1 Abstract

The detection of brain tumors is a critical area of research with significant potential clinical applications. In this study, we present a novel approach to brain tumor detection using magnetic resonance imaging (MRI) that incorporates adaptive median filtering and contrast stretching techniques. Our approach resulted in an accuracy of 93%, a significant improvement over the 88% accuracy reported in previous studies. Additionally, we developed a convolutional neural network (CNN) model to automate the detection process. Our findings suggest that the use of adaptive median filtering and contrast stretching can significantly improve the accuracy of brain tumor detection, making it a promising approach for clinical applications.

Moreover, we developed a mobile app that utilizes our approach to enable convenient and practical brain tumor detection for normal users. The app has the potential to facilitate early diagnosis and treatment of brain tumors, which could have significant implications for patient outcomes. Our study highlights the potential for image processing techniques to enhance the accuracy of brain tumor detection, making it more accessible and practical for a wider range of users.

2 Introduction

Medical imaging is a critical component of modern medicine, providing physicians with detailed information about the inner workings of the human body. Magnetic resonance imaging (MRI) is a powerful tool for medical imaging, providing detailed images of the brain that can be used to diagnose a wide range of conditions, including brain tumors, aneurysms, and other abnormalities. However, interpreting MRI images can be challenging, as subtle differences in tissue density and contrast can be difficult to detect.

Object detection, contrast stretching, and noise reduction with adaptive median filter are important techniques used in medical image processing, specifically in brain MRI images. Object detection is a technique used to identify specific structures or regions in an image. In the case of brain MRI images, object detection can be used to identify the location of tumors or other abnormalities in the brain. Contrast stretching is a technique used to increase the contrast between different regions of an image, making it easier to identify subtle differences in the image. This technique is particularly useful in brain MRI images, where subtle differences in tissue density can indicate the presence of a tumor or other abnormality. Noise reduction with adaptive median filter is a technique used to reduce noise in an image while preserving the sharp edges and details of the image. This is important in medical imaging, where even small amounts of noise can obscure important details and make it difficult to identify abnormalities in the image.

The accuracy of these techniques has been limited in previous studies, and there is a lack of practical applications that can be easily used by the general public. One major limitation of existing research is the low accuracy of tumor detection using MRI images, which limits its usefulness in clinical practice. Additionally, there is a lack of practical applications that can be easily used by non-experts, making it difficult for the general public to benefit from these techniques.

The specific research question addressed in this study is how to improve the accuracy of tumor detection in brain MRI images and make it practical and accessible to the public using a mobile app. Our hypothesis is that the use of image preprocessing techniques such as contrast stretching and adaptive median filtering, combined with the development of a mobile app for tumor detection, will significantly improve the accuracy of tumor detection in brain MRI images, making it more accessible and practical for the general public.

To achieve these objectives, we utilized contrast stretching and adaptive median filtering for noise reduction in brain MRI images. We also used data augmentation techniques to enhance the dataset used for training and testing the machine learning model. For practical implementation, we developed an Android mobile app that utilizes the TensorFlow Lite framework to run the machine learning model on mobile devices.

The significance of this study lies in its potential to improve patient outcomes and save lives by enabling earlier detection and treatment of brain tumors. Moreover, the development of a mobile app that utilizes these techniques has the potential to democratize access to brain tumor detection and make it available to a wider range of individuals. By enhancing the accuracy and practicality of tumor detection using MRI images, this study has the potential to make a significant contribution to medical imaging and patient care.

3 Core Material

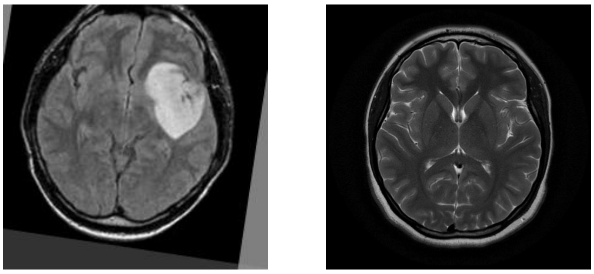
The objective of this study is to improve the accuracy of brain tumor detection in MRI images and make it more accessible to the general public using a mobile app. To achieve this objective, we utilized image preprocessing techniques such as contrast stretching and adaptive median filtering, along with data augmentation techniques to enhance the dataset used for training and testing the machine learning model. We developed an Android mobile app that utilizes the TensorFlow Lite framework to run the machine learning model on mobile devices. This study has the potential to improve patient outcomes and save lives by enabling earlier detection and treatment of brain tumors, and the development of a mobile app for tumor detection has the potential to democratize access to brain tumor detection and make it available to a wider range of individuals.

