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Brain Tumor Detection and Classification Using VGG16 Deep Learning Algorithm and Python Imaging Library

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Abstract

Early diagnosis and treatment of brain cancer depend on the detection and categorization of brain tumors. Deep learning algorithms have produced amazing results in medical imaging applications including tumor identification. Most of this field's research has concentrated on applying CNN algorithms like VGG16, DNN, and ANN to this problem. This work describes the identification and classification of brain tumors using the Python Imaging Library (PIL) and the VGG16 deep learning algorithm. A dataset of 7000 MRI pictures categorized by tumor type served as the foundation for the research. The main objective of this study was to develop a high-efficiency, high-accuracy model. We suggested utilizing the VGG16 architecture and preprocessing images with PIL to ensure consistent images for training on a sizable dataset of brain magnetic resonance imaging (MRI) images. A novel technique we have used in our work is one that can analyze a single image and predict the presence of a tumor from the results. The research's methods produced robust tumor detection across the dataset with 96, 9% accuracy, indicating the value of the method in helping medical professionals make informed decisions when diagnosing the presence of tumors.

Keywords: Brain, Tumor, Detection, Deep Learning, VGG16, Python Imaging Library, MRI, Segmentation, Preprocessing, Model, Accuracy

1. Introduction

Brain cancer is a serious health problem that affects people worldwide. Early diagnosis and treatment of brain cancer depend on the detection of brain tumors. Brain tumors must be diagnosed accurately and quickly to improve patient outcomes and deliver the proper medical interventions. Recent advances in imaging technology and machine learning algorithms have greatly benefited the field of brain tumor detection, enabling more precise and rapid diagnosis. Because of their intricate structure and hidden locations within the brain, brain tumors can be challenging to identify. [1] Conventional methods for identifying tumors, like radiologists' eye screening, can be time-consuming, arbitrary, and prone to human error. But as deep learning algorithms have advanced and large medical imaging datasets have become more widely available, computerized diagnosis systems have emerged as a competitive alternative for raising the accuracy of brain tumor detection. [2] Deep learning methods, like the VGG16 architecture, have shown to be extraordinarily successful in image recognition and classification. These algorithms can learn intricate patterns and features from enormous amounts of data, which makes them perfect for spotting anomalies in medical images, like brain tumors. By using pre-trained models such as VGG16 and refining them on medical imaging datasets, researchers have achieved significant gains in the diagnosis accuracy of brain tumors. The importance of early brain tumor discovery cannot be overstated. Early diagnosis allows for prompt medical intervention, including radiation therapy, targeted medication therapies, and surgical resection. Early identification can also improve patient prognosis, quality of life, and overall survival rates. The development of accurate and efficient computer-assisted diagnosis tools that can assist medical professionals in identifying and categorizing brain tumors has thus gained momentum. Through the use of deep learning algorithm advancements and the availability of large-scale medical imaging datasets, researchers are pushing the boundaries of brain tumor identification. This research aims to add to the growing body of knowledge in this field with the goal of improving the efficacy and precision of brain tumor identification for better patient outcomes.

2. Related work

Early brain tumor detection is essential for the diagnosis and treatment of brain cancer. Recent advancements in medical imaging techniques and deep learning algorithms have led to an improvement in the classification accuracy of brain tumors. Several techniques and algorithms have been developed to help identify this problem early on. The most relevant works on this subject are included in this section. We focused on covering the most relatable works in this area. A model was for classifying brain tumors was developed by Chandra and her colleagues [3], they created a model for brain tumor classification with image preprocessing, data augmentation and VGG16 CNN model. Their model focused on utilizing the advantages of the VGG16 algorithm and its classification advantages by providing well processed data to the model. When using the VGG16 algorithm, the claim that having a small kernel size helped them avoid model overfitting while using the VGG16 algorithm. Their model achieved an accuracy of 84%, with noticeable room for improvement in future studies. The work of Santos [4] as well as many in this area focused on data augmentation and VGG16 algorithm, as can be concluded data augmentation and quality image preparation is very important in such a problem to create a quality solution. Santons mentions that he used a model containing 13 convolutional layer and 3 fully connected layers in his model, as he states convolutional layer provide a small filter and they are used for capturing spatial patterns while the fully connected layer are used to make prediction on the learned features. On the training set the model achieved an accuracy of 88%, while on the testing dataset, it has achieved accuracy of 80%. In the research of Younis [5] and her colleagues they opted for creating three models to evaluate the best possible outcome for this issue they created a CNN model, VGG16 and ensemble model. CNN model consisted of image input layer, following was a convolutional layer containing feature maps and pooled feature maps from which the fully connected layer was created, this model provided them with accuracy of 89%. VGG16 model was the second model they created, a multi-layer convolutional model consisting of 32 filters entangled with input layer. The model yielded quality results especially in malignant cases with accuracy of this model being 97.6% percent. The final model they created in the work is an ensemble model which combined the CNN and VGG16 ensemble models utilizing specific characteristics derived from VGG16 fully connected layer to produce predictions for each data point. This model generated the best results on the training dataset with the 98,41% but on the test set only 91.29%. In general, looking over many works on this topic a common issue we have seen was lack of bigger datasets used for this problem, all these works have been based on smaller datasets. Md. Monirul Islam and colleagues [6] conducted a comprehensive study on the same dataset, implementing models such as InceptionV3, VGG19, DenseNet121, and MobileNet. Their results showcased impressive accuracies, with DenseNet121 (98.4%) and MobileNet (97.4%). Their work highlighted the efficacy of DenseNet121's dense connectivity and MobileNet's parameter-efficient design, leveraging depth-wise separable convolutions. Notably, their investigation revealed InceptionV3's superior performance, attributed to its intricate architecture involving diverse convolutions, pooling techniques, batch normalization, and auxiliary classifiers, demonstrating its prowess in image recognition tasks on various benchmark datasets. Another work focused on the same dataset as in our research was conducted by Gomez-Guzman [7] and colleagues. They tested several models, best performing of them being InceptionV3, ResNet50, and InceptionResNetV2, with InceptionV3 showing particularly good accuracy (97.1%). The 50-layer deep convolutional neural network ResNet-50 demonstrated improved training performance and accuracy because of residual connections that allow for direct gradient flow providing 96.9% accuracy. InceptionResNetV2 achieved 96.7% accuracy, which combined modified inception blocks, residual connections, and filter expansion layers. Their preprocessing techniques which included adjusting brightness, rotation, and zoom made sure that the images were perfectly ready for these models and added insightful information to the dataset analysis. Numerous studies have been conducted on this subject, with different conclusions drawn from each case. However, it is clear from related research that one of the most crucial aspects of this problem is properly preprocessing images and selecting the best model for the data such as VGG16, InceptionV3, or ResNet.

