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Deep Feature Extraction for Brain Tumor Identification Based on Deep Convolutional Neural Network

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ABSTRACT

The presence of a brain tumor can cause an increase in pressure inside the skull, which can lead to brain injury or even death. To diagnose a brain tumor, various techniques such as computerized tomography, magnetic resonance imaging (MRI), positron emission tomography , as well as blood and urine tests are used. However, these methods can be time-consuming and may sometimes provide inaccurate results. In order to overcome these limitations, deep learning models have been implemented. These models are less time-consuming, require less sophisticated equipment, provide more accurate results, and are easier to implement. This research paper proposes a deep transfer learning-based model that utilizes a pretrained VGG 16 model. The model has been modified by incorporating transfer learning and deep feature extraction along with data augmentation. The proposed model achieved an accuracy of 99% and a precision of 98.73%. The results indicate that the proposed model outperforms other state-of-the-art models.

Keyword: Convolutional Neural Network; VGG-16; Transfer Learning; MRI, Brain Tumor; Deep Learning;

1. Introduction

The growth of abnormal cells in the human nervous system leads to the development of a life-threatening neurological disorder known as a brain tumor (Wiestler et al., 2023). Over the past two decades, there has been a steady increase in the incidence of brain tumors across all age groups. Recent predictions indicate that brain tumors are now the third most common type of cancer, particularly affecting adults and teenagers(Zhu et al., 2023). According to the International Agency for Research on Cancer (IARC), more than 136,000 individuals worldwide are diagnosed with brain tumors each year, resulting in over 87,000 deaths in 2017(Srinivas et al., 2022). Despite the efforts of medical professionals to combat the complexities of brain tumors, the World Health Organization (WHO) estimates that approximately 251,329 people succumb to cancerous brain diseases annually (Anilkumar & Kumar, 2019). Therefore, accurate diagnosis of brain tumors is crucial for patient survival and the delivery of effective medical interventions (Saba, 2020)(Chahal et al., 2020). When analyzing brain image data, various image modalities are utilized, such as Magnetic Resonance Imaging (MRI) (El-Dahshan et al., 2014), Single Photon Emission Computer Tomography (SPECT), BIOPSY scan, and computer tomography (CT) (Aggarwal et al., 2021). Among these, MRI is the most commonly employed imaging techniques for brain scans. (Kalam et al., 2023). This medical imaging technique employs a strong magnet, magnetic field gradients, and computer-generated radio waves to capture and exhibit internal organ images in the human body. The analysis of MRI medical images by radiologists is a time-intensive process, and their decision-making efficiency reflects their expertise in the medical domain (Wiestler et al., 2023). Therefore, a computerized brain tumor classification system aids radiologists in their analysis and significantly reduces their workload.

There are two main methods for detecting brain tumors: those based on traditional machine learning (ML) (Tandel et al., 2019) and those based on deep learning (DL) (Masood et al., 2021). Traditional ML-based methods generally rely on handcrafted features. Here, the term "hand-crafted features" refers to features that must be retrieved from training data in order to begin the learning process. In this case to select the most crucial features, an expert with vast experience may be needed. As a result, the quality and representation are key factors in determining how accurately ML-based algorithms discover data. DL-based algorithms, on the other hand, have demonstrated excellent performance in several fields, including medical imaging (Masood et al., 2021). These benefits have caused researchers to pay attention to DL-based brain tumor classification (Mzoughi et al., 2020)(Falah et al., 2022). CNN is the most popular deep learning models (Zakir Hossain et al., 2019), which, because of its weight-sharing structure, can naturally learn salient features from the training data. However, it takes a lot of images to train a CNN model because of the large number of parameters to learn. Additionally, conventional CNNs are prone to overfitting, especially when working with smaller datasets. Recently, several sophisticated CNN variations with deeper structures have been developed for image identification, outperforming the traditional CNN models in terms of performance.

Particularly, the VGG 16 has recently been shown to be effective in computer vision and its extraordinarily deep representations have made it the benchmark for many significant image classification algorithms (Bhanothu et al., 2020). In light of this, this study proposes a strategy based on VGG 16 for further increasing the classification accuracy of MRI for brain tumor detection. The proposed model which utilizes deep transfer learning, deep feature extraction mechanism along enhanced data augmentation for better classification. The major contributions of the proposed model are as follows:

- We developed an enhanced data augmentation approach alongside preprocessing techniques that apply various strategies to MRI images for improved classification accuracy.
- We proposed an improved CNN model based on the VGG-16 architecture, leveraging transfer learning and deep feature extraction to optimize MRI classification.
- We conducted extensive experiments, including ablation studies, using public datasets to evaluate the performance of the proposed model.