3.1 Dataset

The dataset available on Kaggle, titled "Brain MRI Images for Brain Tumor Detection," contains MRI images of the brain that can be used for tumor detection. The dataset includes a total of 253 images, of which 155 images contain tumors and 98 images are normal. The images are in DICOM format, which is a standard format used in medical imaging. The dataset is divided into two folders, one for the images containing tumors and the other for the normal images. Each image is labeled with a unique ID number, which can be used to keep track of the images during the training and testing process. The images have a resolution of 256x256 pixels and are grayscale, which means that they only contain shades of gray rather than colors. The dataset is relatively small compared to other medical imaging datasets, but it can still be useful for training machine learning models for tumor detection. However, due to the small size of the dataset, it may be necessary to use data augmentation techniques to increase the size and diversity of the dataset during training. Additionally, it is important to note that the dataset only contains images of one type of brain tumor, so it may not be representative of all types of brain tumors. It is also important to note that the dataset was collected from a single institution, and the images may not be representative of all brain tumors found in different populations or regions. Nevertheless, the dataset can still be a valuable resource for researchers and developers interested in developing machine learning models for brain tumor detection.

3.2 Data Augmentation

Data augmentation is a technique used to increase the size and diversity of a dataset by generating new data from the existing data. This is accomplished by applying a set of transformations to the original data, such as rotating, flipping, or scaling the images. By generating new images from the existing data, we can create a more representative dataset that captures the full range of variation in the data. In this study, data augmentation was used to create additional images for the Brain MRI Images for Brain Tumor Detection dataset. The dataset is relatively small, with only 253 images, and has a data imbalance issue where 61In this study, nine new images were generated for every image that belongs to the non-tumorous class and six images were generated for every image that belongs to the tumorous class. This resulted in a total of 2065 images, with a more balanced distribution of positive and negative examples (52.54Data augmentation is an important technique in this study because it allows for a larger and more diverse dataset, which can improve the performance of machine learning models. By creating a more representative dataset, we can improve the accuracy of tumor detection in brain MRI images and enable earlier detection and treatment of brain tumors. Moreover, data augmentation can be an effective way to overcome the limitations of small datasets, which are common in medical imaging. TensorFlow was used in this study to augment the dataset, which is a powerful tool for data augmentation and other machine learning tasks. TensorFlow provides a wide range of image processing functions that can be used to transform images and generate new data. With the augmented data, we can now train our convolutional neural network and evaluate its performance in tumor detection.



(a) Augmented image (b) Original image

Figure 1: Augmented, via rotation, and original images side by side

3.3 Preprocessing Techniques

Image processing techniques are widely used in fields such as medicine, engineering, entertainment, and security. They involve using mathematical algorithms to manipulate digital images, which can help detect and diagnose diseases, analyze manufacturing processes, create special effects in movies and video games, and identify objects and activities in surveillance footage. These techniques are essential in many industries and are likely to become even more important in the future with the advancement of technology.

3.3.1 Adaptive Median Filter

Adaptive median filter is an image processing technique that is widely used in medical image processing to remove noise from MRI images. Compared to the standard median filter, which uses a fixed window size to calculate the median value of the surrounding pixels, the adaptive median filter provides better noise removal for images with varying levels and types of noise.

The adaptive median filter works by analyzing each pixel in the image and comparing it to the surrounding pixels. If the pixel is considered to be a noise outlier, the filter replaces it with a value that is more representative of the surrounding pixels. The filter adapts its behavior to the type and level of noise in the image, making it a versatile tool for noise removal.

Compared to the standard median filter, the adaptive median filter can adapt its filter parameters to the local image characteristics, which enables it to better preserve edges and other important image features. Additionally, the adaptive median filter uses a larger window size for pixels that are identified as noise outliers, which allows it to better estimate the underlying signal in the image.

