Identification and Classification of Brain Tumor

Manisha L, Deepthi Yadav G

Guide- Shwetha B N

Department of Computer Science and Engineering

Sapthagiri College of Engineering, #14/5 Chikkasandra,

Hesaraghatta main road, Bangalore-57 India

[1]manishalvaibhav76@gmail.com

[2]deepthiyadav112@gmail.com

[3]shwethabn@sapthagiri.edu.in

Abstract- In this study, we delve into the intricate realm of brain tumors, a condition arising from the abnormal growth of cells within the brain. Categorized into non-cancerous (benign) and cancerous (malignant) types, predicting the survival rate of individuals prone to tumors proves challenging due to the rarity and diversity of these afflictions. The course of treatment is contingent on several factors, including the tumor type, the degree of cellular abnormality, and its location within the brain. The integration of Artificial Intelligence, particularly deep learning models, has revolutionized the diagnostic landscape. By leveraging magnetic resonance imaging (MRI) scans, this project employs Convolutional Neural Network (CNN) classification techniques to discern the presence of a brain tumor. The model not only identifies whether the tumor is cancerous or non-cancerous but also further classifies benign tumors based on type. Practical implementation is achieved through Python and TensorFlow. The core of our approach lies in utilizing CNN to analyze and classify brain tumor types. This involves a comprehensive examination of quantitative characteristics such as shape, texture, and signal intensity. The model aims for high accuracy in detection with a minimized error rate, showcasing its potential as an invaluable tool in medical diagnostics. The results section provides an in-depth exploration of the algorithms and methodologies applied to address specific research challenges. Strengths and limitations of the proposed model are thoroughly examined, offering insights into its performance and potential areas for improvement. This study marks a significant stride in the application of deep learning to enhance the precision and efficiency of brain tumor diagnosis.

I. Introduction

The human brain, a marvel of complexity with billions of cells orchestrating myriad functions every second, becomes vulnerable when subjected to damage. The manifestation of abnormal tissue development within the brain, impeding its optimal functionality, is identified as a brain tumor. Recognizing the imperative need for enhanced outcomes in medical scenarios, computer assistance has made significant strides in therapeutic organizations.

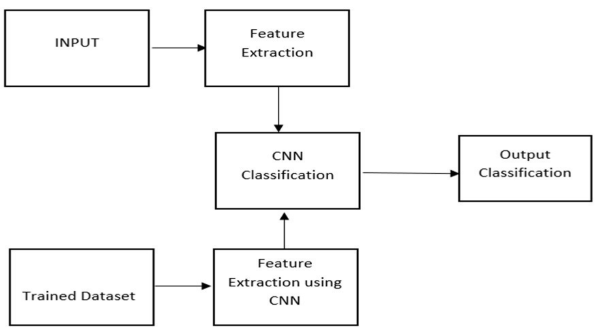
While the cost of traditional two-dimensional MRI readings remains high, there is a burgeoning interest in the development of sophisticated software to aid clinical practitioners. Human observers traditionally delineate tumor features, but to augment accuracy, a mechanized diagnostic framework incorporating specific anatomical features has been implemented. The existing framework has been further refined through the introduction of a diagnostic system to elevate precision.

The inefficiencies associated with manual segmentation, including time consumption and reduced accuracy leading to inter and intra-rater errors, have prompted the need for automated segmentation. Automated segmentation becomes crucial as it provides information about the surrounding tissues adjacent to the tumor, addressing the intensity variations within similar groupings.

The utilization of MRI segmentation in treatment monitoring has gained prominence, especially with advancements in image-guided surgical methodologies. A pivotal step in this process involves outlining tumor contours, and this method relies on Convolutional Neural Networks (CNN) to learn specific features crucial for gliomas detection and segmentation. This integration of advanced technology marks a significant stride in improving the accuracy and efficiency of brain tumor diagnosis and treatment.

II. Methodology

A. Block Diagram



B. Gathering the Data Set

To lay the foundation for constructing a deep learning network, the initial step involves assembling our primary dataset. This dataset encompasses both the images themselves and the corresponding labels associated with each image. These labels must originate from a finite set of categories, including glioma tumor, meningioma tumor, pituitary tumor, and the absence of a tumor. To ensure the efficacy of the classifier, it is essential that the number of images for each category is approximately uniform, preventing biases towards overfitting in heavily-represented categories. Addressing class imbalance, a common challenge in machine learning, requires employing various techniques.

