Project Title

Brain Tumor Detection Using Image Segmentation

Submitted by

Ayesha Islam Qadri 2020-CE-36

Ayesha Shafique 2020-CE-39

Submitted to

Ma'am Sahar Waqar

Course

CMPE-371 Digital Signal Processing

Semester

6th

Date

23rd May 2022

Department of Computer of Engineering

University of Engineering and Technology, Lahore

Table of Contents

Problem Statement

Detecting brain tumors through image segmentation is a critical issue in medical imaging due to the complexity of brain anatomy and the similarity of tumor tissues to healthy tissues. Early detection is crucial for effective treatment and improved patient outcomes. Traditional methods relying on manual segmentation are time-consuming, prone to errors, and can cause inter- and intra-observer variability, affecting the accuracy and reproducibility of results. Thus, there is a need for automated and efficient methods to detect and segment brain tumors accurately.

Abstract

Correct and timely identification of brain tumours is critical for effective treatment and better patient outcomes. Image segmentation techniques have gained popularity in recent years for brain tumour detection, providing advantages over traditional diagnostic methods. These techniques employ algorithms to accurately identify and delineate tumour boundaries from healthy tissue, resulting in consistent and reproducible results. Image segmentation is a minimally invasive, cost-effective method that is increasingly being used in clinical practise and research for brain tumour detection. [1]

Scope

The purpose of the Brain Tumour Detection Using Image Segmentation project is to create a precise and efficient method for recognizing and segmenting brain tumours from MRI images. It entails pre-processing MRI images with image processing techniques and applying segmentation algorithms to accurately detect the tumour region. Using thresholding, region-growing, or clustering techniques, the image is divided into smaller regions and tumour pixels are identified. The project will also optimize and evaluate various segmentation algorithms for maximum accuracy. The output will be a segmented image of the brain tumour region, which will be useful for further analysis and diagnosis, resulting in improved brain tumour detection accuracy and efficiency, as well as better diagnosis and treatment planning.

DSP Concepts

Following are the concepts are used in the brain tumor detection by using image segmentation:

Filtering

For brain tumor detection and image segmentation, filtering refers to the process of removing noise and unwanted information from medical images. This is important as medical images are often subject to noise from various sources, such as patient motion, scanner artifacts, and environmental interference. Filtering techniques are used to enhance the quality of medical images, making them easier to analyze and interpret. Common filtering techniques used in brain tumor detection and image segmentation include Gaussian filtering, median filtering, and wavelet filtering.

Image Segmentation

Image segmentation is a technique used in digital image processing to partition an image into multiple regions or segments. For brain tumor detection and image segmentation, this technique is used to identify and delineate the boundaries of tumor tissues from surrounding healthy tissues in medical images such as MRI and CT scans. The segmentation process is performed by applying a set of algorithms that analyze the intensity, texture, and other features of the image to determine the boundaries of the different tissue types. The resulting segmented image provides a clear visual representation of the tumor, which can aid in the diagnosis and treatment planning process.

Signal Analysis

Signal analysis is a key aspect of digital signal processing for brain tumor detection and image segmentation. Signal analysis techniques can be used to identify the features and patterns that distinguish healthy brain tissue from tumor tissue. These techniques can also help to filter out noise and artifacts in the signals to improve the accuracy and reliability of the image segmentation process. Some commonly used signal analysis techniques in the context of brain tumor detection and image segmentation include Fourier analysis, wavelet analysis, and statistical pattern recognition.

Image Pre-processing

Image pre-processing is a significant aspect of any image-based application. Pre-processing stage is required for the following reasons:

1. Pre-processing prepares the images for higher-level processing such as segmentation and feature extraction.
2. Remove the marks or labels such as name, date, and other details (film artifacts) in the image that can affect the classification task.
3. Image quality needs to be enhanced.
4. Removal of any types of noise in the image.