3. Material and Methodologies

3.1. Dataset

The dataset used in this work was created by combining three datasets: figshare, SARTAJ, and Br35H. The dataset includes 7023 human brain MRI scans that have been classified into four groups: pituitary, glioma, meningioma, and no tumor. [8] In particular, the images from the "no tumor" class were obtained using the Br35H dataset. The comprehensive coverage of different types of brain tumors and non-tumor instances in the diversified dataset facilitates the development and testing of accurate and dependable brain tumor detection algorithms. With multiple classes and a large number of images, the dataset is more valuable for creating and testing deep learning models for brain tumor detection.

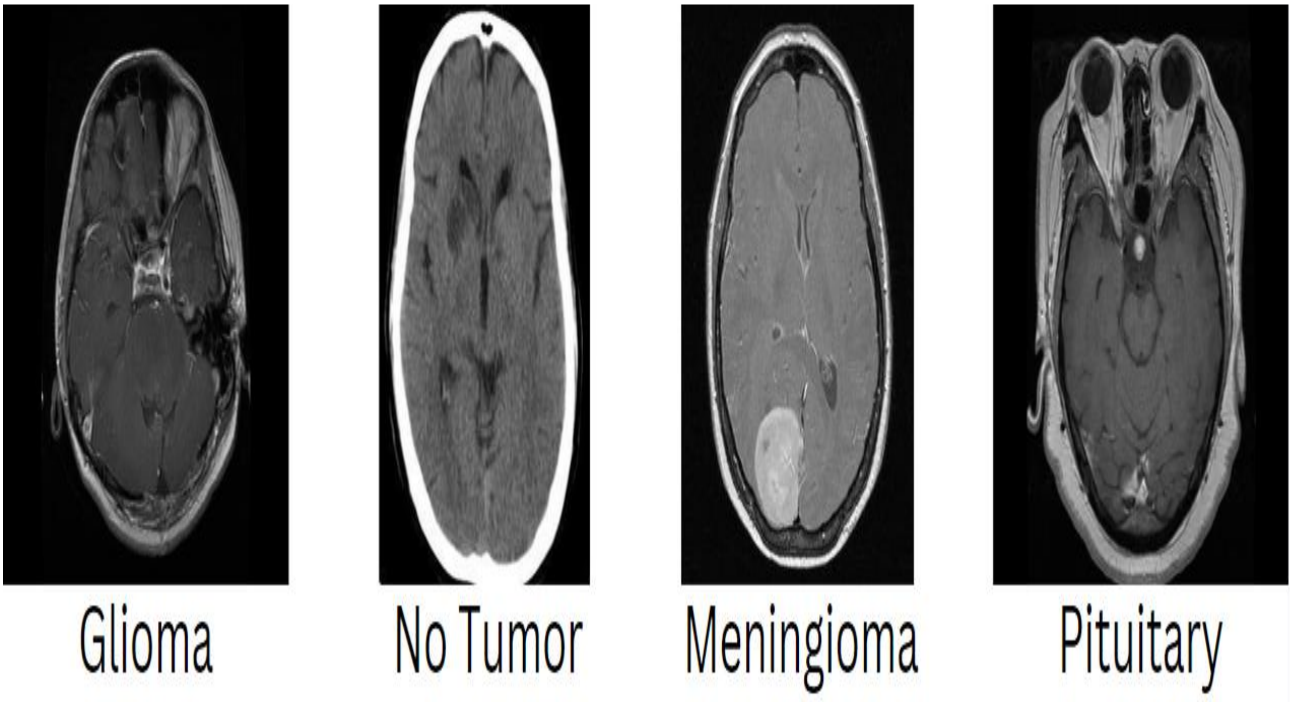


Figure 1. Representation of the dataset images (source:authors)

The training and testing subsets of the dataset are separated, and the ratio of the data is plotted in the figure below, where all four types of tumors are present in the respective sets of the training and testing datasets. Simple random sampling ensured that each image had an equal likelihood of being included in the training or the testing subset. With over 80% of the images in the training subset of the data and less than 20% going toward actual testing, it is evident from the pie chart that the focus is on the model's training. However, in these situations, the most crucial aspect is on accurately training the model.

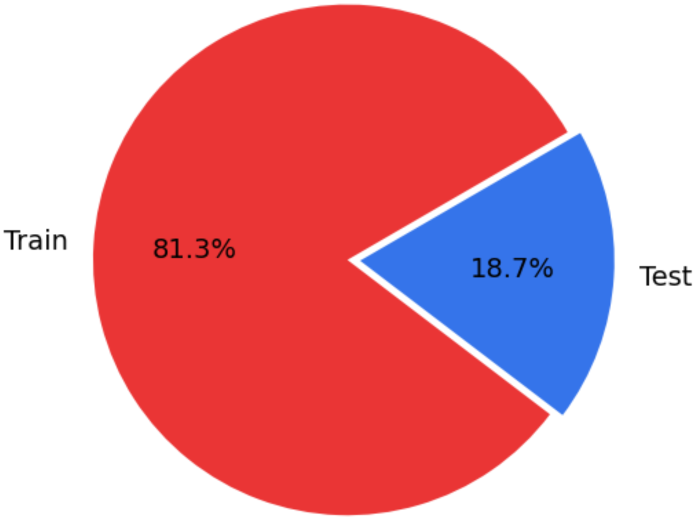


Figure 2. Dataset ratio representation (source:authors)

The dataset includes the four major groups discussed previously, and Figure 3 shows their uniform distribution. For the purposes of testing and training, each group includes the following numbers of images: There are 1595 images in the training dataset for "notumor," 405 in the testing dataset, 1457 images in the training dataset and 300 images in the testing dataset for "pituitary," 1339 images in the training dataset and 306 images in the testing dataset for "meningioma," and 1321 images in the training dataset and 300 images in the testing dataset for "glioma."