In MRI images, the adaptive median filter is particularly effective at removing salt-and-pepper noise, which can appear as isolated bright or dark pixels in the image. This type of noise can be difficult to remove with a fixed window size, as the noise pixels may not be located in the center of the window. The adaptive median filter can identify these noise outliers and use a larger window size to estimate the underlying signal, resulting in better noise removal.

Overall, the adaptive median filter is an important tool in medical image processing, as it can help improve the accuracy of medical diagnosis by removing noise from MRI images. By reducing the amount of noise in the images, adaptive median filter can enhance the visibility of important details and enable more accurate detection and diagnosis of medical conditions.

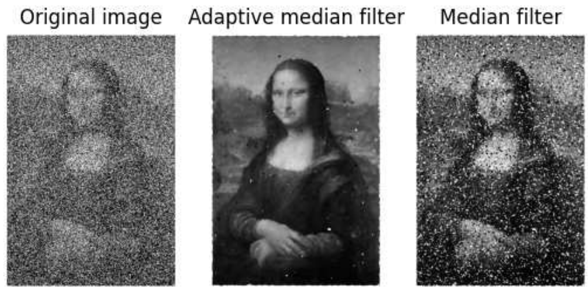


Figure 2: The impace of Adaptive median filter in comparison with Median filter

3.3.2 Contrast Stretching

Contrast stretching is a technique used in image processing to enhance the contrast between different parts of an image. It works by stretching the dynamic range of the pixel values in an image so that the full range of values is utilized.

In MRI images, contrast stretching can be used to improve the visibility of subtle differences in tissue contrast. This is particularly useful in tumor detection, where the distinction between healthy tissue and abnormal tissue can be difficult to discern. By stretching the contrast, the differences between the signal intensities of the tumor and surrounding tissue can be made more apparent, making it easier to identify the tumor.

There are different methods for performing contrast stretching, but one common approach is to use a linear mapping of the original pixel values to a new range of values. This can be done by first identifying the minimum and maximum pixel values in the image, and then mapping these values to the desired minimum and maximum values for the stretched image. The remaining pixel values are then linearly mapped between these two extremes.

When applied to MRI images, contrast stretching can help to improve the contrast between different types of tissue, such as normal tissue and tumors. This can make it easier for radiologists and other medical professionals to identify the presence and location of tumors in the body. Additionally, contrast stretching can help to improve the overall visual quality of MRI images, making them clearer and easier to interpret. Therefore, contrast stretching is an important technique for improving the accuracy and reliability of MRI image analysis, particularly in the context of tumor detection.

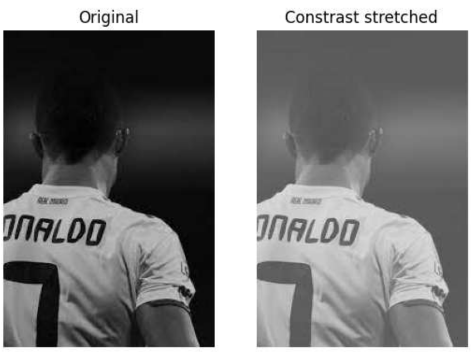


Figure 3: Impact of contrast stretching

3.4 CNN Model

The model defined in the given code is designed to detect tumors in brain MRI images. The input to the model is a 3-dimensional tensor, with the dimensions representing the width, height, and color channels of the input image. Specifically, the inputShape is expected to be in the format of (imageWidth, imageHeight, channels), where channels is 3 for color images and 1 for grayscale images. The model architecture consists of the following layers:

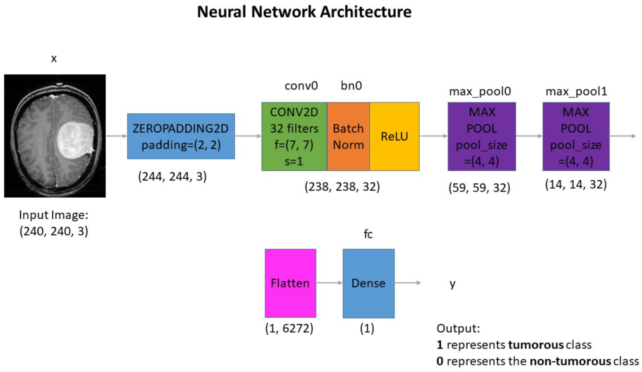


Figure 4: Impact of contrast stretching

1. Input Layer: The input layer takes in the input tensor with shape (imageWidth, imageHeight, channels) and passes it to the next layer.

