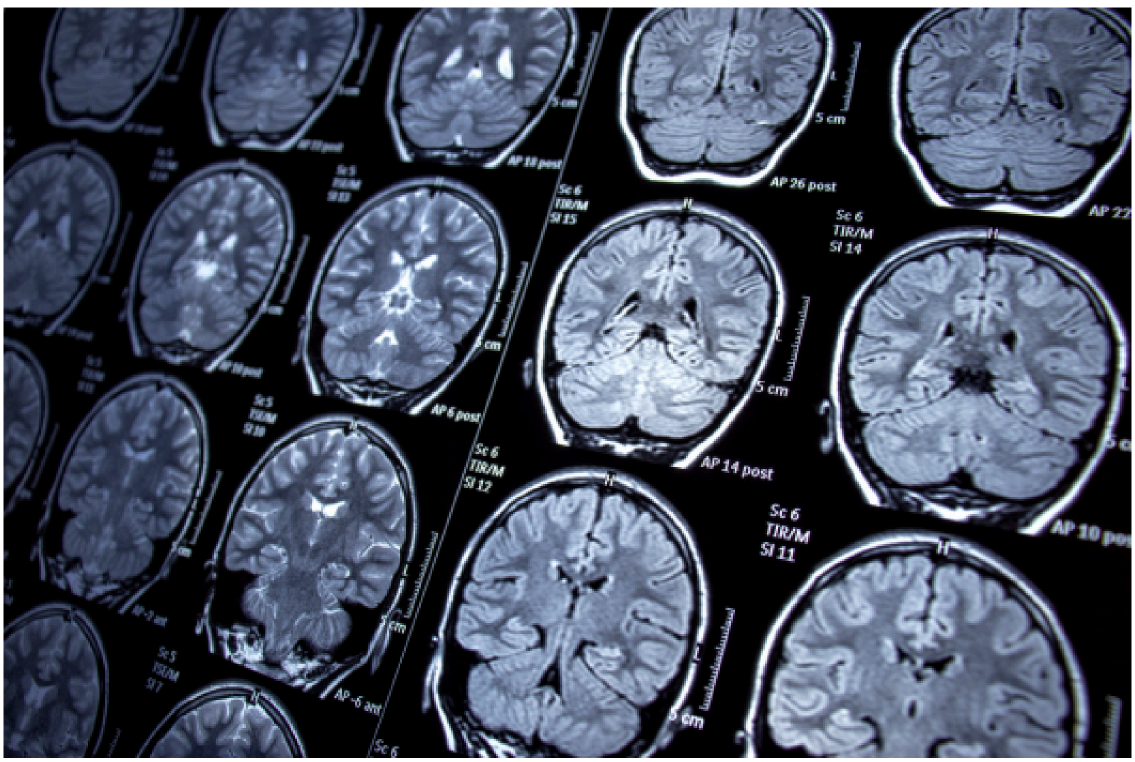
University of Calgary

Brain Tumor Detection Using UNet



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Abstract

This project presents a deep learning pipeline for brain tumor identification that integrates segmentation and classification using a modified U-Net architecture. Leveraging multimodal imaging data from a Kaggle dataset (1496 images; 26 misclassifications), the model achieved an overall accuracy of 98.26% (Healthy: 98.35%, Tumor: 98.19%). The approach produces both pixel-wise segmentation maps and tumor probability scores, offering a comprehensive tool for automated diagnosis. The code and full implementation are available at GitHub.

Introduction

Early Detection of brain tumors is critical for effective treatment and improved patient outcomes. Deep learning has emerged as a powerful tool for medical image analysis, particularly for tasks such as segmentation and classification. U-Net and its variants have proven highly effective in delineating tumor boundaries in MRI and CT scans. In this project, we propose to utilize U-Net to both segment tumor regions and classify images of brains as either healthy or tumor-bearing.

Related Work

Several studies have explored deep learning for brain tumor detection, with UNet emerging as a powerful tool for medical image segmentation due to its ability to capture fine details. Research has also shown that CNNs and ResNet variants excel in tumor classification, improving diagnosis accuracy. A study on DeepSeg combined multiple CNN architectures within a modified UNet to enhance segmentation performance (MDPI) [1]. Another study integrated CNNs for detecting and classifying glioblastomas, demonstrating deep learning's potential in comprehensive tumor analysis (Nature) [2]. Inspired by these advancements, this project integrates segmentation and classification into a unified framework, aiming to contribute to more accurate and efficient methods for brain tumor detection.

