation dataset, the model is confused by the unseen data. This means that the model complexity is higher than the available training data. Fig. 5 indicates that the model tends to be biased after 5 epochs. Scenario 1 gives an accuracy of 0.902, a precision of 0.904, a recall of 0.863, an F1-score of 0.883, and a loss of 0.261. Nevertheless, overfitting can be prevented by stopping training early or using data augmentation.
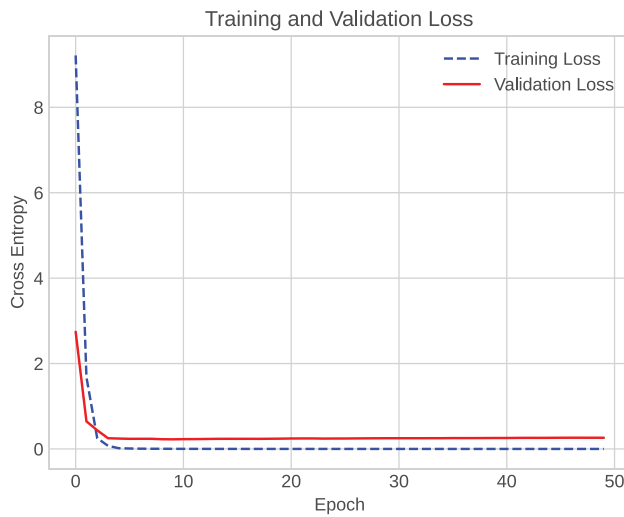

Fig. 5. Training and validation loss of the baseline transfer learning model (scenario 1).

TABLE II
DATA AUGMENTATION TRANSFORMATION

Transformation	Description	Value
Rotation range	Random rotation within a specified degree	$[-20°, +20°]$
Width shift range	Shift the pixels of an image along the horizontal axis.	10%
Height shift range	Shift the pixels of an image along the vertical axis.	10%
Shear range	Skewing images along a particular axis	10%
Zoom range	Altering the scale of an image by zooming in or out	10%
Horizontal flip	Horizontally mirrors an images	True

C. Evaluation of Transfer Learning with Data Augmentation

We have increased the number and variance of our dataset with data augmentation to teach the model to be more robust to new data. We set the generated number of augmented samples to 200. The applied data transformations are described in Table. II, while the augmented data samples are given in Fig. 6 (the tumor is marked within the red rectangle). Fig. 7 presents the training and validation accuracy, while Fig. 8 presents the training and validation loss of the transfer learning with data augmentation according to scenario 2. The increased size provides the model with more images from which to learn while training. The increased variance allows the model to ignore unimportant features and select only those that are truly important in classification, allowing it to generalize more effectively. The accuracy is increased from 0.902 to 0.941 in scenario 2. Similarly, precision, recall, and F1-score are increased from 0.904 to 0.913, 0.863 to 0.954, and 0.883 to 0.933, respectively. The loss decreased from 0.261 to 0.203.

D. Evaluation of Improved Transfer Learning Model with Data Augmentation

Our model architecture is enhanced with the inclusion of regularization and dropout, which helps improve its generalization capabilities. Regularization techniques control model complexity caused by the limited dataset provided, while dropout promotes diversity in feature learning and reduces co-adaptation among neurons. By combining these techniques, we have created a more robust and generalized model that can handle variations in the data.
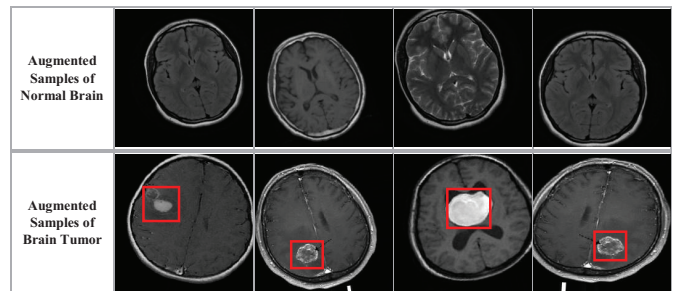