Block Diagram

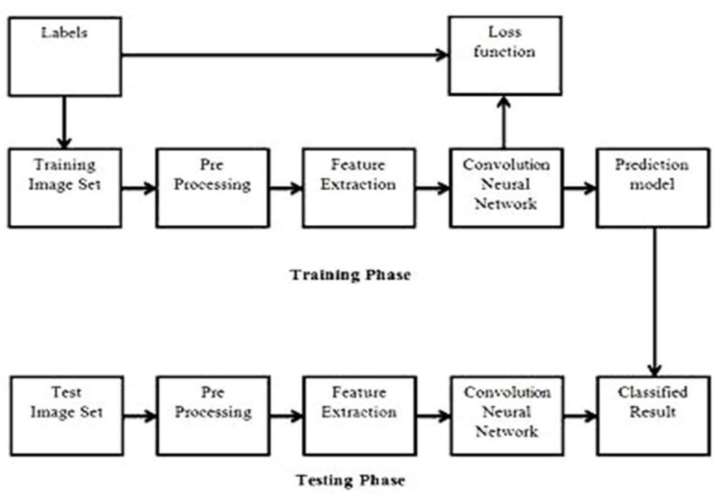


Figure 2 Block Diagram for brain tumor classification using CNN [2]

U-NET Architecture

1. U-Net Architecture Overview

The U-Net architecture has gained significant popularity for brain image segmentation tasks due to its effectiveness in capturing spatial context and preserving fine-grained details. The architecture exhibits a distinctive U-shape design, featuring an encoder path and a decoder path connected by skip connections. These skip connections play a vital role in combining both low-level and high-level features, allowing the network to localize and segment objects accurately within the brain images. By utilizing skip connections, the U-Net architecture overcomes challenges associated with loss of spatial information during downscaling and up sampling operations, enabling precise segmentation outcomes.

2. Pre-processing

Pre-processing steps specific to brain image segmentation and detection are employed to enhance the quality and consistency of the input data. Intensity normalization is typically performed to normalize image intensities across different scans, ensuring uniformity and aiding in comparisons. Skull stripping is employed to remove non-brain tissues from the images, focusing the segmentation process on brain structures of interest. Registration techniques are utilized to align the images to a common template, mitigating variations caused by factors such as subject-specific anatomy or imaging modalities. Additionally, noise reduction techniques are applied to reduce noise artifacts and improve the overall image quality, facilitating more accurate segmentation and detection results.

3. Encoder Path

The encoder path plays a crucial role in the U-Net architecture, capturing the context and extracting high-level features from the input brain images. It typically consists of multiple convolutional layers with increasing filters, enabling the network to learn hierarchical representations of the image data. Each convolutional layer is often followed by a rectified linear unit (ReLU) activation function, introducing non-linearity and enhancing the network's ability to model complex relationships within the data. Downscaling operations, such as max-pooling or strided convolutions, are employed to reduce the spatial dimensions of the feature maps while extracting context from the input image.

4. Bridge

The bridge in the U-Net architecture connects the encoder and decoder paths. It acts as a bottleneck layer and is designed to retain important spatial information while facilitating communication between the encoding and decoding stages. The bridge typically consists of a stack of convolutional layers without any down sampling operations. By preserving detailed information from the encoder path, the bridge allows the network to recover fine-grained details and aids in accurate segmentation and detection of brain structures.

5. **Decoder Path**

The decoder path in the U-Net architecture is responsible for up sampling the feature maps from the bridge and refining the segmentation results. Up sampling techniques, such as transposed convolutions or interpolation, are employed to gradually increase the spatial resolution of the feature maps. The skip connections, established during the encoding stage, play a crucial role in the decoder path. The corresponding feature maps from the encoder path are concatenated with the up sampled feature maps, allowing the network to recover spatial details lost during downscaling. Convolutional layers are applied to refine the segmentation further, extracting localized features and enhancing the accuracy of the final segmentation output.

