Brain Tumor Detection: BrainGuard

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***Abstract*—Brain tumors are a serious health risk that require early detection and effective detection techniques. Upon many abnormalities, brain tumors are considered to be the most dangerous ones. In this paper, we propose BrainGuard, a machine learning framework for brain tumor detection. BrainGuard is significant because it can help doctors identify tumors early, get medical help more quickly, and help patients get better. Moreover, our study highlights the use of two machine learning techniques in augmenting diagnostic which are convolutional neural networks (CNN) and VGG-16 models. Through comprehensive experimentation, we evaluate the performance achieving an accuracy of 94.8% for threshold and 82.05% for contrast and segmentation with CNN and 92.3% for threshold and 97.4% for contrast and segmentation with VGG-16. Additionally, this paper highlights the significance of ongoing machine learning advancements for improving healthcare diagnostics, as well as the implications of our findings for clinical practice and future research directions.**

***Index Terms*—Image Processing, Machine Learning, Image Augmentation, MRI brain images, CNN, VGG-16, Threshold, Contrast Stretching, Segmentation**

I. Introduction

The brain is a complicated human body organ that serves as the command center, governing all our thoughts, emotions, and actions. It is made up of billions of neurons that process a lot of information and help us perceive the world, learn, remember, and regulate our body functions. Therefore, any kind of abnormality in the brain can put human health in danger. Among various abnormalities, brain tumors are considered to be the most dangerous ones. Brain tumors occur when cells start growing in an abnormal way. These cells gradually lose their strength and become oppositional and affect normal brain activities. Moreover, brain tumors grow quickly, and if not treated appropriately, the survival rate of the patient is reduced and can rapidly lead to death. For this reason, early brain tumor detection plays an important role in clinical diagnosis and effective treatment. However, because of its complicated structure, it is difficult to identify brain tumors in their early stages. However, the development of new technologies such as deep learning techniques, machine learning techniques, and artificial intelligence have made this possible. These technologies can be utilized to create advanced algorithms capable of detecting even the smallest anomalies that may indicate the presence of a brain tumor. Furthermore, identifying tumor at an early stage allows for more treatment options and the chance of tumor removal. Also, it can help doctors to make informed decisions about treatment plans and reduce the anxiety of the patients and their families.

II. Related Work

Many approaches were proposed for the detection of brain tumor using MRI. Siar and Teshnehlab [1] have proposed a method which uses CNN to detect tumor through brain images. The proposed method used the first-order clustering algorithm for feature extraction with CNN and Softmax classifier. A total of 1892 dataset images, 1666 images used for training and 226 for testing. In order To differentiate the intended segments, the researchers used first order clustering algorithm for feature extraction. The collected images were applied to the traditional CNN after preprocessing. Furthermore, in order to evaluate the CNN performance, other classifiers such as the, Softmax, RBF and DT classifiers have been used. The experimental results showed that, Softmax, RBF and DT classifiers achieved 98.67%, 97.34%, 94.24% respectively. The proposed technique of feature extraction was applied to CNN with Softmax classifier. The accuracy of the proposed technique increased to 99.12% on the test data, outperforming the traditional CNN.

In a study conducted by Chattopadhyay and Maitra [2], the focus is on addressing the challenges associated with manual detection of brain tumors in MRI images by proposing an automatic detection method using convolutional neural networks (CNNs). The study highlights the tedious and inaccurate nature of manual detection due to the large volume of MRI images and the similarity between normal tissue and tumor cells in appearance. The proposed CNN-based method aims to accurately segment brain tumors from 2D MRI images by training the model with diverse tumor sizes, locations, shapes, and image intensities. Various activation algorithms and classifiers are employed to validate the proposed method, with CNN achieving an impressive accuracy of 99.74%. The findings suggest that the CNN-based model could significantly enhance the speed and accuracy of tumor detection in MRI images, thereby improving medical treatment outcomes.

Adding to that, Khan *et al.* [3] introduce a novel approach for the automated classification of brain tumors using deep learning and robust feature selection techniques. Manual identification of brain tumors is prone to errors and time-consuming, which results in the need for automated systems for accurate and efficient diagnosis. Leveraging deep learning models such as VGG16 and VGG19 through transfer learning, the proposed method extracts features from multimodal MRI images. A correntropy-based joint learning approach combined with extreme learning machine (ELM) facilitates the selection of optimal features for classification. Furthermore, robust features obtained from partial least square (PLS) analysis are fused, enhancing the discriminative power of the model. Experimental validation on BraTS datasets demonstrates high accuracy rates, reaching 97.8%, 96.9%, and 92.5% for BraTs2015, BraTs2017, and BraTs2018, respectively. The method's efficiency is affected by its reduced computational time, particularly evident in the ELM classifier, showcasing its potential for accurate and swift brain tumor classification in clinical settings.