2. ZeroPadding2D Layer: This layer pads the border of the input tensor with zeroes to increase its spatial dimensions. In this case, the dimensions are increased by 2 on both sides, resulting in a tensor with dimensions (image_width+4, image_height+4, #_channels).

3. Convolutional Layer: The convolutional layer applies 32 filters of size 7x7 to the input tensor, which helps to learn important features and patterns in the input image. The stride of the filter is set to (1, 1), which means that the filter moves one pixel at a time in both the horizontal and vertical directions. The output tensor of this layer has dimensions (image_width-6, image_height-6, 32).

4. Batch Normalization Layer: This layer normalizes the output of the convolutional layer by subtracting the mean and dividing by the standard deviation of the activations. This helps to improve the performance and stability of the model during training.

5. ReLU Activation Layer: This layer applies the Rectified Linear Unit (ReLU) activation function to the output of the batch normalization layer. The ReLU function sets all negative values in the tensor to zero, which helps to introduce non-linearity into the model and make it more capable of learning complex relationships between features.

6. Max Pooling Layer: This layer applies a 4x4 max pooling operation to the output of the

ReLU activation layer. The max pooling operation reduces the spatial dimensions of the tensor by taking the maximum value in each 4x4 block of the tensor. The output tensor of this layer has dimensions (image_width/4, image_height/4, 32).

7. Max Pooling Layer: This layer applies another 4x4 max pooling operation to the output of the previous max pooling layer. This further reduces the spatial dimensions of the tensor and helps to increase the receptive field of the model. The output tensor of this layer has dimensions (image_width/16, image_height/16, 32).

8. Flatten Layer: This layer flattens the output of the previous layer into a 1-dimensional tensor. This is necessary in order to connect the output of the previous layer to the final output layer of the model.