The Paper proceeded as follows: section 2 presents an overview of the proposed model, section 3 describes the experimental study of the proposed model, section 4 presents the results and discussion and finally, section 5 concludes the paper with a summary.

2. Related Work

In recent times, several deep learning based methods for categorizing brain tumors on MRI brain images have been studied. For example, Hassan Ali Khan et al. (H. A. Khan et al., 2021) introduced an automated mechanism for detecting brain tumors by employing CNN with transfer learning models on an MRI brain image dataset. The authors in (Hatami et al., 2019) analyzed the impact of MRI image data preprocessing steps and found that it enhances the accuracy of brain tumor prediction. Researchers in (Atzori et al., 2016) concentrated on developing a novel CNN-based model to classify the three different types of tumors found in brain MRI images. Toktam Hatami et al. (Hatami et al., 2019) explored the utilization of a pretrained CNN model combined with image segmentation techniques. A study in reference (Rajinikanth et al., 2020) proposed the use of a pretrained VGG-16 CNN model for the classification of brain tumors with multiple grades.

Muhammed Talo and his colleagues introduced the CNN architecture, AlexNet (Talo et al., 2019) to achieve favorable outcomes in various visual recognition tasks. One major challenge in the advancement of deep neural networks in the medical field was the limited availability of labeled image datasets. However, this obstacle was overcome by employing a data augmentation approach, which increased the volume of data from existing labeled image datasets and improved the accuracy rate (Shorten & Khoshgoftaar, 2019).

CNN-based transfer learning models have demonstrated exceptional performance in the medical healthcare domain, as they possess the ability to learn features autonomously without the need for human expertise (Chougrad et al., 2020)(Nemade et al., 2022) . The utilization of weight sharing further enhances the network's robustness, enabling automatic prediction or detection of diseases through MRI brain images. Today, medical scientists have access to publicly available brain MRI image datasets(Byale et al., 2018), which has greatly facilitated the development of new automated classification models for prediction or detection purposes in medical applications. The authors in (Vijayakumar & Chaturvedi, 2013)have developed a computer-aided diagnosis (CAD) system that automatically detects brain tumors in brain MRI images. Their proposed model utilizes the sequential minimal optimization (SMO) algorithm to train a Support Vector Machine (SVM) for classifying malignant tumors such as glioblastoma, sarcoma, or metastatic bronchogenic carcinoma. Kebir et al. (Kebir & Mekaoui, 2018) developed an automated and supervised method for detecting MRI brain abnormalities. The primary objective of this study is to utilize a deep transfer learning approach for brain tumor detection.

3. Methodology

This section presents an overview of the proposed deep feature extraction model which used deep convolutional neural network based on the VGG 16 model utilizing transfer learning for brain tumor classification in MRI. The framework of the proposed system contains three main phases: 1) preprocessing and data Augmentation. 2) Model Construction, and 3) Classification. Detail of the model process is illustrated in Figure 1.

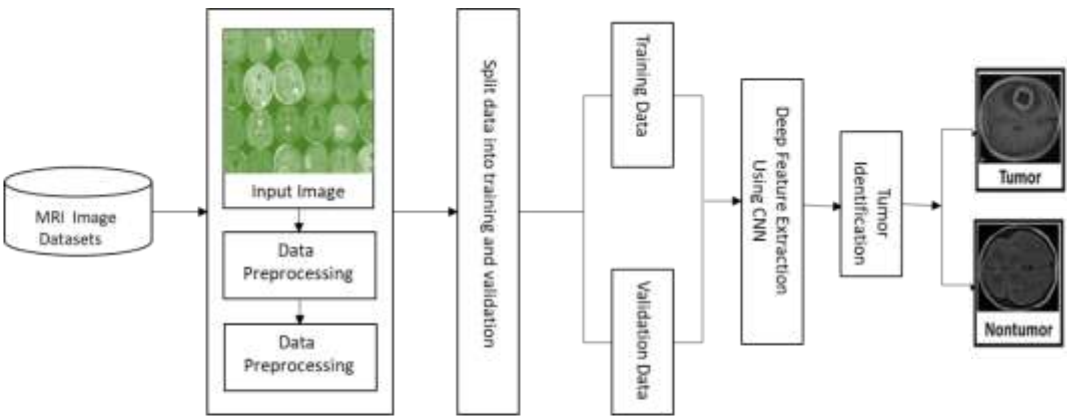

Figure 1: framework of the proposed model.