The study conducted by Hossain *et al.* [4] focused on the challenges and significance of brain tumor segmentation and detection using MRI. It explored various image processing techniques, including skull stripping, filtering, enhancement, clustering, morphological operations, feature extraction, and classification using traditional machine learning algorithms and Convolutional Neural Networks (CNN). The results demonstrated impressive accuracy, with the CNN achieving a rate of 97.87%. The research emphasized the importance of early detection in improving treatment possibilities and survival rates for individuals with brain tumors, while also highlighting the potential of advanced technology and offering a comprehensive approach to brain tumor detection.

According to Methil [5], a novel method is presented for brain tumor detection, which combines deep learning and image processing techniques. The researchers utilized various image processing techniques, including adaptive thresholding, high pass filtering, median blur, global thresholding, histogram equalization, dilation, and erosion, to enhance the dataset for training purposes. These techniques were employed to address common issues encountered in medical images, such as illumination problems, noise reduction, and the specific focus on tumor identification within the images. Additionally, image augmentation techniques were employed by the researchers to diversify the dataset through the generation of different versions of the original images. This combination of image processing techniques and data augmentation significantly contributed to the effectiveness of the proposed method in handling the challenges presented by diverse tumor shapes, textures, and locations. Moreover, the method effectively addresses these challenges through image pre-processing techniques and the utilization of a convolutional neural network (CNN). The method achieves high recall and accuracy when evaluated on a diverse dataset, to demonstrate its effectiveness. The study critically evaluates existing methods, emphasizing the crucial need for accurate and efficient detection to prevent fatalities. Overall, the proposed approach offers a sophisticated and effective solution for brain tumor detection, with significant potential for further advancements and applications.

The researchers in [6] proposed a model based on CNN for brain tumor classification that integrates the strengths of the two algorithms, namely the sine-cosine and grey wolf optimizer algorithm for hyper-parameter optimization. Additionally, the training model incorporates Inception-ResnetV2 to improve the diagnosis of brain tumors. For medical image segmentation, the study utilizes the U-Net segmentation model, specifically the 3D-U-Net segmentation model, known for its capabilities in fast and accurate segmentation. Additionally, a data augmentation technique was employed to generate fresh training data from the existing dataset. The output of the model is a binary value (0: normal, 1: tumor). As a result, the experiment yielded an impressive accuracy of 99.98% due to the effective utilization of the CNN optimization's hyper-parameters.

Lastly, the authors in [7] proposed a model for brain tumor detection and segmentation using two different architectures. The first architecture utilized a fine-tuned ResNet50 model, which was employed for brain tumor detection. This involved discovering the existence of a tumor in MRIs using the CNN-based classification technique. On the other hand, the second architecture incorporated the U-Net model, specifically designed for accurate brain tumor segmentation. The U-Net model was utilized to identify the regions in the image that contain the tumor while distinguishing them from the surrounding healthy tissue. A public dataset named TCGA-LGG and TCIA, containing 120 patients, was used to develop the model. The measures used to evaluate model performance include accuracy, intersection over union, dice similarity coefficient, and similarity index. The output of the experiment shows that the intersection over union: 0.91, dice similarity coefficient: 0.95, similarity index: 0.95 and accuracy: 0.94. The inclusion of the U-Net model has increased the performance of the overall model.

A. Limitations

The following are the limitations from the related work mentioned above. These papers have identified several challenges and constraints in the field, highlighting areas such as the complexity of brain tumor segmentation, the difficulty in distinguishing between similar tumor types, the limitations of certain imaging techniques, the computational time required for certain processes, the potential risks of image pre-processing, and the need for further validation on larger and more diverse datasets. These limitations reflect the current state of research in brain tumor segmentation and serve as valuable insights for future studies and improvements in the field.

III. Methodology

In our proposed methodology, there are two distinct model for brain tumor detection. First model is CNN which was applied on thresholded MRI brain images and contrast stretched and segmented MRI brain images. The second model VGG-16 which was applied on thresholded MRI brain images and contrast stretched and segmented MRI brain images. In this section, more details about the hardware, software, dataset and models are discussed. Fig. 6 bellow shows a visualization of the proposed methodology.