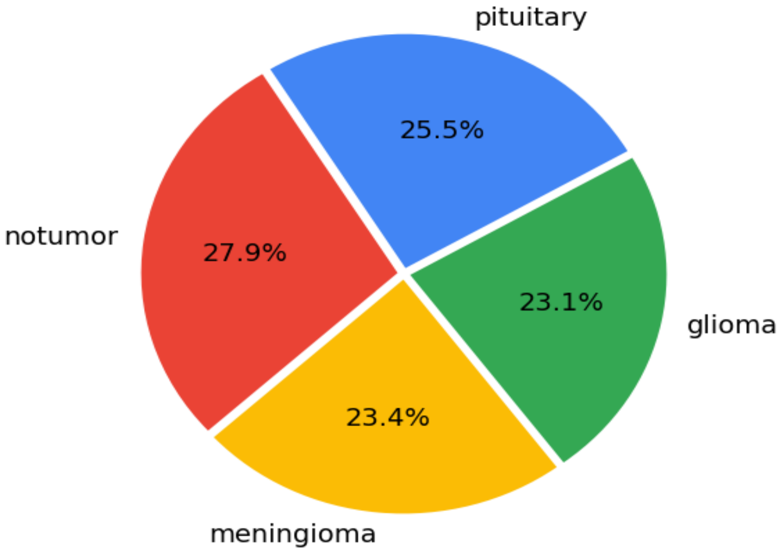


Figure 3. Dataset distribution (source:authors)

3.2. VGG16

The deep convolutional neural network (CNN) architecture known as VGG16, or the Visual Geometry Group 16, has grown significantly in popularity and renown in the field of computer vision. VGG16, created by the University of Oxford's Visual Geometry Group, is renowned for its depth and outstanding performance in picture categorization tasks. [9] There are 16 layers in the VGG16 architecture, consisting of 13 convolutional layers and 3 fully linked levels. It features short (3x3) convolutional filters and max-pooling layers in a simple structure. This design choice allows for high-level representation and classification accuracy because the network can recognize intricate patterns and features from the input images.

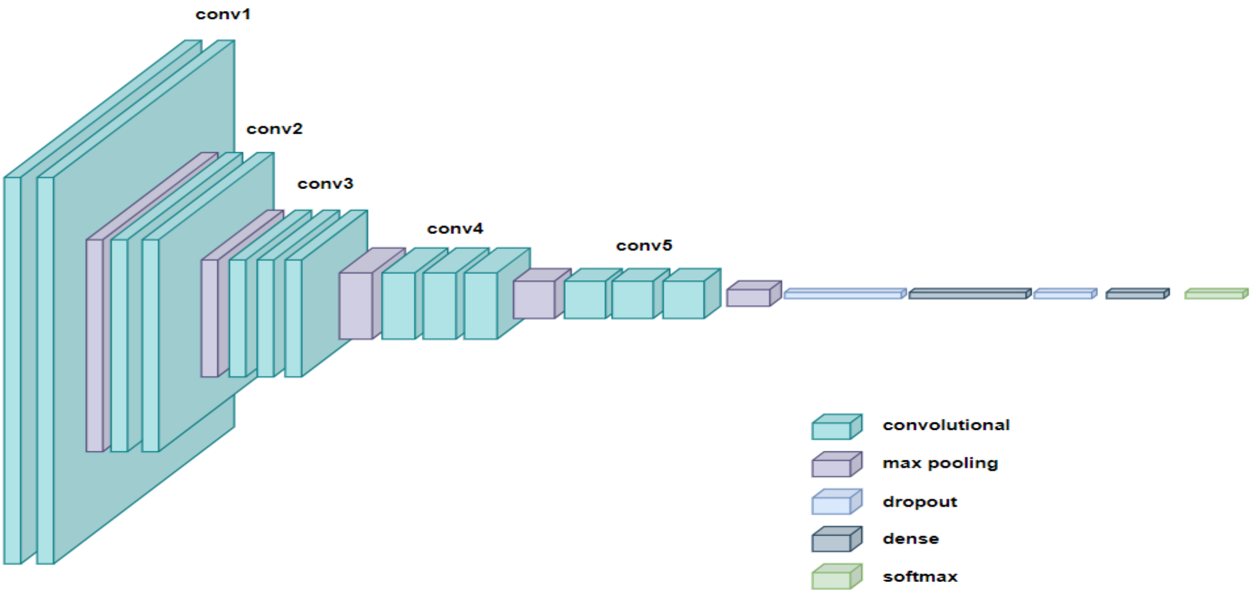


Figure 4. Example of VGG16 model (source:authors)

One of the main achievements of the technology is the ability of VGG16 to learn hierarchical representations through the stacking of multiple convolutional layers. Because of its deep architecture, the model is able to capture both high-level semantic information, such as object shapes and structures, and low-level data, like edges and textures. The network's enhanced depth improves classification performance and aids in its ability to learn complex visual representations. In a variety of computer vision applications, such as object detection, localization, and image classification, VGG16 has demonstrated outstanding performance. [10] The effectiveness of VGG16 has been highlighted in numerous studies in a range of fields. For example, Zisserman and Simonyan [11] suggested VGG16 and demonstrated how it performed better at classifying images than previous CNN architectures. Scholars have extended the application of VGG16 to transfer learning, whereby pre-trained weights of the model serve as a basis for training on datasets, thereby enabling effective learning with limited data. In conclusion, VGG16 has shown to be a strong deep learning architecture for image classification issues. Its depth, consistency, and hierarchical learning have all contributed to its cutting-edge results. The architecture is now a key tool for many applications and serves as a standard and point of reference for upcoming computer vision research.

