Enhancement of Pre-Trained Deep Learning Models to Improve Brain Tumor Classification

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Abstract: The early detection of brain tumors is crucial due to their highly dangerous nature and the potential for life-threatening consequences if left undiagnosed. Brain tumors significantly shorten life expectancy and cause extensive damage. To accurately diagnose brain tumors, medical imaging techniques such as MRI and other diagnostic tests play a vital role in the classification process. Artificial intelligence, specifically deep learning and computer vision, offers valuable techniques for detecting and classifying brain tumors. In this research, our focus is on developing an improved methodology for brain tumor classification. We implemented a proposed model using five pre-trained models: CNN, ResNet101, InceptionV3, VGG16, and VGG19. By employing data augmentation techniques, we enhanced their performance. The achieved Precision, Recall, and F1-Measure for unseen images were 95%, 95%, 95%, 97%, and 95%, respectively, as tested using three open datasets. Furthermore, aside from improving early tumor detection, these accuracy improvements have the potential to reduce disabilities such as paralysis. Data augmentation, accomplished through image rotation, scaling, and flipping, proves to be an effective means of enhancing model performance by generating new images with improved quality.

Povzetek: Za izboljšanje zgodnjega odkrivanja možganskih tumorjev so uporabili pet globokih nevronskih mrež in dosegli signifikantno izboljšanje.

1 Introduction

As one of the most important and sensitive organs in the human body, the brain is among the most complex in terms of its structure. It consists of billions of neurons and deals with the rest of the nervous system in order to control all body functions. Therefore, brain diseases constitute a real fear for humans, especially brain tumors[1]. The growth of brain tumors occurs when abnormal cells divide uncontrollably around or inside the brain[2][3]. In addition to destroying healthy cells, the formation and proliferation of unwanted cells affect normal brain function [4] . It affects normal brain functionality and destroys healthy cells when unwanted cells are formed and propagated. Brain tumors are categorized into two stages primary and secondary [5]. In biological terms, the early-stage tumor with a small size and non-progressive is called benign. However, a tumor in the second stage can grow rapidly; in this case, it is called a malignant [6]. Benign [3][7] refers to low-grade (i and ii) cancer which is non-progressive or non-cancerous, Usually benign tumors do not cause a serious problem for the patient if the situation is normal and there is no pressure on the structure or tissues close to it. A malignant tumor is classified as high-grade (III, IV); it is cancerous and grows rapidly in the human skull [7]. In 2021, the study provided by “Brain and other central nervous system tumor statistics” [8]: In the United States, there are expected to be 83,570 brain and other Central Nervous System (CNS) tumors diagnosed (24,530 malignant and 59,040 nonmalignant), and 18,600 will die [8]. There are 84,170 people with diagnosed brain tumors, it is estimated that 69,950 people over the age of 40 will be diagnosed with the disease. Due to the high mortality rate of brain tumors, they are split into two stages: Low-Grade Glioma (LGG) and High-Grade Glioma (HGG). In addition, the LGG persistence rate is higher than the HGG rate. Given that HGG has a 2-year average survival rate, rapid therapy is necessary [9]. The therapeutic area often accepts imaging techniques like CT, MAR (Magnetic Resonance Angiography), and MRI to capture the internal regions of a brain [10]. In reality, the blood vessels and tumors core portion are often recorded using the widely utilized MRA method. The primary drawback of the MRA-based method is the requirement for the contrast agent gadolinium [11].

The most important medical technology used in detecting brain tumor diseases is the MRI: Magnetic Resonance Imaging technique and CT: Computed Tomography. Based on many medical factors such as shape information and tumor texture, MRI is more effective compared to CT [12]. Using the MRI technique, specialists can easily calculate the size, location, and shape of the affected tissues forming the brain tumor, but

the technology MRI has some disadvantages such as cost and time [13][14].
There are a number of semi-automatic methods that have been described in the literature, and various supervised machine learning classification techniques[15]; however MRI scans present some significant difficulties that have an impact on automated diagnosis [16], such as changes in levels of intensity and poor contrast of MRI images.