A. Hardware

The hardware used to build the model is 13" MacBook Pro (2022) equipped with an Apple M2 processor. The graphics card employed was the Apple M2's built-in GPU. The system was supported by 8GB of LPDDR5 memory.

B. Software

We used Google Colab to apply image processing techniques and build the BrainGuard models because it is a free cloud-based platform that allows programmers to write and execute Python code in the browser without having to install or manage any software.

C. Dataset

The MRI brain images were acquired from Kaggle [8] and were given as input to pre-processing stage. The dataset consists of two folders: yes folder which indicates that there is a tumor, and no folder which indicates that the there is no tumor. The total number of MRI brain images is 253, 155 of them are "yes" and 98 are "no".

1) Pre-Processing:

Image augmentation generates similar but distinct examples after a series of some changes to the images, thereby expanding the size of the dataset. In our situation, we noticed that yes and no classes are imbalanced, therefore, we applied image augmentation using horizontal and vertical flip. After the image augmentation has been applied, the number of images in each class became balanced and this can enhance the model training process. See Fig. 1.

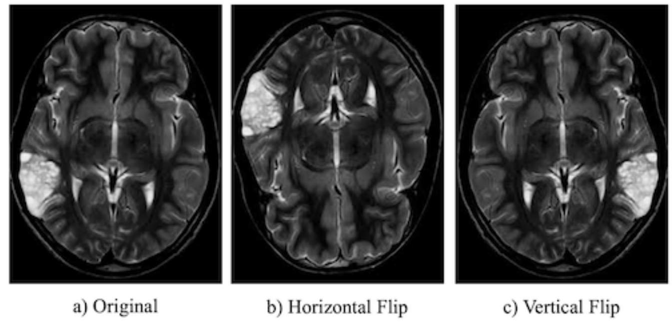


Fig. 1. Image Augmentation

2) Image Processing Techniques:

Image processing techniques are methods and algorithms used to manipulate and analyze digital images. The following are the image processing techniques performed on MRI brain images.

- ***Threshold***

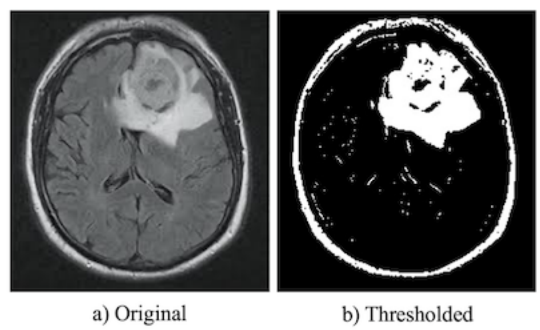


Fig. 2. Brain with tumor after applying threshold

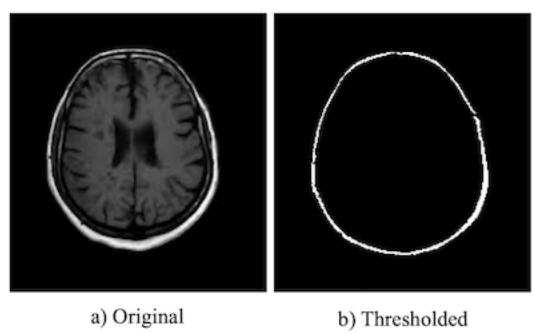
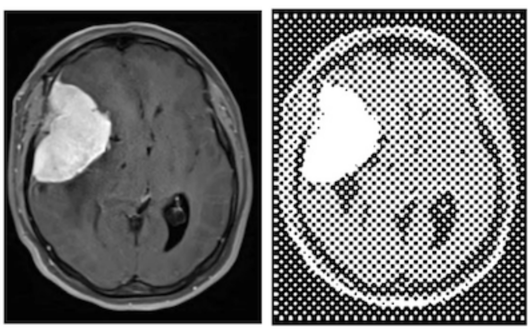