6. **Output Layer and Postprocessing**

The output layer is the final layer of the decoder path in the U-Net model. It generates the segmentation map that delineates the different brain structures. The activation function used in the output layer depends on the specific segmentation requirements. For multi-class segmentation, a SoftMax activation function is commonly employed, producing pixel-wise probabilities for each class. For binary segmentation tasks, a sigmoid activation function is typically used, yielding pixel-wise binary values indicating the presence or absence of the target structure. Postprocessing steps can be applied to refine the segmentation output. Connected component analysis can eliminate small, isolated regions or merge connected components to create more coherent segmentation. Morphological operations, such as erosion or dilation, can be utilized to refine the shape and boundaries of segmented regions. Thresholding techniques can convert the probability map into a binary mask based on a certain threshold value.

7. **Training and Evaluation**

The U-Net model is trained using labelled brain images and corresponding ground truth masks. During training, the model learns to optimize its parameters by comparing the predicted segmentation maps with the ground truth masks. Common loss functions used for optimization include cross-entropy and dice loss, which measure the dissimilarity between the predicted and ground truth segmentation. Training is typically performed using optimization algorithms such as stochastic gradient descent (SGD) or Adam. Evaluation of the trained model is conducted using various metrics, including the Dice coefficient, Intersection over Union (IoU), sensitivity, specificity, or pixel-wise accuracy, to assess the quality and accuracy of the segmentation results.

8. Applications and Challenges

Brain image segmentation and detection have several important applications in the medical field. Accurate localization and segmentation of tumors enable precise diagnosis and treatment planning. Volumetric analysis of brain structures aids in studying anatomical changes and disease progression. Furthermore, the segmentation and detection of lesions or specific regions facilitate disease classification and monitoring. However, several challenges exist in brain image segmentation and detection. Anatomical variations, imaging artifacts, and low contrast in brain images can pose difficulties for accurate segmentation. Researchers address these challenges through techniques such as data augmentation, transfer learning, or assembling models to improve the robustness and generalizability of the segmentation models. [3]

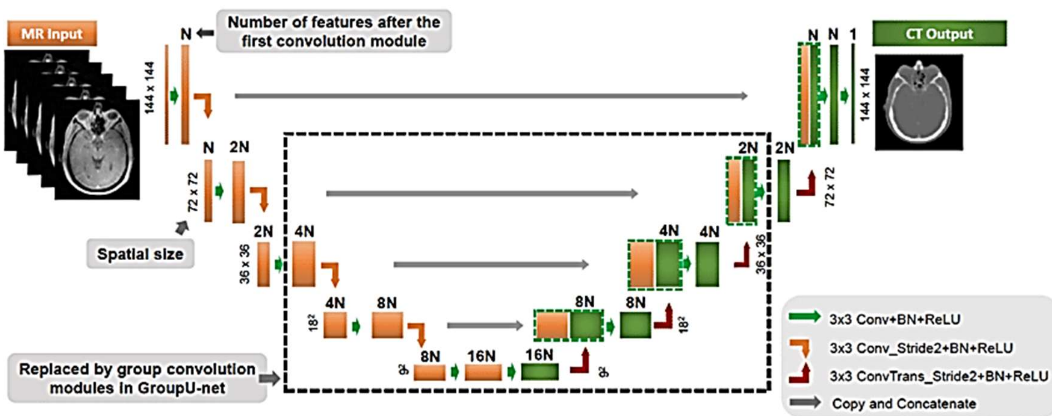


Figure 3 U-NET Architecture [4]