First, using the contrast stretching approach, MRI images are improved at the initial stage. The vast amount of data for the CNN architecture is generated via data augmentation techniques which include rotation and flipping. This also helps to prevent over-fitting. Next, the pre-trained CNN architecture using the ImageNet dataset (Fox et al., 2015) was used on a target brain tumor dataset to extract distinguishing visual features from MRI images. Finally, automated features are classified for tumor detection. The basic steps of the suggested method are further explained as follows:

3.1 Dataset Preprocessing and augmentation

The dataset obtained in this study comprises a set of brain MRI scan images. There are approximately 256 raw MRI images with varying dimensions, typically measured in pixel values. The MRI brain images used in this study are sourced from the Kaggle dataset and are in JPEG format. The image database is divided into two categories, Yes and No, based on the presence of a tumor in the MRI brain image. There are approximately 158 benign tumor images and 98 malignant tumor images. For our research, the dataset is divided into three segments for training, testing, and validation purposes.

3.1.1 Datasets Preprocessing

Preprocessing is the step of cleansing the data that prepares the input data for further processing (M. Khan et al., 2022). Cleaning up MRI and boosting contrast are the main goals of medical imaging analysis. Dealing with thermal noise, magnetic field artifacts, and tiny patient motions during the scanning procedure is one of the biggest challenges in MRI analysis. The MRI scan intensities may differ greatly because the MRI scans may be gathered from several sources (Falah et al., 2022). Therefore, to lessen the inhomogeneity of intensity, the intensity normalization (Elbashir et al., 2019)method based on a linear transformation is applied. Our preprocessing in this work comprises the three main processes: first the intensity normalization is applied to the entire MRI image set, and then a technique for MRI contrast enhancement that was previously developed is used. Finally, in order to optimize memory usage, the input MR pictures is downsized.

Data Augmentation

Data augmentation in computer vision could be viewed as a crucial element that is very successful in deep learning method training (Wei & Zou, 2019). The literature (Shorten & Khoshgoftaar, 2019)has suggested several data augmentation techniques for deep learning in medical imaging, including random cropping, rotation, shears, and flipping. Recent research (Wei & Zou, 2019) demonstrates that some augmentation techniques could more accurately capture medical picture aspects than others. In this research, to enhance the training dataset and give CNNs a vast input space, several data augmentation techniques have been used which include flipping and rotation. Rotation is one of the fundamental data augmentation techniques, in which the input images are rotated by different amounts, such as 90, 180, and 270 degrees. Another common technique is flipping, which mirrors an image both vertically and horizontally. The finalized images of data augmentation are displayed in Figure 2.