Materials and Methods

The dataset utilized in this project is sourced from Kaggle. It contains 1496 images acquired from multimodal CT and MRI scans. For our purposes, we will be using the 2D CT scans. The dataset contains both healthy cases and tumor-bearing images. Notably, the dataset provides only image-level labels (healthy vs. tumor) without corresponding segmentation masks. Therefore, while a segmentation branch was incorporated into the network as a proof-of-concept, it was not trained with reliable supervision. In the training stage, all tumor image-label images are manually assigned with a masking score of 0.5, while healthy-label images are assigned with a score of 0.

Our deep learning model is implemented using PyTorch and comprises of the following components:

Image preprocessing:

1. Resizing input images:
    a. Reads each image using OpenCV
    b. Resize the image to 256 x 256
    c. Store image data, filename, and label
2. Splitting the images:
    a. The dataset Combines healthy and tumor images
    b. Shuffles the images randomly
    c. Splits the images into 70% training, 15% validation, 15% testing
3. Saving each image to the appropriate directory:
    a. Creates 3 directories: train, val, and test
    b. Add 2 label folders healthy and tumor to each directory above
    c. Keep original file name

Model definition (Figure 1.):

1. Input side of model:
    a. 3 Channels for red green blue (RGB)
    b. Encoder path with 4 convolution blocks, each block doubles the number of filters
    c. Each convolution blocks contains two 3 x 3 convolutions, batch normalization, and ReLU activation
    d. MaxPooling reduces spatial dimensions by half
2. Output side of model:
    a. Decoder path with 4 upsampling blocks
    b. Each upsampling block uses transposed convolution followed by a convolution block
    c. Each convolution blocks contains two 3 x 3 convolutions, batch normalization, and ReLU activation
    d. 1 channel for segmentation output
    e. Classification branch with global average pooling (GAP) and fully connected (FC) layers
3. The forward pass:
    a. Processes through encoders
    b. Goes through bridge
    c. Processes through docoder with skip connections
    d. Produces segmentation output
    e. Uses bridge features for classification