SVMs, KNNs, decision trees, and other machine learning algorithms have been developed to address these problems. They consist of the following steps: structure step, contrast improvement step, noise reduction from tumors, and classification using SVMs, KNNs, decision trees, etc. These steps are clustering, thresholding, feature extraction, and classification. These approaches performed better when there were less input data, but as the amount of data increased, the accuracy of these methods decreased [17][18]. In order to find solutions for these issues, CNN-based architectures [19] are developed, which automatically calculate deep properties (features) from the source pictures before classifying them with the help of the softmax classifier [20][21]. The literature presents many CNN techniques for classifying tumors [22][23].

CNNs have demonstrated remarkable performance on large labeled datasets, such as ImageNet [24], which contains over one million images. However, in the medical field, utilizing such deep CNNs presents several challenges. Firstly, the size of available medical datasets is often limited, as they require the expertise of experienced radiologists to manually evaluate and identify images, making it a difficult, time-consuming, and costly process. Secondly, training deep CNNs with a small dataset poses difficulties due to issues like overfitting and convergence. Additionally, continuous improvement and modification of learning parameters require domain expertise. Therefore, training deep CNNs from scratch becomes a demanding and time-consuming task that demands dedication and patience. In this research, a novel CNN-based classification model for brain tumors is introduced. The model incorporates convolution and rectified linear unit (ReLu) layers along with a pooling layer. Notably, this method eliminates the need for tumor segmentation during the pre-processing stage, setting it apart from other techniques that rely on this step.

The used algorithm was tested using three open datasets. Our major contributions to this effort include the following:

• For the automated categorization of brain tumors, a new and reliable model is provided. It is considered successful and effective in the process of extracting the characteristics and features of the brain pictures used in the MRI dataset.

• In contrast to existing models, which employ 11 x 11 or 9 x 9 as kernel sizes with bigger strides, the proposed model recommended using (3X3) kernels for all (CNN) convolutional network layers with a tiny stride in order to learn the small texture of tumors in brain pictures.

• In contrast to conventional strategies, which require a tumor segmentation step before the classification phase, the innovative proposal offers an excellent degree of accuracy in a minimum time of preprocessing for brain tumor classification.

• Despite the few training data sets, our model achieves respectable classification accuracy when compared to new techniques [25].

2 Related works

Slow-growing tumors that are not malignant are classified as grade-I tumors, the grade class-II can be both malignant and benign. The researchers of [26] suggest more research to rate meningioma tumors differently. There are malignant tumors of grade III, and they can spread swiftly, different characteristics are used as radiological and contextual features, and no preprocessing or segmentation is carried out; Multiple logistic regressions were utilized by the authors in the classification phase. Their scheme is evaluated using MRI scans from 120 patients, of which 90 had Grade I and 30 had Grade II or III. They used a number of sequences as FLAIR T1 and T2 models, and DWI transformation to extract features. The findings, with the utilized dataset, were satisfactory. To guarantee the validity of this sort of approach, several sizable datasets are needed.

The renowned dataset was first utilized by Cheng et al [27], They provided an approach to use of the manually drawn tumor boundaries to extract features. As an area of interest (ROI), they used the increased tumor region, which was divided into sub regions using the adaptive spatial division technique. The features were retrieved using the intensity histogram, the bag of words, and the gray-level co-occurrence matrix (GLCM) (BoW). In this research the most accurate model was SVM, and all studies were conducted using a typical four-fold cross-validation method. Finally, the concluded that: the performance measures include accuracy, sensitivity, and specificity 91.28% is the greatest accuracy rate.

Using convolutional neural networks (CNN), in the research [21], a novel multi-grade brain cancer classification approach was presented, by separating tumor spots from an MR image using a deep learning system as the first step, then significant data augmentation is employed to adequately train the recommended system, which eliminates the lack of data problem when using MRI for multi-grade brain tumor classification. A pre-trained CNN model for grading tumors is augmented using the improved data.