Given the primary focus of our system on brain tumor detection, the dataset has been curated specifically with MRI images. This dataset comprises numerous images, with some depicting the presence of a tumor and others showcasing the absence of a tumor. This meticulous curation forms the cornerstone of our deep learning network, setting the stage for accurate and nuanced brain tumor detection.

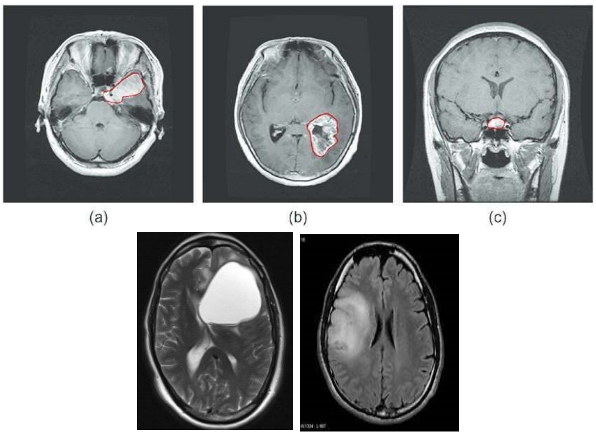


Figure 1. (a) Glioma (b)Meningioma
(c) Pituitary (d) Glioblastoma Multiforme (e)
Oligodendroglioma Tumors

C. Image Pre-Processing

The primary target is to improve image highlights needed for additional processing. The following techniques are used in the preprocessing step.

1. Greyscale Image Conversion

The initial step in processing a grayscale brain tumor MRI image involves cropping through the application of vertical and horizontal profiles. This cropping procedure is executed first to enhance the image, as the background region can otherwise impede intensity enhancement.

In a grayscale image, each pixel is represented by a scalar value ranging from 0 to 255. Here, zero signifies "black," and 255 corresponds to "white." The values between 0 and 255 represent varying shades of gray, with lower values indicating darker shades and higher values indicating lighter shades.

2. Scaling and Aspect Ratio

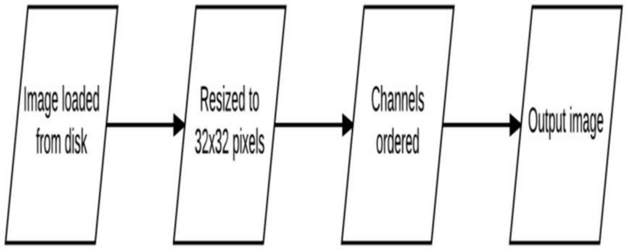


Figure 2. Image pre-processing pipeline that (1) loads an image from disk, (2) resizes it to 32_32 pixels, (3) orders the channel dimensions, and (4) outputs the image.

Scaling, or resizing, is the adjustment of an image's size by increasing or decreasing its dimensions in terms of width and height.

During the resizing process, it is crucial to consider and maintain the aspect ratio of the image.

3. Histogram Equilization

Histogram equalization normalizes the pixel intensities, thereby normalizing some of the illumination problems. The technique does a great job in normalizing the pixel intensities of the brain MRI image. The image belongs to the non-tumor class but the whiter patch on the top left part of the brain looks like a tumor although it is not. Histogram equalization reduced the visual difference between that area and the rest of the brain. This was an encouraging result and we can proceed to fit a Convolutional Neural Network (CNN) model on histogram equalized images.

4. Adaptive Thresholding

Thresholding serves as a segmentation technique by assigning all pixels with intensity values above a specified threshold to a foreground value and designating the remaining pixels to a background value. In adaptive thresholding, commonly applied to grayscale or color images, the output is a binary image that encapsulates the segmentation.

In this process, for each pixel in the image, a threshold is computed. If the pixel value falls below the threshold, it is set to the background value; otherwise, it takes on the foreground value. This methodology allows for effective image segmentation based on intensity levels, aiding in the extraction of meaningful features from the image.

5. Erosion and Dilation

For erosion, the process involves convolving a kernel (a matrix of odd size, such as 3x3, 5x5, or 7x7) with the image. In this operation, a pixel in the original image, designated as either 1 or 0, is considered 1 only if all the pixels under the kernel are also 1. Otherwise, it undergoes erosion and is set to zero. Consequently, pixels near the boundary are discarded based on the kernel size, leading to a reduction in the thickness or size of the foreground object. Essentially, the white region in the image decreases. On the other hand, dilation follows a similar convolution process with a kernel of odd size (3x3, 5x5, or 7x7). In this operation, a pixel element in the original image is assigned the value '1' if at least one pixel under the kernel is '1'. Dilation has the effect of increasing the white region in the image or expanding the size of the foreground object.