3.3. Python Imaging Library

Python Imaging package (PIL) provides an extensive range of image processing options to the Python programming language. With a multitude of tools and functions for picture enhancement, alteration, filtering, and analysis, it is a flexible and useful tool for a wide range of image-related tasks. Users can easily edit images by cropping, resizing, rotating, and flipping them with PIL. It also permits more sophisticated functions like picture filtering, mixing, and compositing. In order to extract important information from images and perform intricate image processing tasks, PIL also includes features for color space conversion, histogram analysis, and pixel-level modification. [12] PIL is a popular choice because of its simplicity and intuitiveness among Python programmers and scholars working with image data. Its extensive documentation and strong community support contribute to its widespread acceptance. Furthermore, PIL integrates well with larger data analysis workflows and facilitates efficient data sharing and integration with other Python libraries such as NumPy and matplotlib. [13] The accessibility of PIL has shown to be important in a number of domains, such as academic research, medical imaging, and computer vision. Its extensive feature set and ease of use are beneficial to both inexperienced and experienced users. [14]

3.4. Proposed method

During this research's experimental phase, MRI (Magnetic Resonance Image) images are processed. To do this, the Python Imaging Library (PIL) was used. The following operations were performed on the images that were taken from the datasets during the processing phase. First, the MRI images were converted into PIL image objects in order to utilize the basic manipulation and processing provided by the PIL library. After that, each image was randomly exposed to brightness and contrast adjustments in order to enhance the visibility of any aberrant cells detected in the MRI scans. By applying the same processing criteria to every image, this method seeks to enhance the visibility of important details in the pictures. Normalization was the next stage of the MRI image processing to ensure consistent and standardized image representation. To do this, the pixel values in each image had to be divided by 255. The pictures were normalized in this way. Once the processing of the MRI images was finished, we decided to use VGG16 as our preferred algorithm to solve this issue.

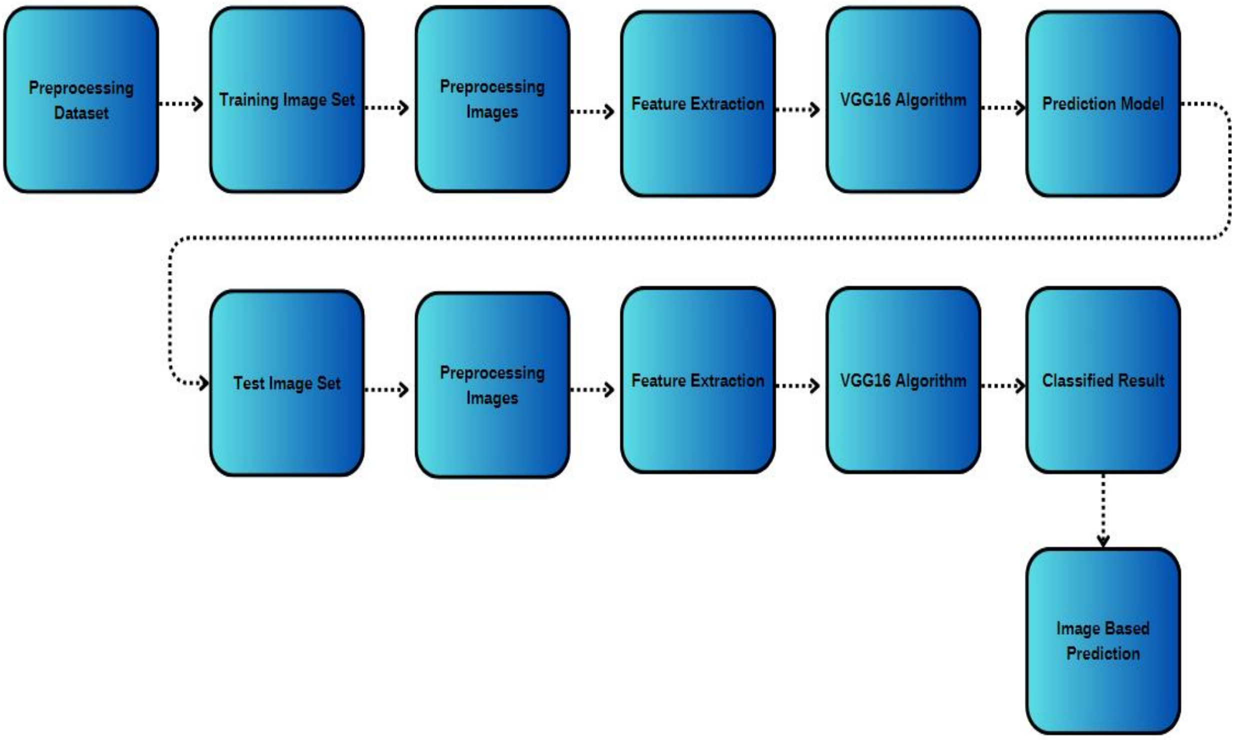


Figure 5. Diagram of the proposed method (source:authors)

The following steps make up the model we developed for our research. In order to maintain uniformity, we first filled the VGG16 model with the input shape, which for this study was set to match the image size from our processing phase (128 x 128 pixels). Additionally, we decided not to include the final fully connected layer to allow for greater flexibility in the model's learning phases. Finally, we set the crucial "weights" parameter to "imagenet," which simply means the model will be pre-trained on a dataset comprising more than one million images. Subsequently, we established a loop that designates all base model layers aside from the final three as non-trainable. This ensures that the layer weights remain unchanged throughout the training stages. As the next stage of our model, we built a sequential model that starts with the pretrained layers. These procedures allowed us to add more layers to our model. First, we added a flatten layer, which essentially gathers all the data from the previous layer and arranges it into a single row by reshaping the output from the previous layer into a 1D tensor Next, we added two dense layers and two dropout layers. In order to prevent our model from overfitting, we added two dropout layers: the first, 0.3, means that 30% of connections will be cut off, improving the model's ability to generalize, and the second, 0.2. A fully connected layer with 128 neurons in the first layer and the length of the unique labels in our dataset in the second layer are the functions of the two dense layers, which are added in between the dropout layers. One significant field activation is set to softmax, which transforms the model output into probabilities for each of the classes in our dataset. To enhance comprehension, refer to Figure 6, where the models layer are shown.

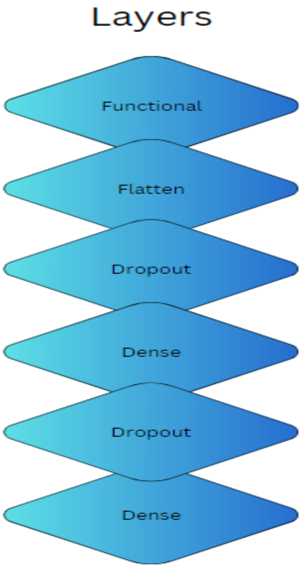


Figure 6. VGG16 model layers (source:authors)

Once the model has undergone testing and training and produced acceptable outcomes. Our approach includes the ability to classify MRI images as well as provide a percentage estimate of the presence of a tumor from a single image. The processed image is then sent back to the model user. The following section will display the results of our model and methodology.