Using AI algorithms, CNN, and Deep Learning in “Brain Tumor Classification Using Deep Learning” [28], the authors seek to improve the capability and effectiveness of MRI equipment in categorizing and recognizing different forms of brain tumors; For implementing proposed algorithms, they used five pre-trained models Xception, ResNet50, InceptionV3, VGG16, and MobileNet [29], 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% were the respective F1-scores for unseen photos.

In their research, S. Das, O. F. M. R. R. Aranya, and N. N. Labiba [21][30] focused on creating a CNN model for identifying brain cancers in three different brain tumor types on T1-weighted contrast-enhanced MRI images. By utilizing convolution layers, pooling layers, and fully connected layers in a back-propagation process, the CNN adaptively identified relevant features. The authors achieved impressive results with a high level of testing accuracy at 94.39%, an average precision of 93.33%, and an average recall of 93% using this CNN model[30]. Their work demonstrates the effectiveness of CNN in accurately detecting brain cancers across multiple tumor types.

In the study [31], the effectiveness of an enhanced CNN model based on U-Net for brain tumor segmentation is examined, along with the utilization of the SegNet architecture for classification and the RefineNet for pattern analysis. The enhanced CNN model showcases its capabilities by achieving remarkable results when applied to the benchmark dataset for brain tumors. The U-Net architecture proves effective in segmenting brain tumors by leveraging both local and contextual information from MRI images. By employing the SegNet architecture, the model selects crucial properties and features for classification while reducing the number of trainable parameters. Overall, this method yields an impressive accuracy of 96.85%, underscoring its effectiveness in accurately classifying brain tumors.

In the study [32], the authors propose a comprehensive learning-based elephant herding optimization technique. The paper focuses on determining the optimal values of the smoothness factor in bi-histogram equalization using adaptive sigmoid functions. The authors' work introduces a novel approach that combines learning-based methods and optimization techniques to enhance the effectiveness of bi-histogram equalization. By leveraging the elephant herding optimization technique, the study aims to find the optimal parameters for smoothness factor selection.

Using the transfer learning approach, Khan, Hassan Ali, et al [33]; ResNet-50, VGG-16, and Inception-v3 models that had been pertained were used to compare the performance of the initial CNN model. Even though the experiment was performed on a small dataset, the accuracy achievement was very high (100%) with a very low degree of complexity rating, whereas achieved 96%, 89%, and 75% of accuracy for VGG-16, ResNet-50, and Inception-V3 respectively. In general, the accuracy of this model is much better than that of other pre-trained models since it requires very little computational power. The summary of discussed research work in this section is shown in Table No 1.

Research Work	**Approach**	**Dataset**	**Performance**
"Multi-grade Classification using CNN with extensive data ugmentation"[21]	CNN-based brain cancer classification, data augmentation	MR images	Testing accuracy: 94.39%
"Classification of MR tumor images based on Gabor wavelet analysis"[26]	More research is needed to rate meningioma tumors differently	MRI scans from 120 patients	Satisfactory results
Brain tumor dataset Kaggle [27]	Manual tumor boundary extraction, intensity histogram, GLCM features	brain tumor dataset contains 3064 samples	Accuracy: 91.28%
"Brain tumor classification using deep learning"[28]	CNN-based brain tumor classification using pre-trained models	Unseen photos	F1-scores: 98.75% - 97.25%
"Brain Tumor Classification Based on Enhanced CNN Model"[31]	SegNet, RefineNet, and enhanced CNN for brain tumor classification	Benchmark dataset for brain tumors	Accuracy: 96.85%
"An Approach for Enhancement of MR Images of Brain Tumor"[32]	Learning-based optimization technique for bi-histogram equalization	3064 T1 contrast-enhanced MR samples (233 patients)	Optimal values presented
"Brain tumor classification in MRI image using convolutional neural network,"[33]	Transfer learning with pre-trained models (ResNet-50, VGG-16, Inception-v3)	Small dataset of 253 brain MRI images	Accuracy: 100% (CNN model)

back-propagation, CNN [30]	adaptively using pooling layers, convolution layers, and fully connected layers		93.33%)

Table 1: Summary of overviewed research

The proposed model in this research uses five pre-trained models: CNN, ResNet101, InceptionV3, VGG16, and VGG19. These models were enhanced using data augmentation techniques such as rotation, scaling, and flipping of the images in the dataset, this issue can increase the number of samples, and lead to more accurate results. The performance of the model was evaluated using three open datasets, achieving Precision, Recall, and F1-Measure values ranging from 95% to 97% for unseen images.