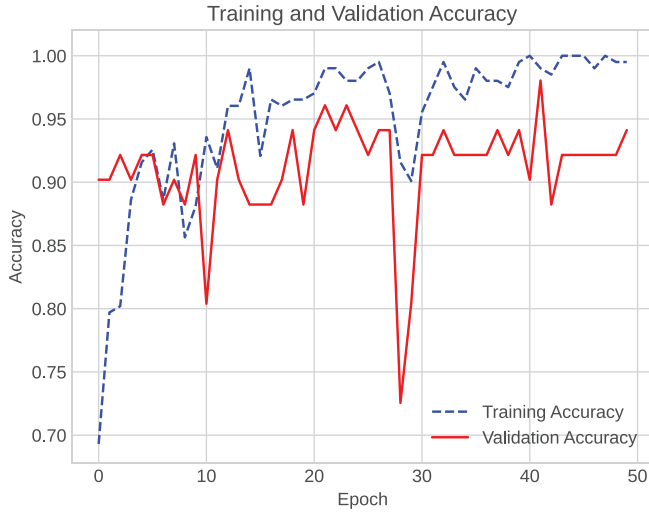Fig. 6. The augmented data samples of normal brain and brain tumor.

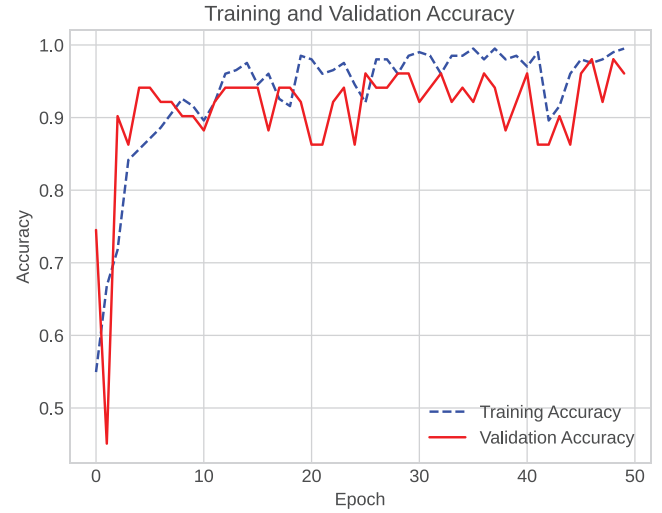Fig. 7. Training and validation accuracy of the transfer learning with data augmentation (scenario 2).

Fig. 9. Training and validation accuracy of the improved transfer learning model (scenario 3).

Fig. 9 presents the training and validation accuracy, while Fig. 10 presents the training and validation loss of the improved transfer learning model according to scenario 3. The results give an accuracy of 0.960, a precision of 0.954, a recall of 0.954, an F1-score of 0.954, and a loss of 0.490. This improved model shows an increase in accuracy of 6.430%, a precision of 5.531%, a recall of 10.545%, and an F1-score of 8.040% compared to the baseline method. Scenario 3 outperforms all scenarios in terms of accuracy, precision, recall, and F1-score, as shown in Table. III which is written in bold.