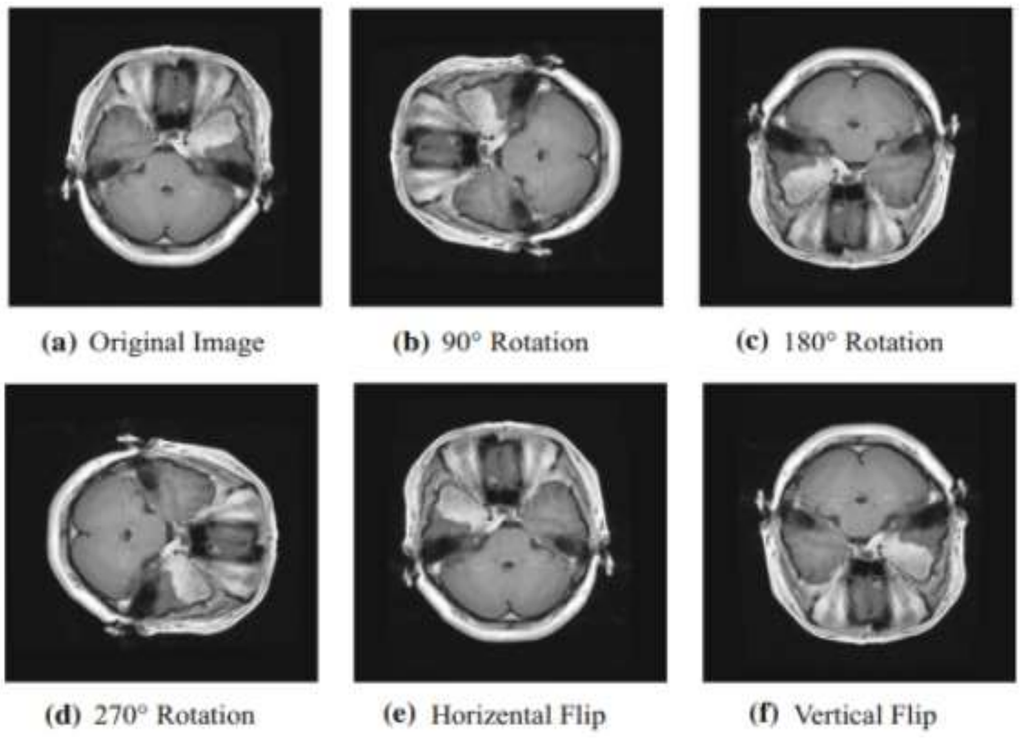

Figure 2: Example of Data augmentation on MRI

3.2 Model Construction

In this section we present the model construction process of the proposed deep feature extraction that use deep CNN model for the brain tumor identification. Following data augmentation, a large number of image samples are produced for the training set, from which the next step is the extraction of visual and discriminative features to reflect their qualities. Since deep learning has been so successful in computer vision, CNN models have been employed to extract features. Many efficient contemporary advanced CNN versions have been introduced recently, including VGGNet (Kumar et al., 2020), AlexNet (Rehman et al., 2019), GooLeNet (Binder et al., 2016), etc. These networks displayed outstanding results in the field of large-scale image classification. Because of its extraordinarily deep representations, such as those used for ImageNet classification and object identification tasks, the VGG 16 model recently succeeded on several image classification tasks(Bharati et al., 2020). Therefore, based on this inspiration, in this study an improved CNN-based VGG 16 model was proposed for the image classifcation. In contrast to the original VGG 16, the proposed model uses a transfer learning strategy in which a deep feature extraction strategy is used to enhanced the network structure. The detail of the model transfer learning and the deep feature extraction strategy is provided in the following subsection:

3.2.1 Deep Transfer Learning

Transfer learning is a method that leverages existing knowledge to enhance problem-solving in new domains. This learning approach can be applied to two similar tasks, even if one has limited data available. The CNN model introduced in this study is structured based on the VGG16 network, consisting of 13 convolution layers and millions of parameters. Adequate training images are essential to develop an efficient multi-label classification model. However, gathering and annotating a large-scale multi-label dataset can be challenging. Fortunately, the ImageNet dataset, which is a large single-label image dataset, can be utilized for pre-training the shared CNN to initialize parameters. Through parameter transfer, the pre-trained parameters from ImageNet are directly integrated into our model, excluding the last fully-connected layer due to differing category numbers between the datasets. Fine-tuning is then conducted based on the pre-trained ImageNet parameters to adjust the model's parameters. This process involves using the parameters from the single-label image training model to further train the multi-label image, resulting in reduced training time and promising outcomes.

3.2.2 Deep Feature extraction

For CNNs, distinct depth features correspond to different semantic levels (Mzoughi et al., 2020). Generally, deep networks extract features with more high-level semantic information, while shallow networks focus on more detailed features (Bakator & Radosav, 2018). As the network depth increases, the feature map becomes increasingly abstract, leading to a reduction in the amount of information contained in the features and subsequently impacting the detection accuracy. The traditional approach to address this issue involves using image pyramids or multi-scale training (Chen et al., 2022). However, this method is computationally demanding and is utilized by most current techniques that have shown promising results in classification. Therefore, enhancing the recognition accuracy by refining the network structure presents a new challenge.

The conventional VGG16 model features a single pathway for extracting features, leading to inadequate recognition capabilities due to underutilization of features before Conv5 (Kumar et al., 2020). This deficiency is attributed to the pooling layer filtering out a significant portion of information. To enhance the recognition accuracy by fully leveraging multi-layer convolution features, we have integrated pooled features into subsequent convolution layers, enabling direct transmission of feature maps learned by the preceding layer.. Our concat layer merges the feature map along the channel dimension rather than the num dimension, maintaining the same number of outputs from the concat layer. Following the concat layer, feature maps of identical sizes exhibit a richer array of feature representations. Batch normalization and scaling have been incorporated between each pooling layer and its subsequent convolution layer. This adjustment accelerates training speed and enhances classification effectiveness, as demonstrated in. By implementing minor alterations in network connections, the model's ability to classify images has been enhanced without significantly increasing computational load.