3 The proposal model

In this research, a new model for the classification of brain tumors is proposed, as shown in Fig. 1, it consists of five modules. The first one "Importing Dataset" is used to import MRI images from the data set [34], and the second module "Feature Extraction" which used to read and extract properties and features from the input dataset images, then pass image properties and features to the next step (Training module) to classify them against CNN, VGG16, VGG19, InceptionV3, and ReseNet101, the step number four is the testing and validation (Validation module), where the proposed model will be tested using a set of testing data. Finally, the result evaluation module will be used to identify the Precision, Accuracy, Recall, and F1-Measure. In this section, this model will be discussed in more detail. All the experiments are performed on Google Colab, Windows 10 operating with 32bit. The detailed structure of the proposed work is shown in Figure 1.

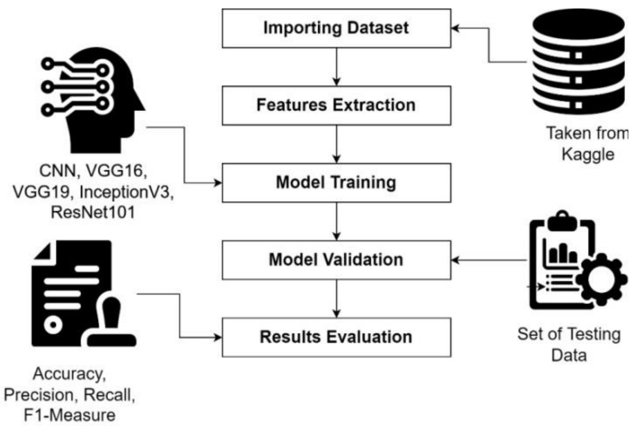

Figure 1: The general structure of the proposed model

3.1 Dataset

The dataset utilized in this work, obtained from Kaggle [34], consists of four tumor categories: pituitary tumor (PT) with 74 files, no tumor (NT) with 105 files, meningioma tumor (MT) with 115 files, and glioma tumor (GT) with 100 files. In total, the dataset comprises 3264 MRI pictures, with 500 images obtained from healthy patients and the remaining 2764 images obtained from patients with brain tumors. This dataset provides a diverse collection of images to analyze and enables the investigation of various tumor types.

Figure 2 displays an example of normal and brain tumor-affected MRI scans. A total of 2048 features were retrieved from 3264 MRI scans, and a total of 2054 variables were employed. Category, picture name, image link, size, width, and height are the additional six attributes. These six features offer details about each MRI image but do not significantly contribute to detection.

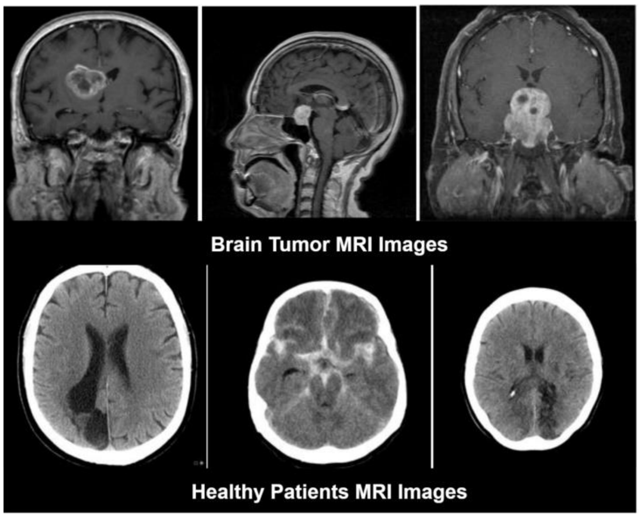

Figure 2: Samples of MRI images in dataset

3.2 Performance assessment

The performance assessment measures, including Precision, Accuracy, F1-Measure, and Recall, are detailed in this subsection. By providing information details, we outline the calculations used to evaluate the performance of our research approach. These assessment measures play a crucial role in determining the effectiveness and reliability of our methodology; they are:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad [35] \qquad (1)$$