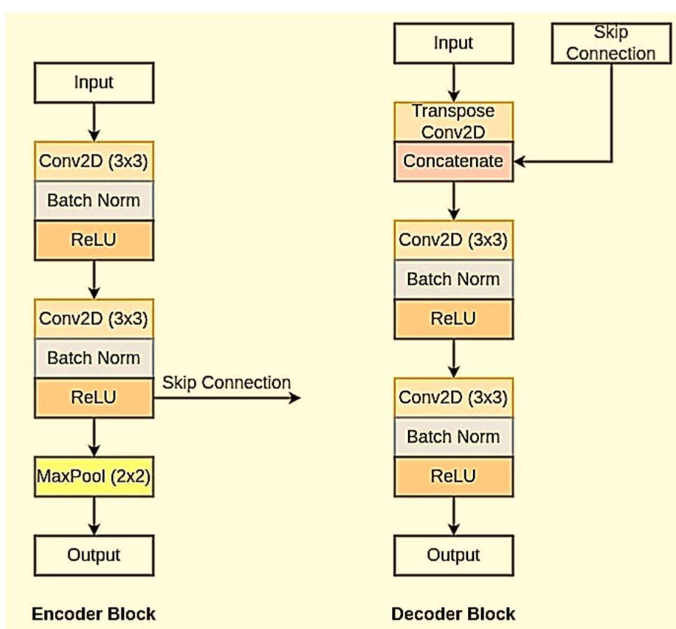


Figure 4 U-NET Block Diagram

Watershed Modelling

1. Introduction

Brain tumor detection is a crucial task in medical imaging, as it helps in diagnosing and treating brain tumors. Image segmentation plays a vital role in identifying and delineating tumor regions within brain images. Watershed modelling is a technique that can effectively be used for brain tumor detection and segmentation.

2. Pre-processing

Pre-processing is performed to enhance the quality of brain images and improve the accuracy of tumor segmentation. It involves various steps such as noise reduction using filters like Gaussian smoothing or median filtering. Intensity normalization is applied to standardize the dynamic range across different scans. Additional pre-processing techniques like skull stripping (removing non-brain tissues), registration (aligning images to a common reference), and contrast enhancement may also be employed to address variations caused by different acquisition protocols, patient positioning, or image artifacts.

3. Gradient Computation

The gradient of the brain image is computed to detect tumor boundaries and regions of intensity transitions. Gradient computation techniques, such as the Sobel or Prewitt operators, estimate the rate of change in intensity values. This process generates a gradient map that highlights areas with significant intensity transitions, which are often indicative of tumor boundaries.

4. Marker Selection

Markers are selected to guide the watershed algorithm during tumor segmentation. These markers can be generated automatically or provided manually. Automatic marker selection techniques may involve thresholding the gradient map to identify areas with pronounced intensity changes or employing morphological operations to extract regional minima or maxima. Manual markers can be placed by an expert based on prior knowledge or visual inspection of the image.

5. Watershed Segmentation

The watershed algorithm is applied to segment the brain image and detect tumor regions. The algorithm treats the image as a topographic surface and simulates the flooding process. It starts from the selected markers and assigns each pixel to its closest marker based on intensity values. As flooding progresses, watershed lines are formed where flooding basins from different markers meet. These watershed lines correspond to tumor boundaries. The flooding process continues until all pixels are assigned to catchment basins, resulting in a segmented image with distinct tumor regions.

6. Postprocessing and Refinement

The initial watershed segmentation may produce over-segmented regions or small isolated regions. Postprocessing techniques are employed to refine the segmentation and improve the accuracy of tumor detection. Region merging can be performed to combine adjacent regions with similar characteristics, forming larger tumor segments. Morphological operations, such as noise removal, smoothing boundaries, or filling small gaps, can be applied to enhance the segmentation quality. Iterative refinement of the segmentation can be done by adjusting the watershed parameters or incorporating additional features or priors.

7. **Evaluation and Validation**

   The segmented tumor regions obtained through watershed modelling are evaluated against ground truth or expert annotations to assess the accuracy of the detection. Evaluation metrics such as Intersection over Union (IoU), Dice coefficient, or pixel-wise accuracy can be used to quantify the agreement between the segmented tumor regions and the ground truth annotations. Validation of the segmentation results may involve comparing the detected tumor regions with clinical findings, histopathological analysis, or follow-up imaging studies to ensure the accuracy and clinical relevance of the segmentation.