4. Results

Image processing and model definition are the two primary steps we discussed in our proposed work. We will review and evaluate the outcomes we were able to attain in this section. Initially, we processed the images using PIL, and the images in Figure 7 illustrate the outcomes of the uniform image processing.

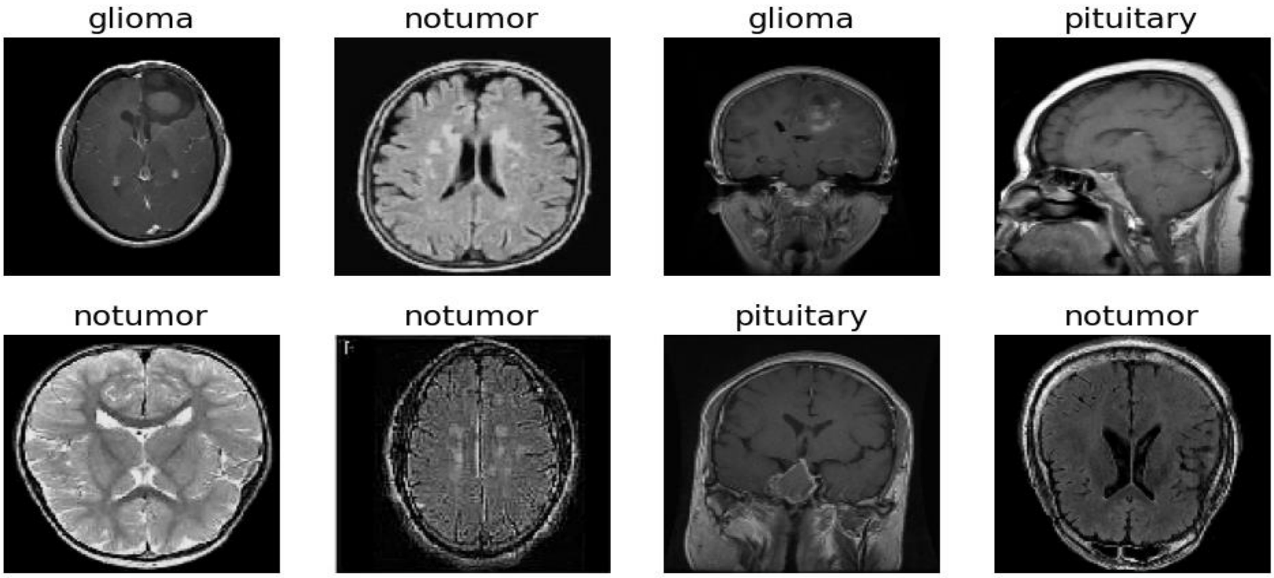


Figure 7. Images after PIL processing (source:authors)

The next stage after processing the images was to add data to our model and train it. The mode will train on 20 images at a time since we fitted the model with the data and set the batch size to 20. We also set the epochs to 5, which means the model will go through the training dataset five times, continuously obtaining random images from the dataset. Figure 8. is a graphic representation of the accuracy and loss results from our five epochs, as we can see from Figures 8 and 9, each epoch produces results with higher accuracy and lower loss. As we can see from the exact values displayed, the accuracy increased with each epoch, going from 83% to 96,9%. These results, given the size of the dataset, are satisfactory.

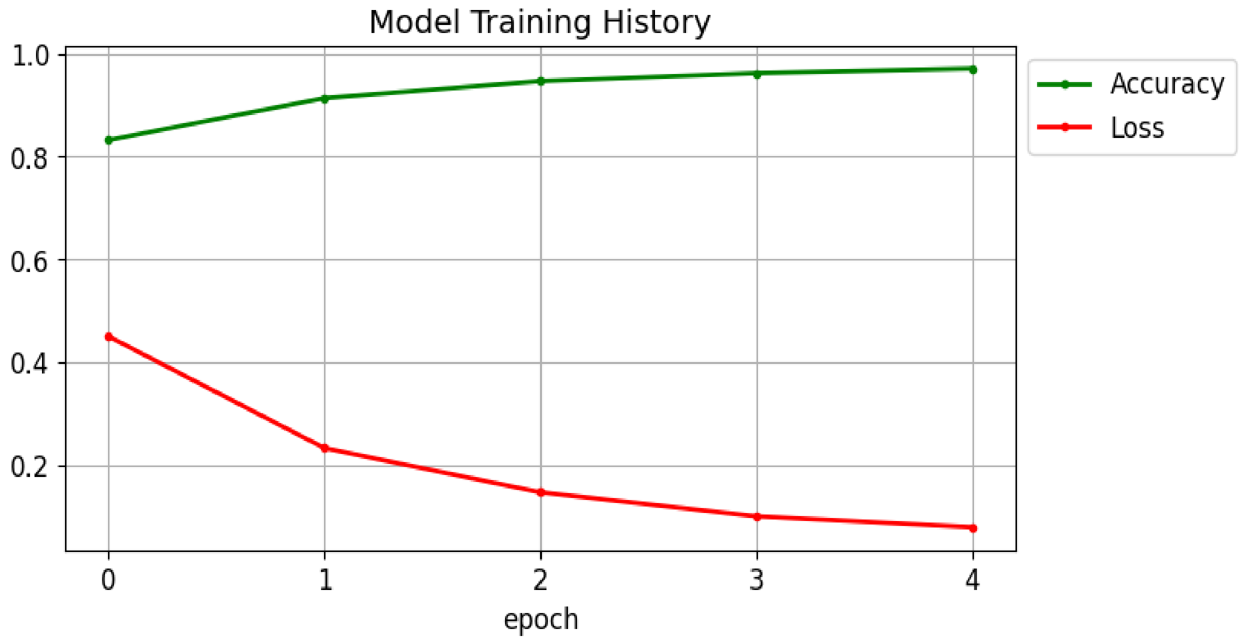
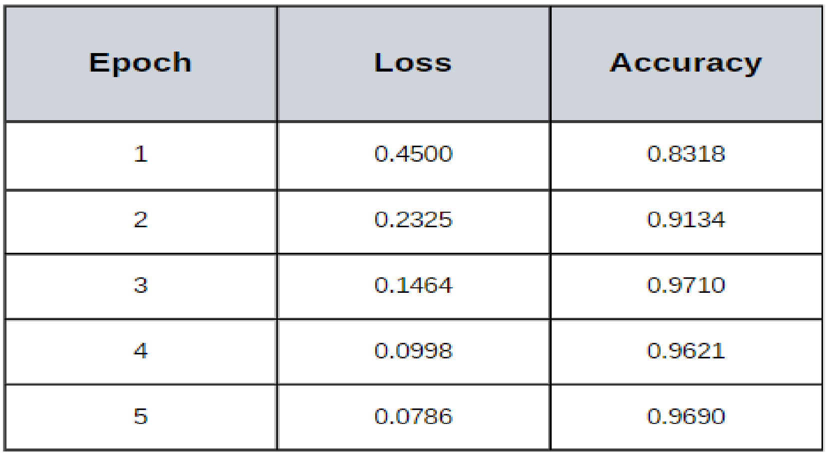