Fig. 3. Brain without tumor after applying threshold

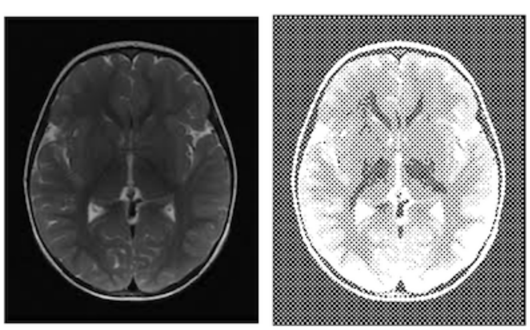
Image thresholding is the process of converting grayscale images into binary images by replacing each pixel in an image with a black or white pixel based on a fixed value called the threshold. We chose threshold technique to be able to isolates the object by partitioning the image into a background that contains the pixels that are fully black and foreground that consists of pixels that are fully white which is region of interest. As mentioned before that our dataset is divided into two folders “yes” and “no”, we had to perform the thresholding twice, once for the MRI brain images labelled as “yes” and a second time for the MRI brain images labelled as “no”. The function used to apply thresholding to MRI brain images is cv2.threshold(). This function takes four parameters. The first parameter is the source image, in our case, MRI brain images labelled as “yes”, and MRI brain images labelled as “no”. The second parameter is the threshold value, which used in order to classify the pixel values, for images labelled as “yes” the threshold value set to be 125 and images labelled as “no” the threshold value set to be 177. The third parameter is the maximum value, which is assigned to the pixel values that exceeds the threshold, for images “yes” and “no” same value which is 255 was applied. The fourth parameter specifies the type of thresholding, which in this case is set to THRESH_BINARY. See Fig. 2 and Fig. 3.

- ***Contrast Stretching and Segmentation***



a) Original   b) Contrast Stretched and Segmented

Fig. 4. Brain with tumor after applying contrast stretching and segmentation



a) Original   b) Contrast Stretched and Segmented

Fig. 5. Brain without tumor after applying contrast stretching and segmentation

Contrast stretching is a technique that adjusts intensity values by mapping the original intensity values of an image to a new range of values to enhance contrast and brightness, making images more visually appealing and detailed. We applied contrast stretching on MRI brain images labelled as “yes”, and MRI brain images labelled as “no” using ImageEnhance.Contrast() function. The function takes an enhancement factor as an parameter. Specifically, the enhancement factor for MRI brain images labelled as “yes” is set to 1.3, while for MRI brain images labelled as “no”, the enhancement factor is set to 3.

Image segmentation is the process of dividing an image into multiple segments with similar intensity properties to identify objects in an image. The chan_vese() function used to perform the segmentation. It typically takes several parameters. In our case, it only takes input image, number of iterations and extended output. However, input images here are the images labelled as “yes” and “no” resulting from contrast stretching. The max number of iterations is set to 15 iterations, and extended output is set to true which give us additional information about the segmentation process.

The MRI brain images we used have low contrast; therefore, we have applied contrast stretching as a preliminary step before segmentation. Without contrast stretching, it would be challenging for segmentation algorithm to distinguish between adjacent regions with similar intensities. So, by increasing the contrast, the boundaries between regions become more distinct making it easier for segmentation algorithm to accurately identify the object of interest. See Fig. 4 and Fig. 5.

D. *Machine Learning Models*

Each of the following models has been trained on two different MRI brain images datasets. One dataset was processed using thresholding, while the other dataset processed contrast stretching and segmentation.

1) CNN:

A convolutional neural network (CNN) is a form of artificial neural network used mainly for image identification and processing, since it has the ability to identify patterns in images [9]. The model has three Conv2D layers which extract features from 2D input data. Each Conv2D layer has 9X9 kernel size and ReLU activation function. The model also has three MaxPooling 2D layers which is used to decrease the spatial dimensions width and height of the input while preserving the most significant properties to minimize the computational complexity of the model. Each MaxPooling 2D layer has pool size 2. Also, the model contain four dropout layers to generalize the feature learning and prevent overfitting. Moreover, our model involves two dense layers to learn complex patterns and relationships in the input data. a flatten layers has been used to convert the multi-dimensional input into a one-dimensional vector, making it easier for the dense layers to process the input.

2) VGG-16:

The Visual Geometry Group (VGG) at the University of Oxford devised a convolutional neural network (CNN) architecture that is well-known for its depth and efficiency in obtaining high performance on many computer vision applications [10]. the model consist of four layers. The first layers is the VGG-16 which already has its convolutional layers and fully connected layers, followed by The flatten layer that converts the multidimensional input into a one-dimensional vector, allowing the dense layers to handle it more efficiently. The dropout layer, which is the third layer, generalizes feature learning and prevents overfitting. Finally the dense layer learns complex patterns and relationships in the input data.