8. **Applications**

   Accurate detection and segmentation of brain tumors using watershed modelling have significant clinical applications. It aids in tumor localization, allowing clinicians to precisely delineate the tumor boundaries and understand its extent within the brain. The segmented tumor regions can be used for volumetric analysis, assessing tumor growth, or monitoring response to treatment. Additionally, the extracted tumor regions can serve as inputs for further quantitative analysis, such as radiomics or machine learning-based classification, to provide additional information about tumor characteristics and aid in treatment decision-making. [5]

Literature Review

Adel Kermi et al proposed automatic brain cancer segmentation procedure in three dimensional-magnetic resonance imaging utilize similarity analyses of brain and standard group. Pre-processing of photograph is done to remove noise. The FBB technique is effective and unsupervised. Using the FBB method, the detection of tumors is done automatically. A geodesic level set based 3 D deformable model is applied to detect the boundaries of the tumor, in any case of its form and volume. The average calculation time of detecting and segmenting tumors is around five minutes. The accuracy and sensitivity obtained were 38.04% and 89.01 respectively. V. Anitha, S. Murugavalli presented the technique of clear and systematic examination using an algorithm. information of lesions is specific by segmentation of MRI, which is based on anatomical structures and potential abnormal tissue data. The K means techniques are applied to achieve successful segmentation and classification by a two-tier approach. The feature extraction obtained after applying the discrete wavelet transform and used to learning the neural network's self-organizing map and the outcome filter factors are then learned by the KNN neighbor and the testing procedure is similarly done in double phases. It has better performance than traditional classification methods and the experiment indicates enhanced performance. Two-tier classification segmentation systems organize the regular and irregular MRI efficiently. MATLAB R2013a platform is used to apply the algorithm. sensitivity and specificity expressions are applied to a statistical measure of this two-level classifier method. The indicated outcome marks the superiority over SVM based classification technique and also indicates that it can be incorporated in medical imaging application for image classification and also in CAD. They achieved 85% in the accuracy factor, and 100% in the sensitivity. Parveen and Iitpalsingh proposed data mining techniques for the classification of magnetic resonance imaging photos. Classification is accomplished in four stages: pre-processing, partition, attributes extraction, and classification. In the first stage, improvement and skull stripping is undertaken to increase speed and accuracy. A fuzzy C-means gathering technique is applied during the segmentation stage. The extraction of magnetic resonance imaging photos features is performed using a grey level matrix. The final stage applies SVM for classifying the images. The final results of this study exhibited a high degree of accuracy and efficiency with respect to MRI image classification. Daniele Ravi et al propose a new dimensionality reduction and processing method to achieve a detailed structural map for into operative margin definition. Due to manifold embedding and inconsistent results in other dimensionality reduction techniques, tissue classification is hindered. While this method does the same work in two phases – first. The tissue classification is done after T distributed stochastic neighbour process flowed by semantic segmentation method using Semantic Texton Forest. The suggested system can support in realization of cancer development. The actual time nature of the methods can perfect clinical precision, offering extra knowledge that can as well minimize the likelihood of faulty re-sectioning of healthy tissue. The great quality and precision of the gained tumor maps can be obtained by applying a proper establish way shared with a classifier that considers only the spectral worth of every pattern nevertheless similarly their spatial context. The accuracy and sensitivity achieved were 81.90 and 80.91 respectively. Lamia Salemi et al presented a convivial algorithm for Glioblastoma modelization. The extracted tumor region is done by applied by rapid spreading matching based global pixel wise data. The new model uses an algorithm related to cellular automata and a speedy marching technique to assess the cancer evolution during the time. This method has an optimized runtime of less than 0.5 seconds for every image and does not need long training. Glioblastoma presents different gray level potency compared to safe cells. This information is used to slice the brain image into two regions. Regions with Glioblastoma is then matched with the estimated model based on intensity levels. The proposed system extracts the tumors in real-time which is then used for growth estimation using CRMM. Mukambika P. S., Uma Rani K. suggested phases that the MRI Image was processed in 4 phases: Pre-processing, Segmentation, patterns extraction, and pattern recognition stages. In the pre-processing stage, the skull is removed from the MRI image by applied a double thresholding procedure The proposed research introduces the comparative learning of dual methods applied for cancer recognition of MRI pictures. The first method is established by utilizing the non-parametric deformable models with an active contour to section the brain cancer from the magnetic resonance imaging brain pictures. The second method is the K-means segmentation technique. A decision making is achieved in dual phases next to segmentation: DWT applied for feature extraction and "Gray Level Co-occurrence Matrix". finally, SVM utilized in the classification stage. Dataset of MRI brain tumor images of different patients. SVM with Level Set and KMeans segmentation classifies the image into normal brain, or tumor with 94.12% and 82.35% accuracy respectively The level set produces the best outcome compared to K-means segmentation.