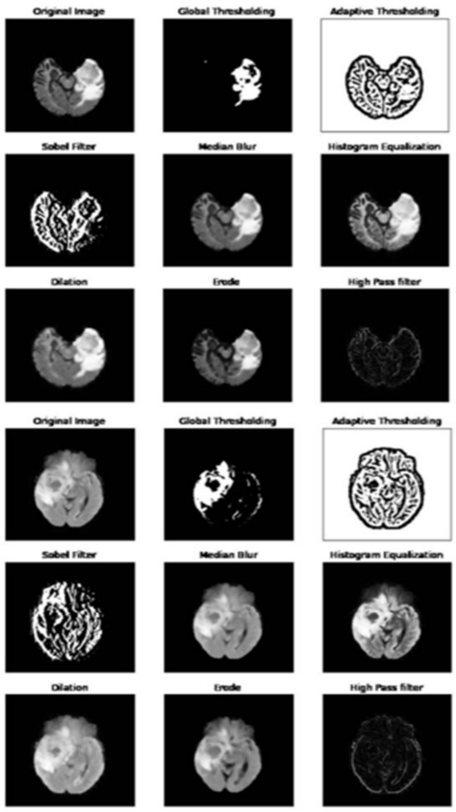


Figure 3. Image pre-processing employed MRI scans

D. Splitting the Data Set

The dataset is divided into training, testing, and validation sets. The training set is instrumental for the classifier to grasp the characteristics of each category. It learns through predictions on input data and adjusts itself when these predictions are incorrect. Once the classifier is trained, its performance is evaluated on a distinct testing set.

It is imperative that the training set and testing set remain independent of each other to ensure unbiased evaluation

Neural networks are equipped with various adjustable parameters or "knobs and levers," such as learning rate, decay, regularization, etc., collectively known as hyperparameters. Fine-tuning these hyperparameters is essential to achieve optimal performance. To facilitate the tuning process, a validation set is created. This set is derived from the training data and serves as "fake test data" for hyperparameter optimization. Only after determining the optimal hyperparameter values using the validation set do we proceed to gather final accuracy results in the testing data. This systematic approach ensures a robust and unbiased evaluation of the neural network's performance.

E. Training

The training dataset serves as the foundation for training the Convolutional Neural Network (CNN). After each epoch or iteration, the model's learned parameters up to that point are tested on a validation set. This validation set acts as a form of unseen data since the model was not trained on it, providing a means to evaluate the model's generalization performance. In the CNN process, the input signal is convolved with kernels to generate feature maps.

These kernels, with shared weights across interconnected layers, contribute to the reduction of overfitting. Backpropagation is employed to optimize the information qualities of the image. The use of kernels involves capturing information from the neighborhood, making them a significant source of contextual information.

To introduce non-linearity, an activation function is applied to the output of the neural network. This enhances the model's capacity to capture complex patterns and relationships within the data, ultimately leading to improved results. Convolutional Neural Network (CNN) architecture. Here's a breakdown of each step:

1. Convolutional Layers:

The primary objective of the convolutional layer is to extract features from the input image. Each convolutional layer focuses on specific parts of the picture and passes this information to the subsequent convolution layer.

2. Padding:

Padding involves incorporating a zero layer outside the input volume to prevent the loss of data on the borders. This technique ensures that the output maintains a similar dimension as the input volume. In this context, zero-padding is utilized.

3. Activation Function:

For introducing non-linearity, the Rectifier Activation function (ReLU) is employed instead of the classical sigmoid function. ReLU enhances accuracy in providing results.