E. Validation with State-of-the-Art Methods

To validate our results, we compared the performance of our proposed method in scenario 3 with all state-of-the-art methods on a binary class brain tumor classification problem. To make them comparable, benchmarking has been done with different methods on the related works using the same brain tumor dataset [14]. A more detailed comparison is provided in Table. IV, in which the best performances are written in bold. The results show that our proposed method outperforms all other methods for brain tumor detection.
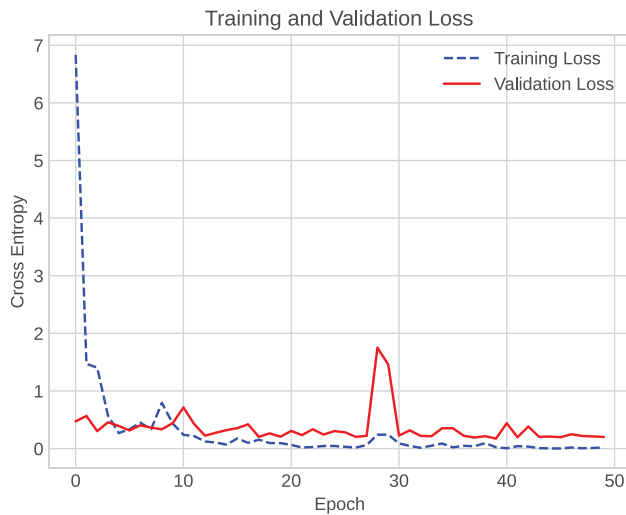

Fig. 8. Training and validation loss of the transfer learning with data augmentation (scenario 2).
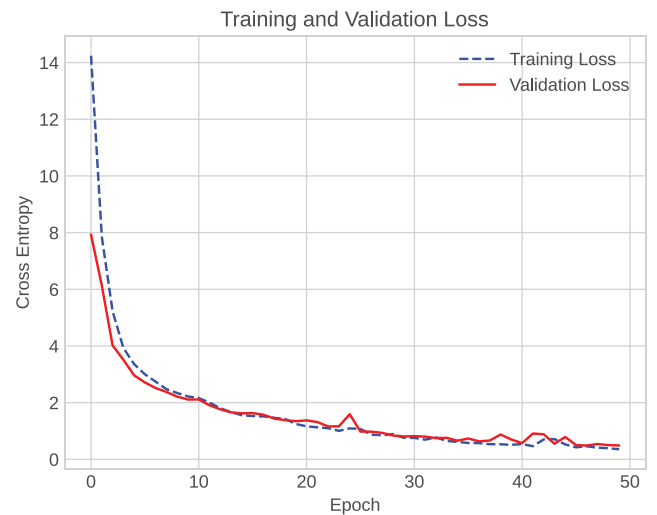

Fig. 10. Training and validation loss of the improved transfer learning model (scenario 3).

TABLE III
RESULTS COMPARISON OF OUR SCENARIOS

Method	Accuracy	Precision	Recall	F1-score
Scenario 1	0.902	0.904	0.863	0.883
Scenario 2	0.941	0.913	**0.954**	0.933
Scenario 3	**0.960**	**0.954**	**0.954**	**0.954**

TABLE IV
PERFORMANCES EVALUATION ON BRAIN TUMOR DETECTION

Method	Accuracy	Precision	Recall	F1-score
CNN [2]	0.932	-	-	0.929
MobileNetV2 [9]	0.855	0.764	0.500	0.604
ResNet-50 [11]	0.950	-	-	0.952
VGG-16 [11]	0.900	-	-	0.909
Proposed Method (Scenario 3)	**0.960**	**0.954**	**0.954**	**0.954**

IV. CONCLUSION

An improved method for detecting brain tumors has been shown using a transfer learning-based InceptionV3 model. The use of InceptionV3 is due to its low computational cost compared to its superior predecessors. This study has been working with a small number of brain tumor datasets that lead to suboptimal results due to overfitting. Data augmentation has been implemented to generate more training samples by transforming the original samples. As a result, the variation of a dataset improves model generalization. We improve the model by applying dropout and regularization to deal with overfitting during training. We set three scenarios to compare our results by measuring accuracy, precision, recall, and F1-score. The results demonstrate that data augmentation succeeds in improving the model's performance. Furthermore, the use of data augmentation combined with dropout and regularization has improved the InceptionV3 model's performance. To validate our proposed method, we have additionally compared our results to those of state-of-the-art methods using the same dataset. We have shown that our proposed method outperforms state-of-the-art brain tumor detection with high-performance results, even with a small number of datasets. Future improvement remains possible using fine-tuning the transfer-learned model with multi-class classification.

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