3.3 Classification and Loss Function

As the useful and important visual features and patterns are extracted successfully using transfer learning techniques, then classification on target dataset is performed. Accuracy and loss both have an impact on DL model performance (Di Ieva et al., 2021). The main goal of a DL model is to achieve the lowest rate of mistakes since a model with a less computed loss is more efficient. This study used binary cross-entropy to determine the average difference between the expected and forecasted values. Equation 1 depicts the binary classification loss measurement, where y stands for binary values of 0 or 1, and p stands for probability (Kang, 2022a).

$$\text{Cross Entropy} = -(y\log(p) + (1 - y)\log(1 - p)). \qquad (1)$$

4. Experimental Study

This section is dedicated to present the experimental study in order to justify the hyper-parameters choice and to validate the real impact of the proposed approach's main contributions. first, the datasets and the experimental results are described. Python 3.4 environment has been used to build the proposed Model using the KERAS and Tensorflow backend library. The network is trained using stochastic gradient descent (SGD) (Bottou, 2012) with a momentum of 0.9 and weight decay of 0.0005. All the fully-connected layers are initialized from zero-mean Gaussian distributions with standard deviations 0.01. To overcome overfitting, the first two fully-connected layers are followed by a drop-out operation with a drop-out ratio of 0.5 and the learning rate of `0.00001 is used.

4.1 Dataset

An open-source dataset from Kaggle was utilized in this study. The dataset is a subset of the Brats2015 brain tumor dataset. The database consists of completely anonymous images obtained from the Cancer Imaging Archive (https://www.kaggle.com/datasets/jakeshbohaju/brain-tumor). It comprises 3762 MR images, out of which 3060 were selected as a subset. Among these, 1500 images were labeled as 1 (tumors), while the remaining 1500 scans were labeled as 0 (non-tumor). To avoid class dominance, the dataset was evenly divided between the two classes, with 80% (2400) of the images allocated for training and 20% (600) for validation. Additionally, 60 images were used for testing the proposed model. To ensure the integrity of the subset selection process, any images that could potentially mislead the model during training were excluded. The image collection does not have fixed dimensions; therefore, all image samples were normalized and resized using a Keras automated resizing method, which resized all input images to 224x224 dimensions. Figure 3 shows the representative images from the MRIs used in the tumor classification.

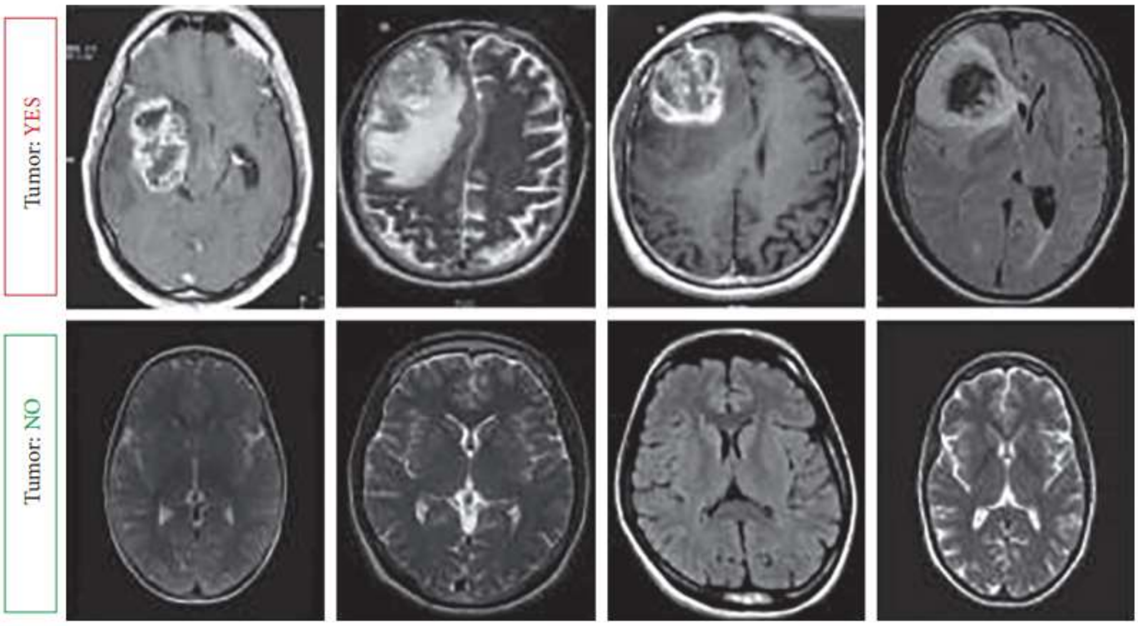

Figure 3: Representative images from the MRIs that was used in the tumor classification.

4.2 Experimental Results and Discussion

In this study to evaluate the model performance, the overall accuracy, precision, sensitivity are used. The experimental results of the proposed model are presented in this section using various evaluation metrics such as Accuracy, Precision, and Specificity.