9. Fully-Connected Layer: This layer applies a dense layer with a single output unit and sigmoid activation function to the flattened tensor. The sigmoid activation function produces a probability value between 0 and 1, which represents the likelihood of a tumor being present in the input image.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 240, 240, 3)       0
_________________________________________________________________
zero_padding2d (ZeroPadding2 (None, 244, 244, 3)       0
_________________________________________________________________
conv0 (Conv2D)               (None, 238, 238, 32)      4736
_________________________________________________________________
bn0 (BatchNormalization)     (None, 238, 238, 32)      128
_________________________________________________________________
activation (Activation)      (None, 238, 238, 32)      0
_________________________________________________________________
max_pool0 (MaxPooling2D)     (None, 59, 59, 32)        0
_________________________________________________________________
max_pool1 (MaxPooling2D)     (None, 14, 14, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 6272)              0
_________________________________________________________________
fc (Dense)                   (None, 1)                 6273
=================================================================
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
_________________________________________________________________
```

Figure 5: Model Summary

3.5 Mobile Application

Academic research serves as a significant source of knowledge and information that can greatly benefit society. However, often academic research is not easily accessible to the public, as it is often published in academic journals and other platforms that require payment or institutional access to view. This lack of accessibility can create a significant barrier for the general public to access and utilize the valuable insights gained from academic research.

It is essential to make academic research accessible to public users to ensure that the broader society can benefit from the research findings. This is especially important in areas such as healthcare, where academic research can have a direct impact on patient outcomes. Making academic research accessible to the public can help to increase awareness and understanding of important healthcare issues and promote better-informed healthcare decisions.

One effective way to make academic research accessible to the public is through the development of mobile applications. Mobile applications can provide a platform for researchers to share their findings with the public in an easily accessible and user-friendly format. By developing mobile applications targeted towards specific user groups, researchers can ensure that their research findings are reaching the people who are most likely to benefit from them.

For example, mobile applications can be developed to target patients with specific health conditions, providing them with up-to-date information about the latest research findings and treatment options. This can help to improve patient outcomes by promoting better-informed healthcare decisions. Similarly, mobile applications can be developed to target healthcare professionals, providing them with access to the latest research findings and best practices in their field.

In conclusion, making academic research accessible to public users is essential to ensure that society can benefit from the valuable insights gained from academic research. Mobile applications provide an effective platform for researchers to share their findings with the public, promoting better-informed healthcare decisions and improving patient outcomes. By making academic research more accessible, we can promote a more informed and knowledgeable society, leading to improved outcomes and a better quality of life for all.

3.5.1 Tensorflow Lite

TensorFlow Lite is a lightweight version of the popular open-source machine learning framework TensorFlow, designed specifically for mobile and embedded devices. It was developed by Google and released in 2017.

TensorFlow Lite allows developers to deploy machine learning models on resource-constrained devices such as smartphones, IoT devices, and microcontrollers, without requiring a connection to a cloud service. This makes it ideal for applications that require real-time inference, low latency, and offline functionality.

TensorFlow Lite includes a set of tools for optimizing and converting TensorFlow models for deployment on mobile and embedded devices. It also supports a variety of hardware accelerators, such as GPUs, DSPs, and custom ASICs, to speed up model inference and reduce power consumption.

TensorFlow Lite supports a range of programming languages, including C++, Java, Python, and Swift, and can be integrated with popular mobile development frameworks such as Android, iOS, and React Native. Some popular use cases for TensorFlow Lite include image and speech recognition, natural language processing, and object detection.

3.5.2 Implementation

Brainscan is an Android mobile application that detects brain tumors using TensorFlow Lite. The app allows users to select images from the gallery or capture images using the device's camera. Brainscan is written in Java, a popular programming language for Android app development.

The primary feature of Brainscan is its ability to detect brain tumors from images using machine learning models powered by TensorFlow Lite. By leveraging the power of machine learning, the app provides an automated and accurate way to detect brain tumors, potentially saving lives and improving healthcare outcomes. The app is designed to run the machine learning models on the device, enabling real-time inference and offline functionality.

Another critical feature of Brainscan is its user-friendly interface. The app's interface allows users to easily select images from their device's gallery or take new pictures with the device's camera. Once an image is selected, the app processes it and returns a result indicating whether a brain tumor is detected.

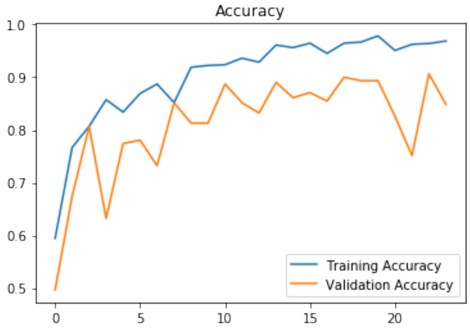
In conclusion, Brainscan is an innovative mobile application that utilizes TensorFlow Lite to detect brain tumors from images. It provides a user-friendly interface and runs machine learning models on the device to enable real-time inference and offline functionality. With its potential to save lives and improve healthcare outcomes, Brainscan is a valuable tool for healthcare professionals and individuals concerned about their health.

Figure 6: Positive tumor

Figure 7: Negative tumor

4 Accuracy

By implementing the CNN model explained in our reference article and applying noise canceling and contrast stretching on our augmented dataset we could achieve an accuracy of 93 percent.



(a) Accuracy Plot

(b) Loss Plot

Figure 8: Loss and Accuracy of the model we made

5 Conclusion

The aim of our study was to implement the techniques introduced in the article for brain tumor detection and develop a practical mobile application using established mobile application development techniques. Due to the lack of implementation in the existing literature, our research focused on translating these practices into a real-world application.

We successfully achieved high accuracy in detecting brain tumors by utilizing image processing techniques and neural networks. In our study, the dataset was relatively small, but we overcame this limitation by using data augmentation methods to create a richer dataset, which ultimately contributed to our high model accuracy.

Our findings demonstrate that contrast stretching and noise canceling with adaptive median filter have a significant impact on the tumor detection process. The developed mobile application, named Brainscan, successfully utilizes these techniques to detect brain tumors from images captured using the device's camera or selected from the device's gallery.

In conclusion, our research demonstrates the feasibility of implementing and adapting the techniques introduced in the literature for practical application in mobile development. Furthermore, our findings highlight the importance of data augmentation, contrast stretching, and noise canceling with adaptive median filter in improving the accuracy of brain tumor detection. The developed mobile application, Brainscan, is a valuable tool for healthcare professionals and individuals concerned about their health, offering a user-friendly and accurate method for detecting brain tumors.

6 Attachments

7 References