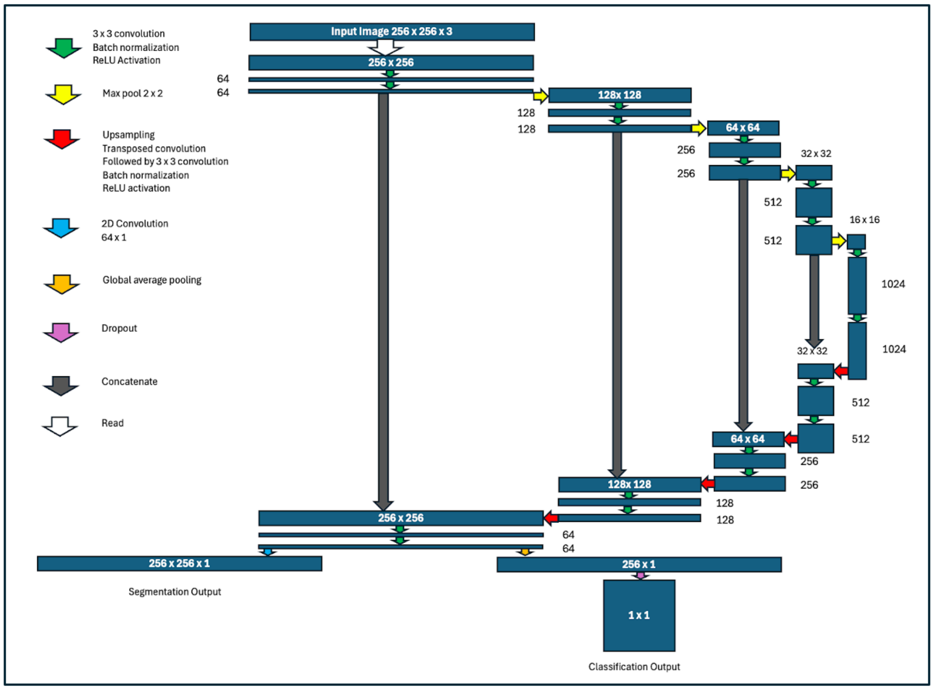
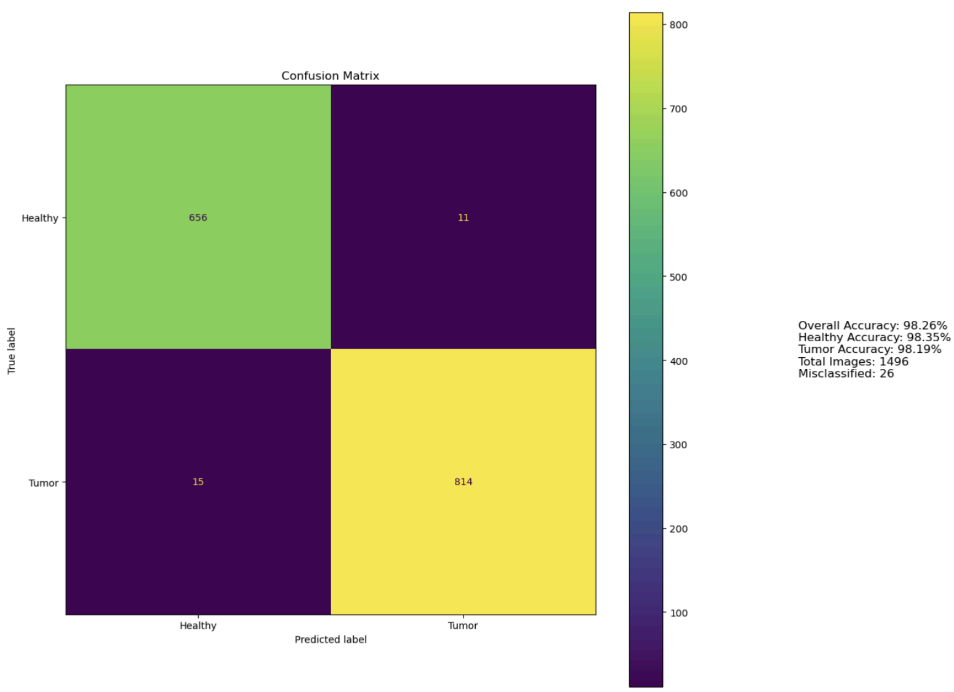
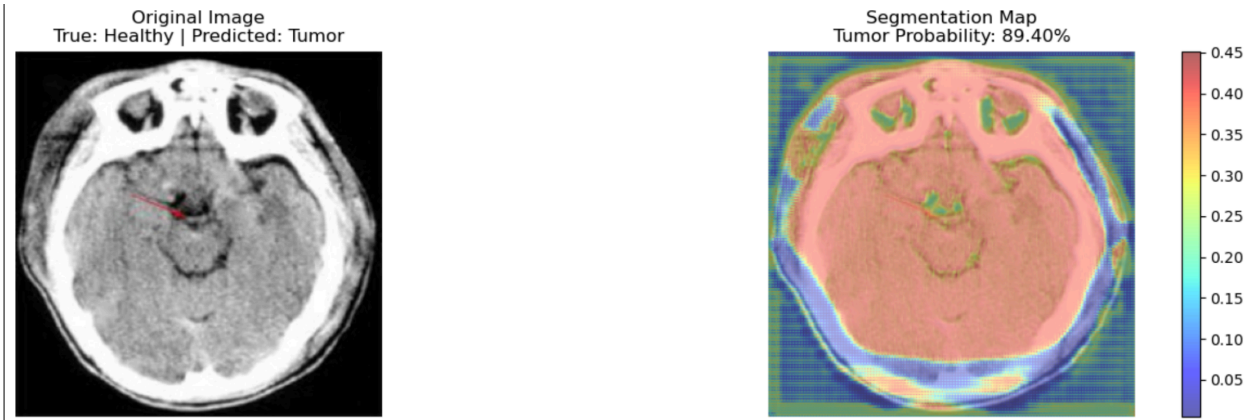


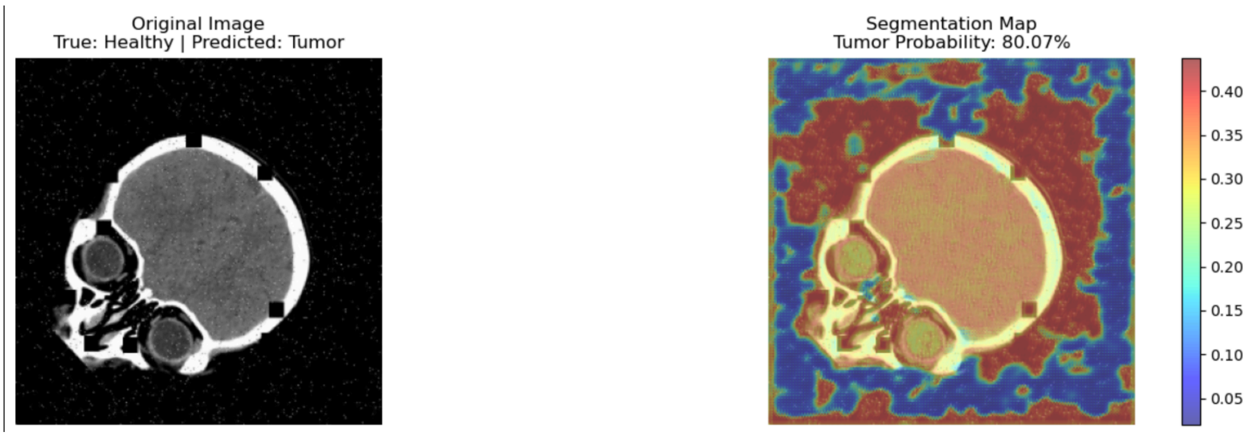
Figure 1. Brain Tumor Classification UNet Architecture