Figure 8. Plot representation of dataset training

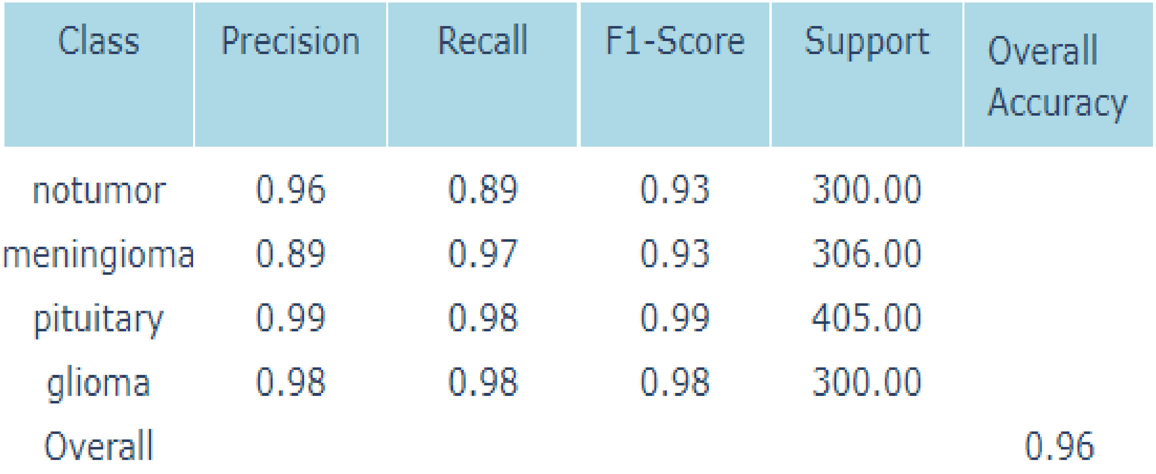


Epoch	Loss	Accuracy
1	0.4500	0.8318
2	0.2325	0.9134
3	0.1464	0.9710
4	0.0998	0.9621
5	0.0786	0.9690

Figure 9. Accuracy and loss values after each epoch

The classification report for our model is shown in Figure 10. As we can see, the model performed extremely well in every class, with the lowest results being 89% for meningioma and the highest being 99% for pituitary, 96% for no tumor, and 98% for glioma. All of these findings are highly consistent with one another, and the data indicates that the model has performed extremely well in its task of classifying the type of tumor.

Additionally, the model's overall accuracy of 96,9% is quite promising for this particular problem and its potential applications in the future. Another figure 11, belove, shows these values in a chart to provide a more readable view of the information obtained from the model. The model's performance in various classes is visually represented by the confusion matrix in Figure 12. It is clear that the model misclassified 32 images in the "meningioma" class, where it performed lowest. This misprediction is consistent with the accuracy metric found in the classification report, which shows that the "meningioma" class has a lower accuracy than other classes. Furthermore, there are tiny percentages of inaccurately predicted images for other classes, which are also represented in the accuracy values given in the classification report. For those particular classes, the differences between the expected and actual classes lead to somewhat lower accuracy percentages. The confusion matrix provides a thorough summary of the model's advantages and disadvantages in every class, effectively demonstrating these misclassifications.



Class	Precision	Recall	F1-Score	Support	Overall Accuracy
notumor	0.96	0.89	0.93	300.00	
meningioma	0.89	0.97	0.93	306.00	
pituitary	0.99	0.98	0.99	405.00	
glioma	0.98	0.98	0.98	300.00	
Overall					0.96