Table 1: Comparison with Popular CNN Architectures.

Model	**Accuracy (%)**	**Precision (%)**	**Sensitivity (%)**	**Specificity (%)**
VGG16 Basic	93.23	89.56	95.03	93.42
GoogleNet	74.52	71.02	83.27	81.03
LeNet	93.23	89.56	95.03	93.42
AlexNet	92.05	88.92	92.32	93.25
VGG16 + DF + TL (Proposed)	**99.12**	**98.07**	**100**	**99.43**

The proposed model's results were compared to well-known CNN models such as ResNet, LeNet (Bouti et al., 2020), AlexNet (Krizhevsky et al., 2012), and GoogleNet (Szegedy et al., 2015). The comparison results in terms of accuracy, precision, and sensitivity are shown in Table 1. From the experimental findings, it is evident that the AlexNet model demonstrates promising results with a high level of accuracy compared to LeNet and GoogleNet. However, our proposed model outperforms AlexNet, as well as other popular architectures like ResNet, LeNet, and GoogleNet, in all cases. The renowned CNN models (LeNet, AlexNet, GoogleNet, and ResNet) often suffer from overfitting and do not perform well in brain tumor classification due to their complex architectures with a large number of layers designed for a vast number of output classes (1000 classes) with RGB input images. This highlights the advantage of our proposed model in terms of better feature extraction.

4.3 Comparison with Existing Methods

In order to further assess the credibility of the experimental findings, the proposed method was evaluated against several existing MR image classification techniques. Specifically, our model was compared with the study conducted by the authors in (Kesav & Jibukumar, 2022), which utilized a two-channel low-complexity CNN network for brain tumor detection and classification. Additionally, comparisons were made with a research by (Majib & Rahman, 2021) utilizing a VGG Net-Based approach for Brain Tumor Detection on MRI Images. Furthermore, our model was also assessed against the methods proposed in (Srinivas et al., 2022) and (Kang, 2022b), which utilized transfer learning and Fine-tuned EfficientNet, respectively, for brain tumor classification based on MRI data. The comparison results, presented in Table 2, demonstrate the superior performance of our proposed model in terms of precision, accuracy, and sensitivity when compared to the existing approaches.

Table 2: comparison results with existing approaches

MODEL	**Accuracy (%)**	**Precision (%)**	**Sensitivity (%)**	**Specificity (%)**
(Kesav & Jibukumar, 2022)	98.21	96.53	97.12	97.54
(Srinivas et al., 2022)	96	94.21	95.64	95.85
(Kang, 2022b)	98.8	97.02	98.45	98.32
Ours	**99.12**	**98.07**	**100**	**99.43**

So, from this section we could conclude that the proposed model can effectively be used for classification between Glioma and Healthy tumor.

4.4 Ablation Study

To assess the performance of the model's different components, an ablation study was also conducted. To this end, different configurations were tested and their results were compared to determine the optimal setup. These configurations include: VGG 16 basic, consisting of the basic VGG 16, model with no transfer learning and the deep feature extraction (DF) component. VGG 16 + DF, which involves the VGG 16, model with out the transfer earning but with deep feature extraction. VGG 16 +TL, utilizing active transfer learning in image fine-tuning on the MRI set without deep feature extraction. Lastly, VGG 16 + DF + TL, the default configuration of the model where both transfer learning and deep feature extraction strategy were implemented. Figure 4 (a-d) displays the comparison results of these different model settings.