Where components of formula no (1) are: TN means True Negative, FP: False Positive, FN: False Negative, and TP: True Positive. For evaluating a predictor's performance in unbalanced classes, precision and recall are helpful metrics. Recall is the metric for actually relevant returned results, whereas precision is the metric for relevancy in the results [36].

$$Precision = \frac{T\,P}{(T\,P + F\,P)} \qquad (2)$$

$$Recall = \frac{T\,P}{(T\,P + F\,N)} \qquad (3)$$

Using the weighted harmonic mean of recall and precision as a starting point, F1-Measure calculates the prediction accuracy [37] as follows.

$$F1 = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \qquad (4)$$

4 Result analysis

In this section, we present the outcomes of our proposed solution. Table 2 shows the confusion matrix (CM) obtained from each approach, displaying the brain tumor classifications as PT, NT, MT, and GT. The CM provides crucial metrics such as classification accuracy (CA), precision, recall, and F1 score, with the columns representing the predicted classes and the rows indicating the actual classes. Additionally, Table 2 highlights the results obtained using F1-Measure, precision, and recall. Through our investigation, we discovered that VGG16 outperforms the other applied approaches, achieving an accuracy of 0.960, a recall of 0.95, and an F1-measure of 0.951. The performance analysis, depicted in Figure 3, further supports these findings by utilizing recall, F1-measure, and accuracy.

Model	**Target Class**	**Predicted**			
		GT	NT	MT	PT
CNN	GT	85	3	0	1
	NT	1	80	2	9
	MT	0	0	50	1
	PT	0	0	0	95
VGG16	GT	4	1	0	0
	NT	0	5	0	0
	MT	0	0	5	0
	PT	0	0	0	5
VGG19	GT	23	27	43	7
	NT	0	107	6	2
	MT	0	0	882	5
	PT	0	18	26	1684
Inception-V3	GT	33	46	21	0
	NT	0	114	0	1
	MT	0	0	886	1
	PT	0	4	15	1709
ResNet101	GT	29	52	16	3
	NT	0	115	0	0
	MT	0	0	887	0
	PT	0	4	0	1715

Table 2: Confusion matric achieved via each technique

Model	**Precision**	**Recall**	**F1-Score**
CNN	0.95	0.95	0.95
VGG16	0.96	0.95	0.95
VGG19	0.92	0.78	0.95
Inception-V3	0.91	0.83	0.97
ResNet101	0.91	0.82	0.97

Table 3: Performance analysis using F1, precision and recall

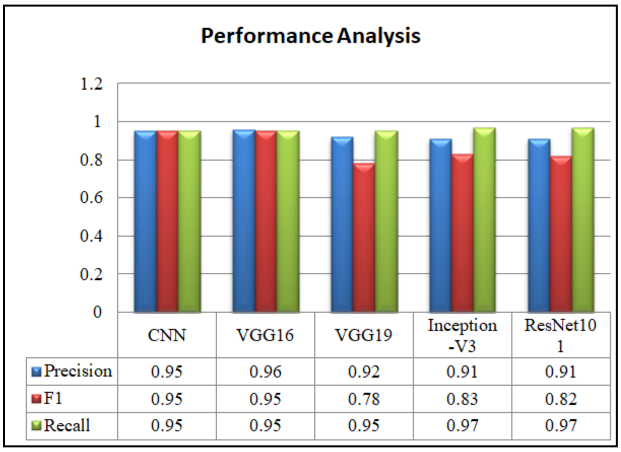

Figure 3: Performance Analysis: F1, Precision and Recall

By analyzing the percentage accuracy presented in Figure 4, it becomes evident that Inception V3 and ResNet101 outperform the other employed techniques, exhibiting a superior AUC of 97.3. This finding highlights the exceptional performance and effectiveness of Inception V3 and ResNet101 in comparison to the alternative methods studied in the research.