Figure 10. Classification report

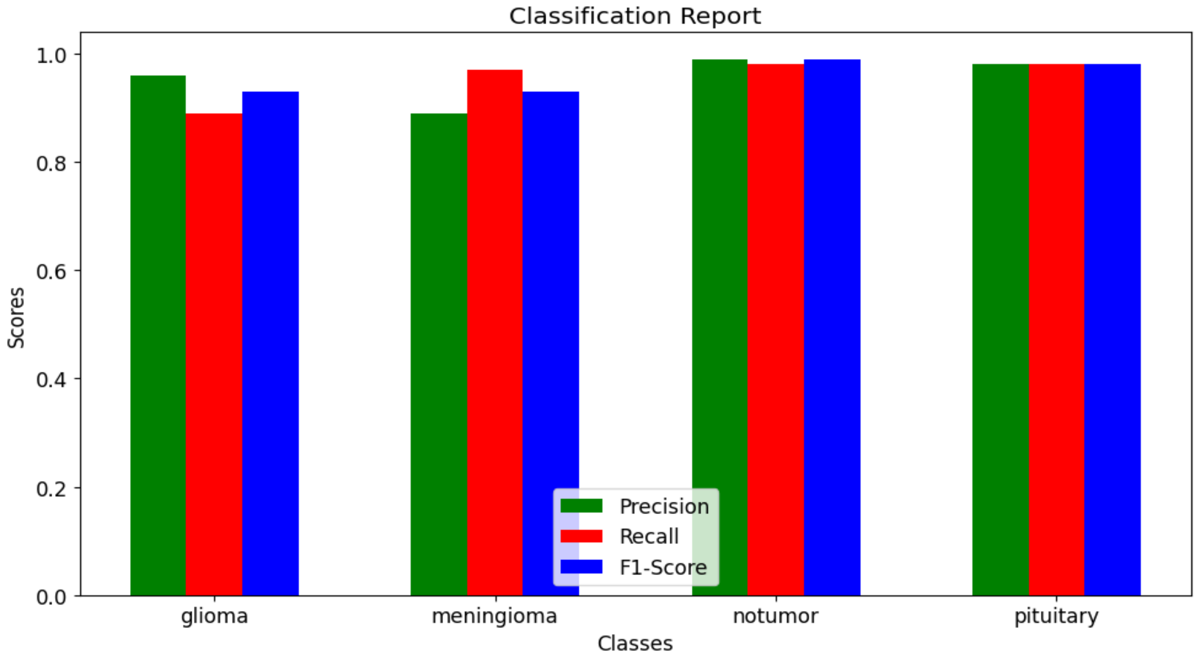


Figure 11. Plot representation of classification report

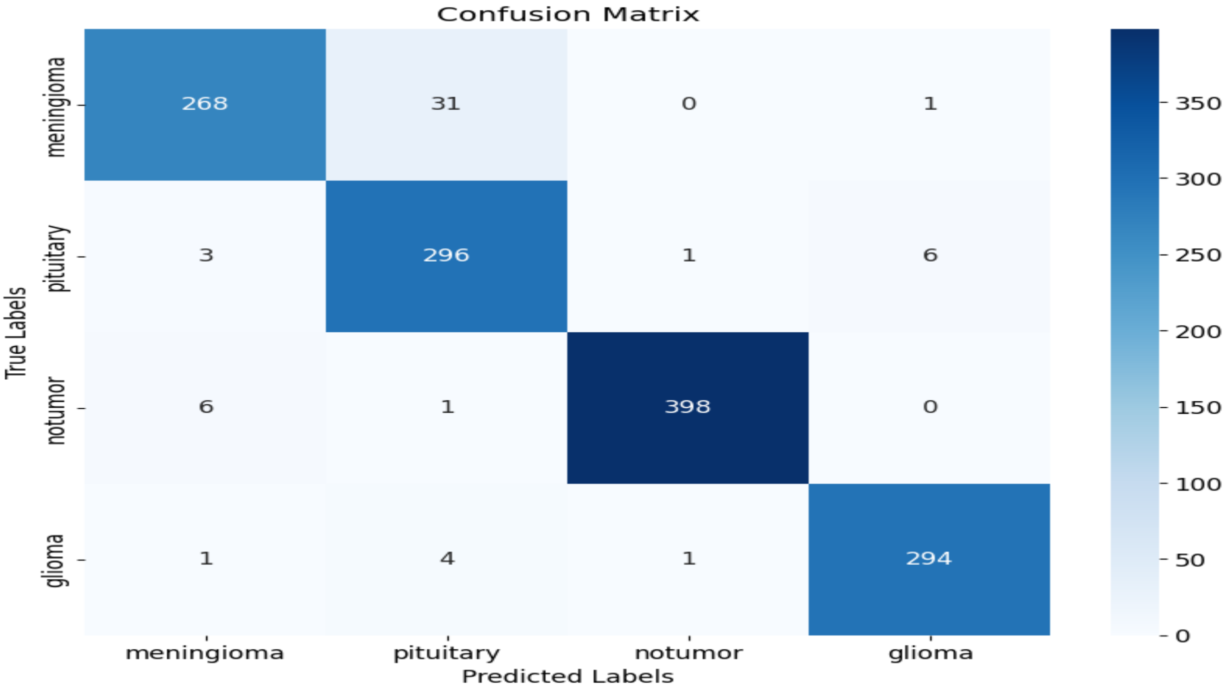
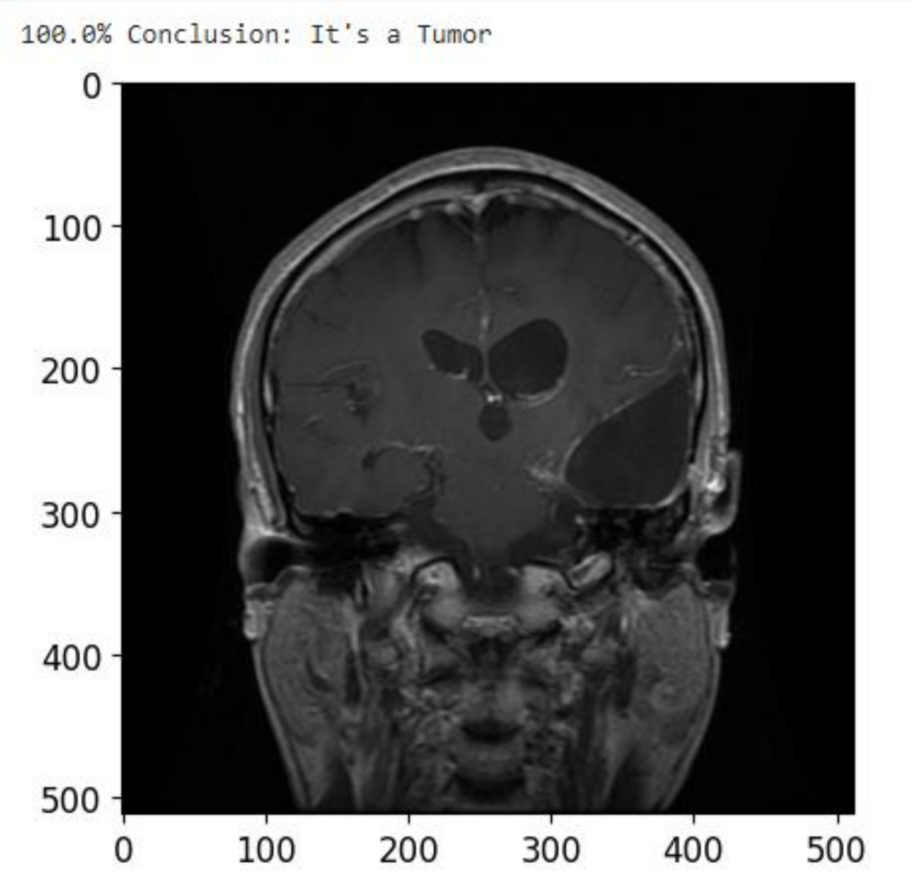