Results and Discussions

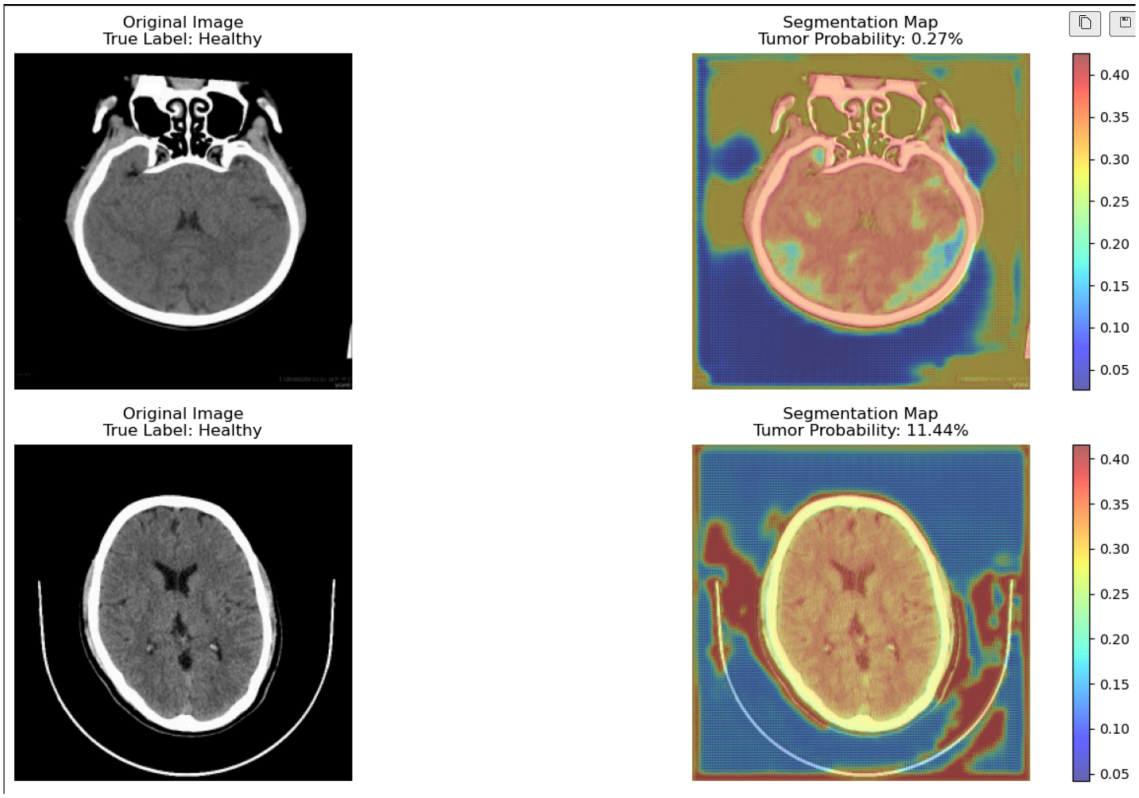


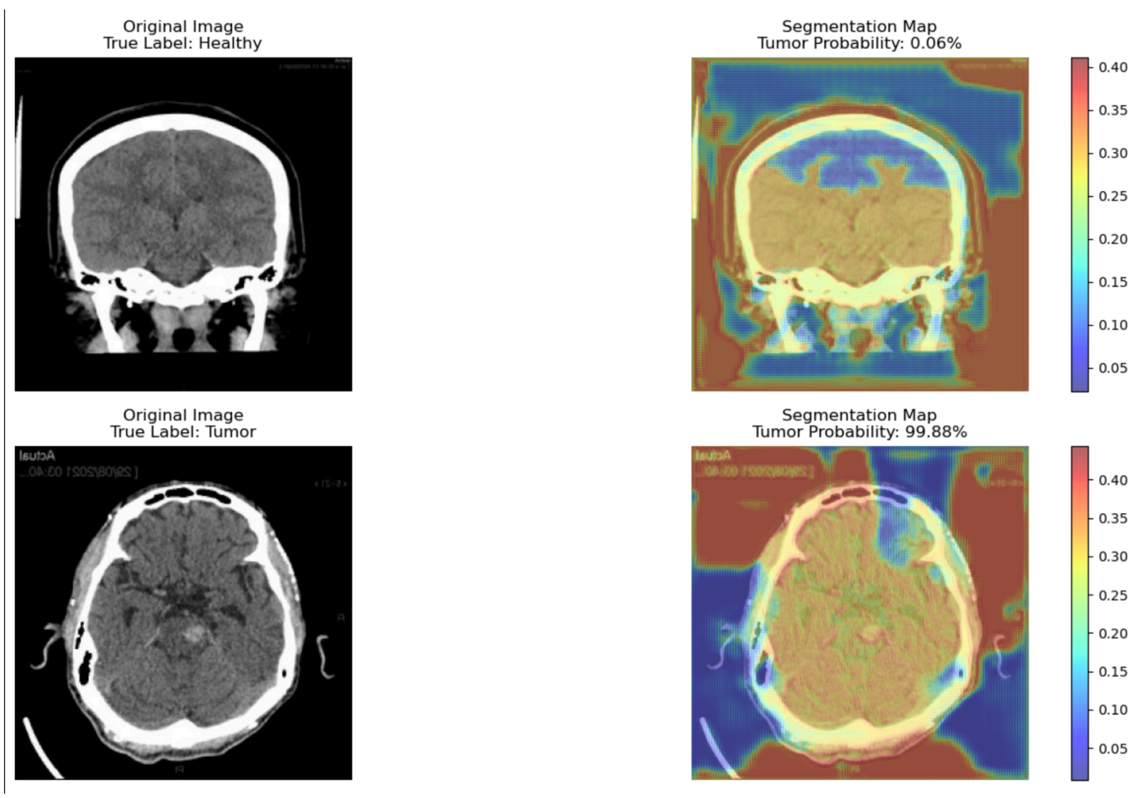
Misclassified examples:





Correct classification examples:





Our integrated U-Net model achieved outstanding performance on the Kaggle dataset. Key performance metrics include:

- **Overall Accuracy:** 98.26%
- **Healthy Image Accuracy:** 98.35%
- **Tumor Image Accuracy:** 98.19%
- **Misclassifications:** 26 out of 1496 images

While the segmentation branch was implemented to explore potential tumor localization, its effectiveness could not be fully evaluated due to the absence of annotated segmentation masks in the dataset. As a result, our analysis focuses on classification, which demonstrates that the model reliably distinguishes between healthy and tumor-bearing images. These results highlight the feasibility of using U-Net–based architectures for automated brain tumor diagnosis, even when segmentation supervision is not available. While the high accuracy demonstrates the potential for real world use of our approach, certain limitations must be acknowledged. The dataset size, although sufficient for the initial evaluation, is relatively small, which may affect generalizability.

Future work will involve dealing with a bigger dataset, incorporating additional image modalities, and even exploring more advanced architectures. We will aim to incorporate datasets with detailed segmentation annotations to fully exploit the benefits of integrated segmentation and classification.

Conclusion

This project illustrates a successful application of a U-Net architecture for brain tumor detection. The promising results encourage further exploration into a more sophisticated model and larger, more diverse dataset to advance automated brain tumor detection. Although the segmentation branch was incorporated as a conceptual extension, its evaluation was limited by the absence of ground truth masks. Nonetheless, the classification branch achieved high accuracy, indicating strong potential for automated diagnosis. Future research will focus on acquiring annotated segmentation datasets and refining the segmentation branch to enhance tumor localization and diagnostic precision further.

References

1. MDPI Article:
López, F. M., & Choi, J. W. (2023). DeepSeg: Combining CNN architectures with a modified UNet for improved segmentation performance in brain tumor detection. Diagnostics, 15(5), 624. https://doi.org/10.3390/diagnostics15050624

2. Nature Article:
Abd-Ellah, M. K., Awad, A. I., Khalaf, A. A. M., & Ibraheem, A. M. (2024). Automatic brain-tumor diagnosis using cascaded deep convolutional neural networks with symmetric U-Net and asymmetric residual-blocks. Scientific Reports, 14, 9501. https://www.nature.com/articles/s41598-024-59566-7