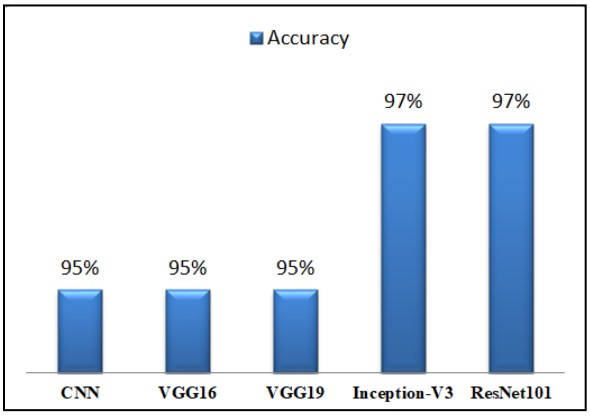

Figure 4: Accuracies of the employed models

5 Discussion

In the dataset, we collected 4480 images from the Kaggle website. From these images, we created two groups of training and testing. The testing directory contains unseen images. For training and testing, we have four classes available: glioma, pituitary, no tumor, and meningioma tumors. The no tumor group has 390 photos, while all the other forms of brain tumors have more than 800 images, contributing to a total of 2870 images in the training group. In the testing group, there are 395 pictures. Each tumor category, except for pituitary tumors, has over 100 images available. The brain tumor images were scaled to 240 by 240 pixels. To address the imbalance in the number of images in the no-tumor dataset, we utilized Python and Data Augmentation to construct additional photos.

To address the limited number of images provided by Kaggle for training, we employed data augmentation and image scaling techniques. This allowed us to enhance the number of images and mitigate the risk of overfitting. We utilized our brain tumor classifier to replace the classifier of the original designs. For each model, we conducted training using 15 epochs, 0.25 dropout, and 4 thick layers. After training, the error loss and final accuracy of each model were recorded.

Based on the error losses and F1-score accuracies presented in Table 3 and Figure 5 to 9, we observed the performance of each model. Furthermore, in Figure 4, we evaluated the accuracy of the five trained algorithmic models using unseen pictures, revealing final accuracy results of 95.75%, 95.50%, 95.00%, 97.50%, and 97.25% respectively. These accuracy levels led us to draw two important conclusions: (1) The trained models demonstrated increased applicability, and (2) The five trained models proved to be highly effective in early cancer detection, thereby potentially reducing the likelihood of tumors causing physical side effects such as paralysis