K. Sudharani, Dr. T. C. Sarma, Dr. K. Satay Rasad Proposed Methodology includes methods like Histogram, Re-sampling, K-NN Algorithm, Distance Matrix. First, Histogram provides the whole amount of the stated amount of pixels spread in a specific image. Re-sampling re-size picture to 629× 839 for appropriate geometrical representation. Brain tumor is classified and identified by applied the KNN algorithm after tuning the K parameter. The distance is calculated by applied the Manhattan metric to classify. Labview was used to implement the algorithm. The data set contains 48 images were used to test the algorithm. The classification score for all tested images is around 95%. [6]

Conclusion

To detect and segment brain tumors in MRI images using a Kaggle dataset.

Figure 5 displays the accuracy graph of the model, illustrating how the accuracy improved during training. Figure 6 represents the loss graph, showcasing the decrease in loss as the model learned from the data.

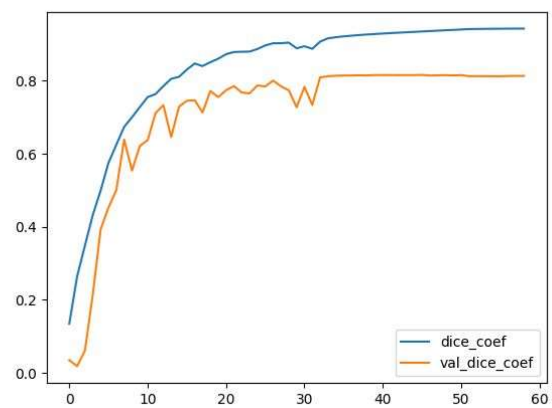


Figure 5 Accuracy graph of model

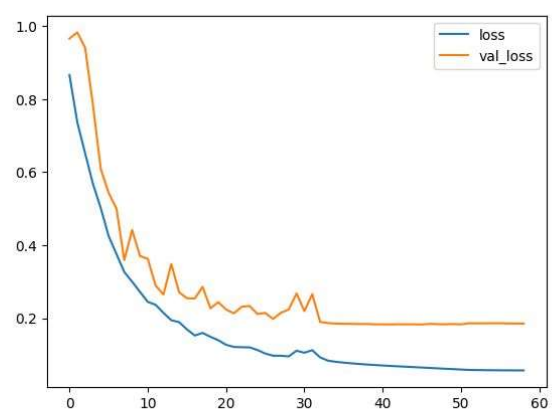
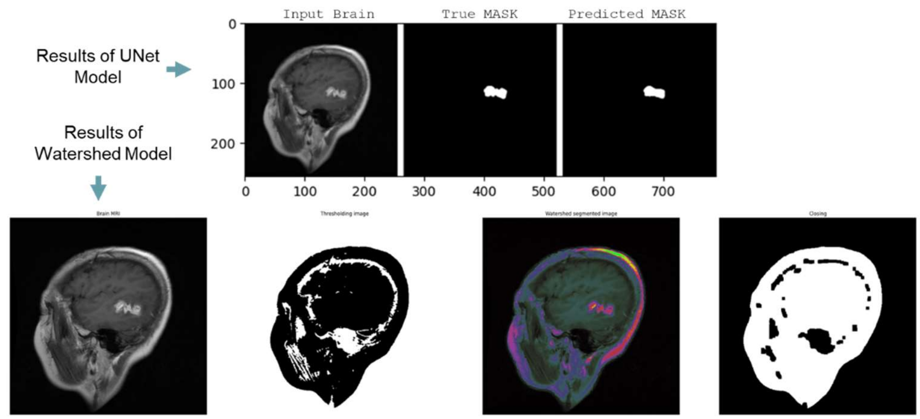