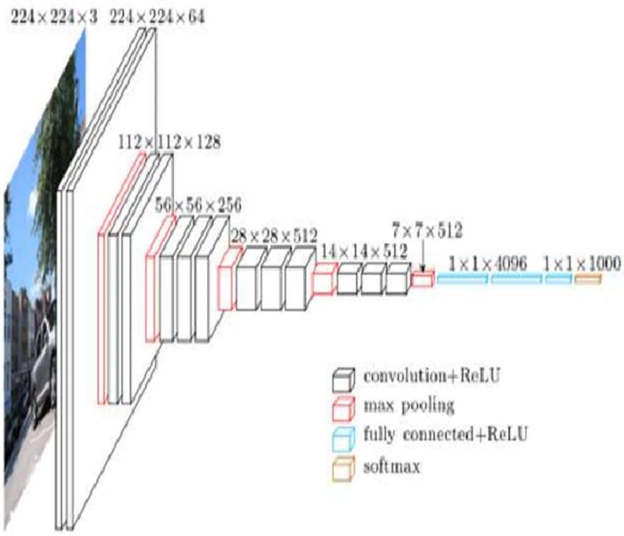


Figure 4. Visualization of VGG architecture

Each layer in a CNN applies a different set of filters, typically hundreds or thousands of them.
In the context of image classification, our CNN may learn to:

1. Detect Edges:

In the first layer, the CNN may learn to detect edges by processing raw pixel data. This involves capturing fundamental visual elements that form the building blocks of more complex features.

2. Detect Shapes ("Blobs"):

Leveraging the detected edges, the second layer of the CNN can learn to identify shapes or "blobs." These are combinations of edges that form more coherent patterns, contributing to the network's understanding of basic visual structures.

3. Detect Higher-Level Features:

Building on the learned shapes, the highest layers of the network have the capability to detect higher-level features. This could include the recognition of facial structures, parts of a car, or other intricate visual components. The network progressively refines its understanding, moving from basic edges to complex and contextually rich features as it ascends through the layers.

F. Testing

In the context of a Convolutional Neural Network (CNN) used for image classification, testing is a crucial phase that evaluates the model's performance on unseen data. Here's an overview of the testing process:

1. Separation of Test Data:

A portion of the dataset, distinct from the data used for training and validation, is reserved for testing. This ensures that the model is evaluated on data it has never encountered during the training phase, providing a reliable assessment of its generalization capabilities.

2. Forward Pass:

During testing, each image in the test set undergoes a forward pass through the trained CNN. The model applies the learned convolutional filters, activation functions, and pooling operations to extract hierarchical features.

3. Prediction and Comparison:

The CNN generates predictions for the classes/categories of the test images. These predictions are then compared with the actual labels associated with each test image.

4. Performance Metrics:

Various performance metrics are calculated to assess the model's accuracy, precision, recall, and other relevant metrics. These metrics provide insights into how well the CNN is classifying images, helping to gauge its overall effectiveness.

5. Confusion Matrix:

A confusion matrix is often employed to visualize the model's performance across different classes. It shows the number of true positive, true negative, false positive, and false negative predictions, aiding in a more detailed analysis of classification results.

6. Fine-Tuning if Necessary:

Based on the testing results, adjustments or fine-tuning of hyperparameters may be performed to enhance the model's performance. This iterative process helps in achieving the desired level of accuracy and robustness

7. Final Evaluation:

The model's final evaluation is based on its performance on the test set, providing a realistic estimation of how well it will perform on new, unseen data. This step is crucial for determining the model's reliability and suitability for deployment in real-world scenarios.

III.Conclusion

Brain tumors are relatively rare, accounting for approximately 1.4% of new cases per year in developed countries. Despite their infrequency, fatalities from brain tumors have been on the rise in recent decades. This project seeks to address this growing concern by widening its scope. Malignant brain tumors, often deemed incurable and fatal, underscore the urgency for early detection.

Early detection becomes crucial as brain tumors can manifest symptoms that initially may not appear alarming. The conventional approach for identifying the type of brain tumor involves a risky medical procedure known as a biopsy. This project proposes a non-invasive method that utilizes Magnetic Resonance Imaging (MRI) scans to detect and identify the type of brain tumor present. The system employs a Convolutional Neural Network (CNN) classification algorithm to precisely identify the nature of the detected tumor.

The significance of this project lies in its potential to significantly reduce the reliance on biopsies, offering a low-cost and less invasive alternative for brain tumor diagnosis. Unlike previous systems that primarily proved the presence of a brain tumor through various machine learning algorithms, our system provides a clear and accurate depiction of the specific tumor present in the patient. Factors such as location and size are taken into consideration, contributing to a more comprehensive diagnosis.

This approach, informed by an extensive review of over 15 papers, positions itself as the most accurate and efficient method for the detection and diagnosis of brain tumors. By leveraging advanced technologies, the project aims to revolutionize the diagnostic landscape and contribute to early intervention and improved patient outcomes.

IV. References

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