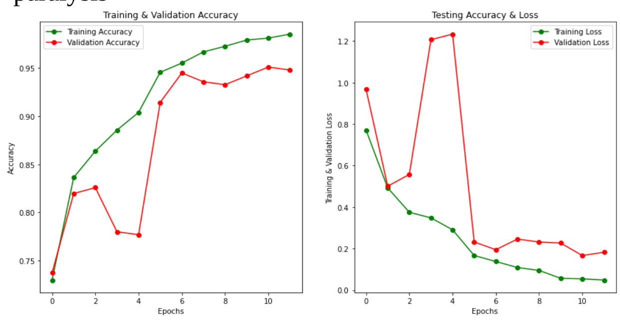

Figure 5: Training and testing accuracy of CNN

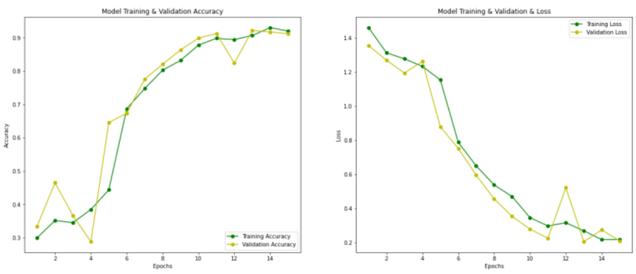

Figure 6: Training and testing accuracy of VGG16

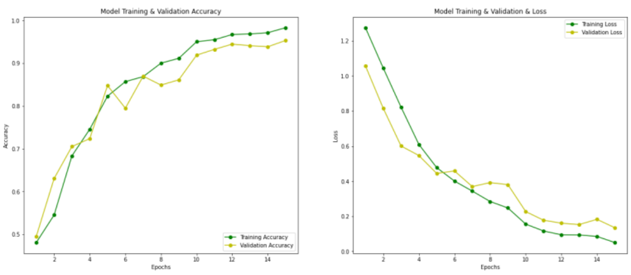

Figure 7: Training and testing accuracy of VGG19

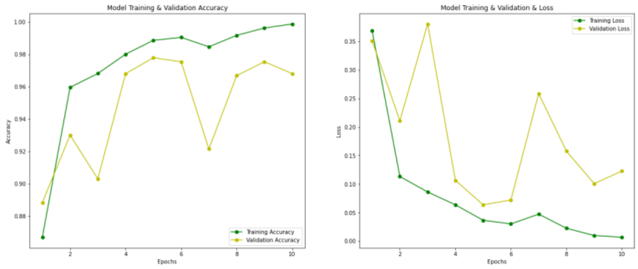

Figure 8: Training and testing accuracy of inception V3

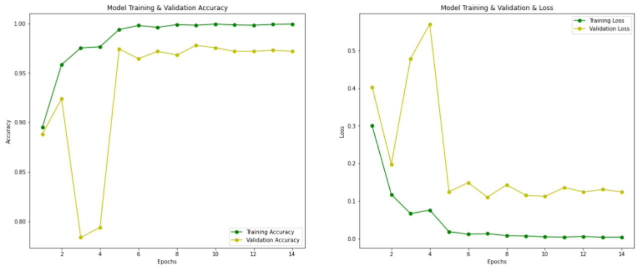

Figure 9: Training and testing accuracy of ResNet101

Our developed model represents a significant advancement in the automated categorization of brain tumors, as demonstrated by its successful testing on three open datasets. Unlike existing models that rely on larger kernel sizes and strides, our proposed model utilizes (3X3) kernels with a smaller stride for all convolutional network layers in the CNN. This approach effectively extracts characteristics and features from brain pictures in MRI datasets, specifically capturing the small textures of tumors. Notably, our innovative proposal eliminates the need for a tumor segmentation step prior to classification, resulting in higher accuracy and reduced processing time compared to conventional strategies. Despite limited training datasets, our model achieved impressive classification accuracy, surpassing newer techniques in brain tumor classification.

The novelty of this work lies in the following aspects: **Methodology**: The proposed methodology incorporates five pre-trained models, including different architectures such as CNN, ResNet101, InceptionV3, VGG16, and VGG19. By utilizing multiple models, the research aims to improve the accuracy of brain tumor classification. **Data Augmentation**: The research employs data augmentation procedures such as rotation, flipping, and scaling of images in the dataset. Data augmentation is a valuable approach to enhance the performance of deep learning models by generating additional training samples and improving generalization. **Evaluation on Multiple Datasets**: The proposed model is tested on three open datasets, which adds to the robustness and generalizability of the findings. Evaluating the model's performance on multiple datasets helps demonstrate its effectiveness across different data sources.

6 Conclusion:

Deep learning (DL) is altering people's perceptions of technology as well as their use of it. DL has a significant impact on human lives and produces amazing results in a variety of domains, including bioinformatics, computer vision, and many more. Numerous deep learning techniques and applications have been put into practice in the real world with a big impact. CNN is one of many neural networks that are used in the medical industry to identify the kind and severity of diseases. In our research, computer vision issues automate the process of cropping the brain from MRI data and CNN, Inception-V3, VGG16, VGG19, and ResNet101 models are used to estimate if the subject is or is not suffering from a brain tumor. It is important to note that the classification of brain tumors is complex, and the specific treatment plan will depend on a variety of factors such as the patient's age and overall health, the location and size of the tumor, and the specific type of tumor.

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