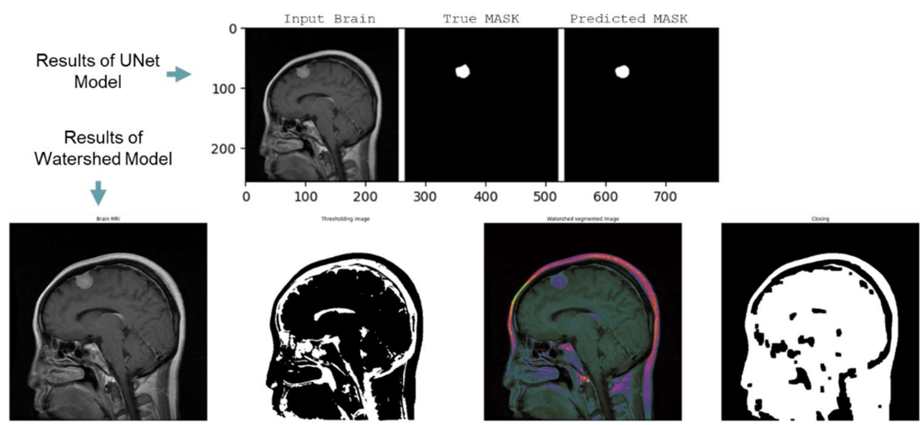
Figure 6 Loss graph

Now from here these are the results comparison from the unet architecture and water modeling as shown in the below images.

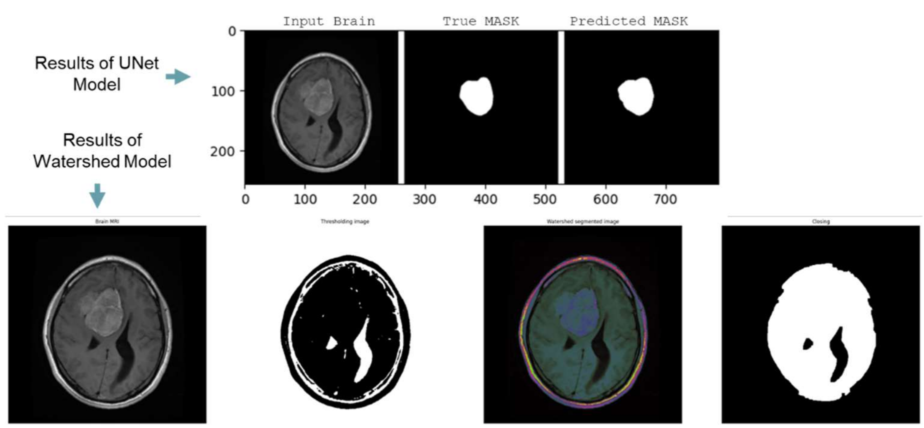
Test Result 1



Test Result 2



Test Result 3



References

[1]https://www.researchgate.net/publication/361465617_Brain_Tumor_Detection_U sing_Image_Segmentation

[2]https://www.researchgate.net/publication/311910368_Design_and_Implementat
ion_of_a_Computer_Aided_Diagnosis_System_for_Brain_Tumor_Classification/fi gures?lo=1

[3]https://www.epa.gov/watershedacademy

[4]https://www.researchgate.net/publication/321901794_Attenuation_correction_for_brain_PET_imaging_using_deep_neural_network_based_on_Dixon_and_ZTE_MR_images/figures?lo=1

[5]https://www.tucson.ars.ag.gov/agwa/download/docs/publications/Watershed%20Modeling%20and%20its%20Applications_A%20State-of-the-Art%20Review.pdf

[6]file:///C:/Users/hifza/Downloads/Brain_Tumor_Detection_and_Segmentation_A_Survey.pdf