IV. Results

In this section, we have evaluated the accuracy of both the (CNN) and (VGG) with the use of thresholding and contrast and segmention. The VGG-16 achieved a higher accuracy with contrast and segmentation of 97.4% and 82.05% for CNN, compared to the CNN's 94.8% accuracy for the threshold which is higher than VGG's accuracy of 92.3%. These outcomes and accuracy levels demonstrate the model's ability for accurate prediction-making. In terms of accurately predicting outcomes or making decisions based on the dataset used, the VGG and CNN both performed well according to threshold and contrast and segmentaion. The analysis includes analyzing the different implementation of threshold and contrast and segmentation for each type of model. For the CNN, when it comes to the threshold. It has performed better than its contrast and segmentation. On the other hand, in VGG-16's contrast and segmentation has performed better than its threshold. Both models have performed efficiently with different accuracy percentages. See TABLE I bellow.

TABLE I
The accuracy of each model

Model	Threshold	Contrast Stretching and Segmentation
CNN	94.87%	82.05%
VGG-16	92.30%	97.43%

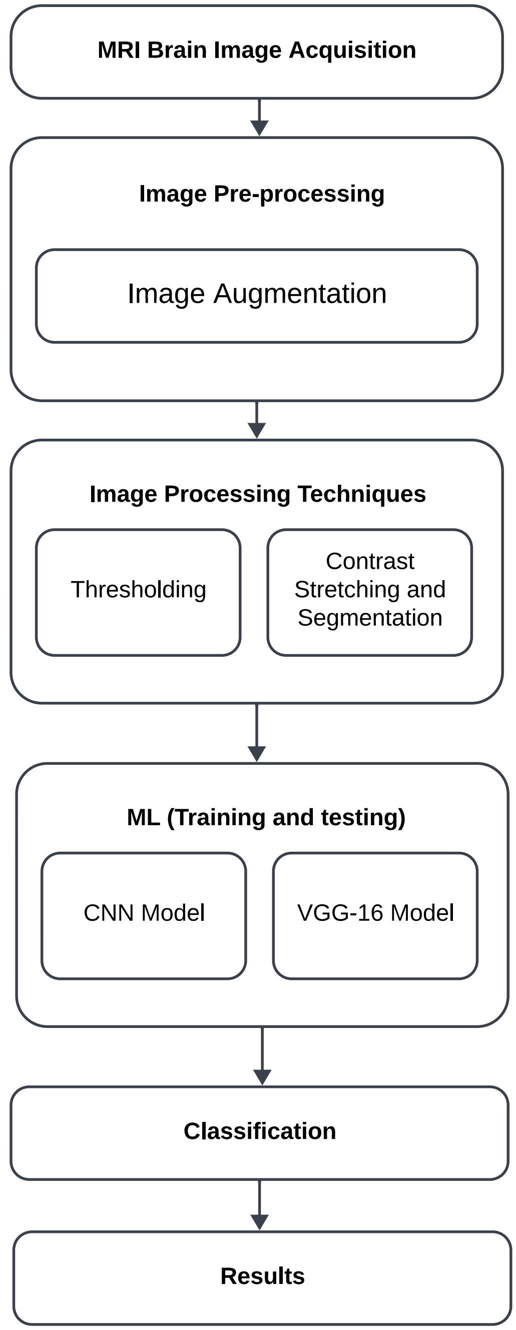


Fig. 6. Proposed methodology of BrainGuard

V. Discussion

The identification of brain tumors is greatly impacted by machine and deep learning. Although the model has produced excellent results, our entire work has certain limitations. One of our model's limitations is that it isn't integrated into an application; therefore, for future work, we suggest creating an application that connects to the model. An additional constraint refers to the dataset chosen, which was obtained from the Kaggle website. As a result, the data is anonymous and no additional information is available. In consideration of this, we suggest applying our model to an actual official dataset that is obtained directly from a hospital, where the data can be more extensive and produce better results.

VI. Conclusion

In conclusion, accurately detecting brain tumors in their early stages is difficult because of their complex structure, which makes early detection crucial for clinical diagnosis and successful treatment. BrainGuard provides evidence of the effectiveness of CNN and VGG models enhanced with contrast and segmentation and thresholding for the identification of brain tumors. CNN is effective at thresholding, yet VGG-16 is good at contrast and segementaion enhancement. Personalized treatment plans and early diagnosis can be made easier by incorporating these methods into clinical practice. Moreover, future work could involve developing user-friendly applications for real-time tumor detection and applying our model to an official dataset that is obtained directly from a hospital to produce better results. Thus, by facilitating early detection and enhancing patient outcomes, the incorporation of deep learning in neuroimaging holds the potential to completely transform the healthcare industry. For further details, including source code and datasets related to this research, please refer to our GitHub repository at [https://github.com/ghd1010/BrainGuard.git].

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