Figure 12. Balanced accuracy confusion matrix

The prediction made from a single image was one aspect of the work that we wanted to be unique. We developed a method that takes in a single image and, after the model has been trained and assessed, returns a percentage indicating the likelihood that a tumor is present in both the processed image and the MRI. And figure 13 shows the outcome that was obtained for a random image.



```
100.0% Conclusion: It's a Tumor
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Figure 13. Specific image prediction (source:authors)

5. Discussion

The findings of this study show how the PIL-VGG16 technique may successfully identify and categorize brain cancers from MRI data. High classification accuracy has been achieved because to the model's ability to learn and extract significant features thanks to the combination of PIL's image preprocessing capabilities and VGG16's deep learning architecture. The outcomes obtained are encouraging and show this method's potential for use in clinical settings. This study's use of a sizable dataset of 7023 MRI scans, which enhances the robustness and generalizability of the proposed model, is one of its major strengths. The addition of several tumor forms, such as glioma, meningioma, pituitary, and non-tumor instances, improves the dataset's diversity and offers a thorough illustration of the range of different types of brain tumors. But there are some restrictions that must be understood. First off, even if the achieved classification accuracy is great, further analysis and validation on a different dataset are required to guarantee the model's dependability. Additionally, the current study only considers image-based tumor detection and ignores additional clinical data or patient-specific factors that can improve the model's accuracy and clinical applicability.

But when comparing the results with similar work from this are we can see that our model has achieved above average results in this problems solution which can make a statement to further keep evolving this model results. When comparing with work of Chandra [3] and hers colleagues we can see that they used the VGG16 algorithm as well, but their dataset only consists of around 260 MRI images and they achieved accuracy of 84% which can be seen from the table below, as our dataset consisted of 7000 MRI images. In Dheiver’s [4] work we can see the utilization of the VGG16 algorithm as well, but he didn’t disclose the layer structure of the model nor the size of the dataset, but his results yielded results of 80% and 88% which are quality results but most likely the models layer structure can be improved as well as the datasets size. The work of Younis [5] and her colleagues achieved very high results 89% using CNN, 97% using VGG16 and 91% using an ensemble model, from this we can see the results for the VGG16 are in similar values with our result even though they used a smaller dataset of 253 images with a good model they achieved very high accuracy results.

Table 1. Comparison of results using similar models

Authors	Model	Accuracy
Dheiver Francisco Santos [4]	VGG16	88%
Chandra, K. Sarath; Priya, A. Sai; et al. [3]	VGG16	84%
Younis, A; Qiang, L; Nyatega, et al [5]	CNN VGG16 Ensemble	89% 97% 91%

As per the works that have used the same dataset as in our research the following work of Md. Monirul Islam [6] and his colleagues have conducted research on the same dataset and have obtained quite substantial results they have implemented four models: InceptionV3, VGG19, DenseNet121 and MobileNet with their respective accuracy’s 98.76%, 98.97%, 99.12% and 99.60% on the training datasets, while on the testing dataset the accuracy’s were the following InceptionV3 (96.8%), VGG19 (95.5%), DenseNet121 (97.41%) and MobileNet (98.4%), from the following data we can see that two of the models outperformed ours model. DenseNet121 is a deep neural network architecture comprising 121 layers, characterized by dense connectivity between layers, enabling feature maps concatenation and fostering effective gradient flow and feature reuse. In contrast, MobileNet optimizes parameter efficiency by utilizing depth-wise separable convolutions, dividing conventional convolutions into depth-wise and point wise convolutions, resulting in a highly efficient network design with fewer parameters. As per the image processing they mention using image augmentation to create altered duplicates of the images, which allows the model to be trained on more image variants, but the most interesting part of this work comes from results investigation as per the author the best performing model with minimal loss was InceptionV3 which architecture combines different convolutions, along with max pooling, average pooling, batch normalization, dropout, factorized convolution, and auxiliary classifiers, achieving stateof-the-art performance on various image recognition benchmark datasets. Another interesting research on the same dataset was performed by Gomez-Guzman [7] and his colleagues they have as well tested multiple models with the following having the best results in their research: InceptionV3 (97.1%), ResNet50 (96.97%) and InceptionResNetV2 (96.78%). In their work they have used InceptionV3 as one of the models they mention that the model consists of 48 layers. ResNet-50 is a 50-layer deep convolutional neural network architecture. Gradients can flow through the network more directly thanks to these connections, which makes it possible to train very deep networks and increases accuracy across a range of computer vision tasks. On the other hand, InceptionResNetV2 is a deep convolutional neural network that combines modified Inception blocks with residual connections and filter expansion layers, utilizing batch normalization to enhance its performance. Before the models can be trained the images are preprocessed with adjustment of the brightness, rotation and zoom to prepare the images for the mentioned models. The results of the mentioned works are displayed in Table 2.

Table 2. Comparison of results using the same dataset

Authors	Model	Accuracy
P. B. M. Md. Monirul Islam [6]	InceptionV3	96.8%
	VGG19	95.5%
	DenseNet121	97.41%
	MobileNet	98.4%
M. Gómez-Guzmán, L. Jiménez-Beristaín, E. García-Guerrero, et al. [7]	InceptionV3	97.1%
	ResNet50	96.97%
	InceptionResNetV2	96.78%

6. Conclusions

In summary, this study has demonstrated the potential benefits of using the VGG16 deep learning algorithm in conjunction with the Python Imaging Library (PIL) for brain tumor detection. Combining the feature extraction capabilities of VGG16 with the image preprocessing and manipulation capabilities of PIL has resulted in accurate and reliable tumor detection. The combination of PIL and VGG16 has shown great promise in the automated diagnosis of brain cancers from MRI images. The results of this study show how effectively this approach classifies different types of tumors with accuracy. The combination of PIL's image processing capabilities and VGG16's deep learning capabilities has improved the analysis and interpretation of brain MRI data. Subsequent research endeavours may investigate the integration of advanced deep learning models and methodologies to enhance the identification of brain tumors.

In conclusion, the combination of PIL and VGG16 has demonstrated efficacy in brain tumor detection, setting the stage for further advancements in medical image analysis and improving diagnostic abilities in the fight against brain tumors.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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