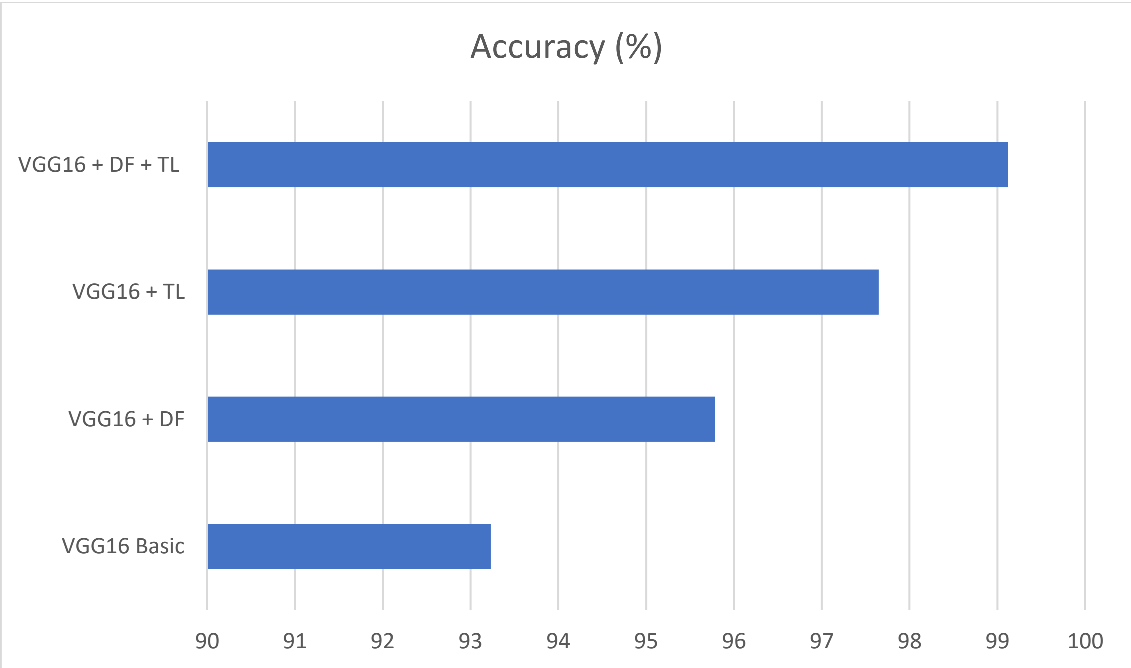

Figure 4 (a) : Comparison results of the different settings of the model

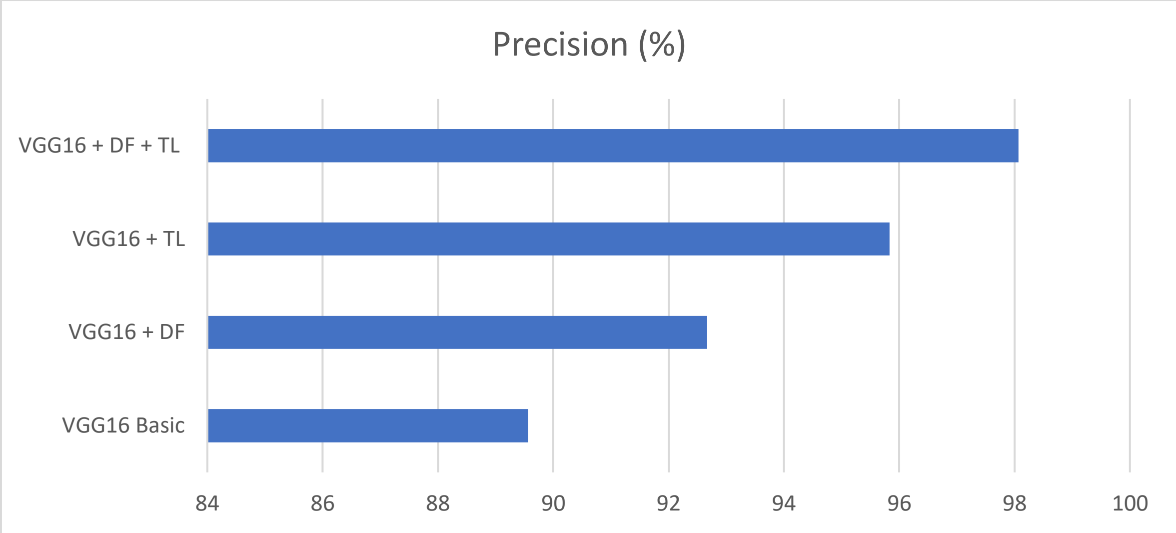

Figure 4(b) : Comparison results of the different settings of the model

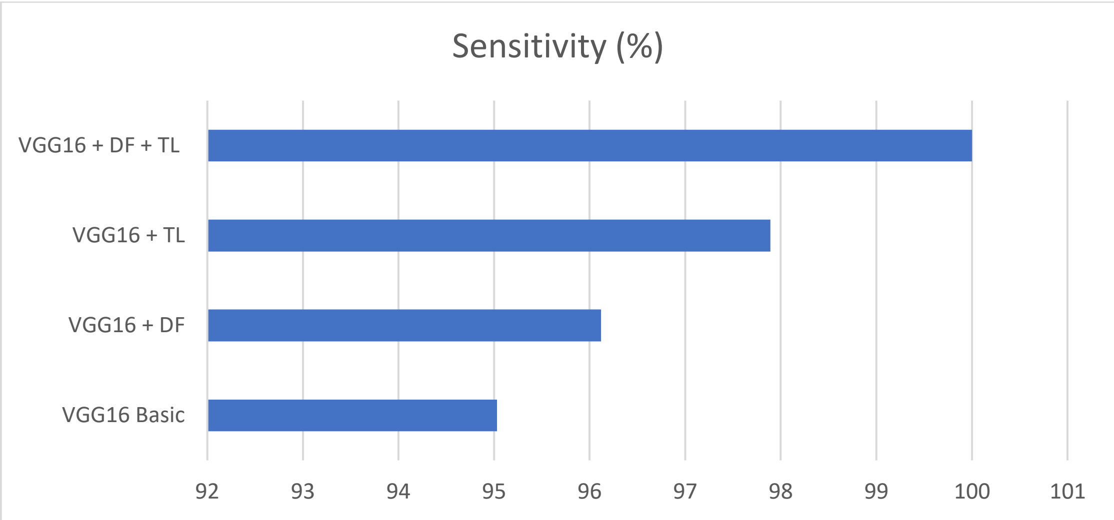

Figure 4 (c) : Comparison results of the different settings of the model

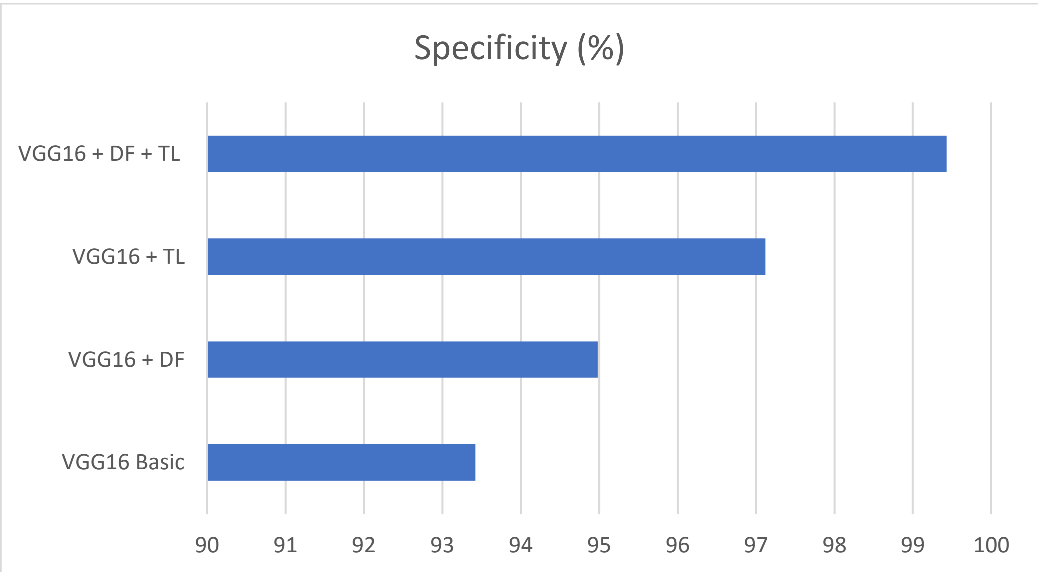

Figure 4 (d) : Comparison results of the different settings of the model

Based on the comparison results in table figure 7, it is clear that the model with the deep feature extraction achieves significant improvements over the VGG16 basic across all metrics, indicating that the deep feature extraction method effectively captures essential features for image recognition.

In contrast to VGG 16, +DF, VGG 16, +TL demonstrates superior performance with notable enhancements. Additionally, the default setting of the model, VGG 16+DF+TL, which incorporates both deep feature extraction and transfer learning, outperforms other model configurations such as VGG 16, basic, VGG 16+DF, and VGG 16+TL. These findings underscore the importance of the Deep feature extraction and transfer learning in image detection ta

5. Summary

The popularity of MR imaging in identifying brain tumors has increased due to the rising need for a precise and efficient evaluation of vast medical data. Manual detection of brain tumors is both time-consuming and reliant on medical knowledge. Brain tumors pose a serious threat. An automatic diagnostic technique will be necessary to identify abnormalities in MRI images. As a result, our research has introduced an effective CNN model utilizing transfer learning architecture for the detection of brain cancers from MRI data. The proposed model used a deep transfer learning-based model that utilizes a pretrained VGG 16 model. The model has been modified by incorporating transfer learning and deep feature extraction along with data augmentation. The proposed model achieved an accuracy of 99% and a precision of 98.73%. The results indicated that the proposed model outperforms other state-of-the-art models. With such promising results, these models can be further developed to create clinically useful solutions for the detection of brain tumors in MRI.

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