Result and Discussion

1. Quantitative Evaluation

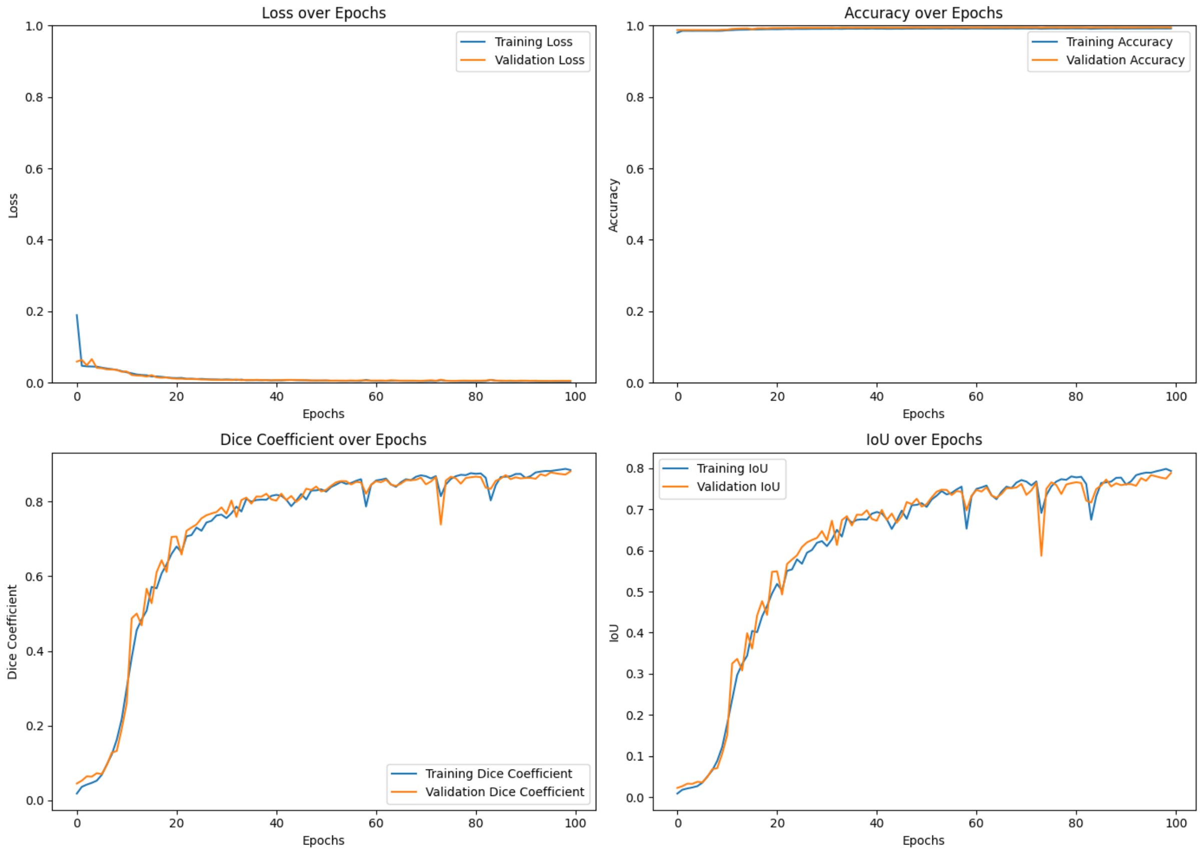

Figure 1: Training and validation performance metrics across epochs, including loss, accuracy, and segmentation metrics—Dice coefficient and Intersection over Union (IoU).

The proposed U-Net model demonstrates exceptional performance in brain tumor segmentation tasks. The model achieved a training accuracy of **99.51%** and a validation accuracy of **99.47%**, indicating its ability to generalize well across the data. The final training and validation losses were as low as **0.0030** and **0.0053**, respectively, underscoring the model's capability to minimize error effectively.

The Dice coefficient, a critical metric for evaluating segmentation overlap, reached values of **0.9054** (training) and **0.8807** (validation), reflecting a high degree of similarity between the predicted and ground-truth masks. Similarly, the Intersection over Union (IoU) coefficients of **0.8275** (training) and **0.7877** (validation) further affirm the segmentation precision.

These results, as shown in the line plots for loss, accuracy, Dice coefficient, and IoU across epochs, indicate consistent improvement throughout the training process with no observable overfitting. The training and validation curves align closely, demonstrating the robustness and stability of the model.

2. Qualitative Evaluation

The qualitative results, illustrated in Figures 2 and 3, showcase the model's performance in segmenting brain tumors across different scenarios:

1. **Ground-Truth vs. Predicted Masks**: The predicted masks closely resemble the ground-truth masks, even for challenging tumor cases, resulting in precise tumor segmentation with minimal false positives or negatives.
2. **Tumor Type Classification**: The model successfully segmented and identified tumors for multiple classes, including **glioma**, **meningioma**, and **pituitary tumors**, while also correctly handling **non-tumor cases** by outputting blank masks. These results validate the model's ability to adapt to diverse tumor morphologies.

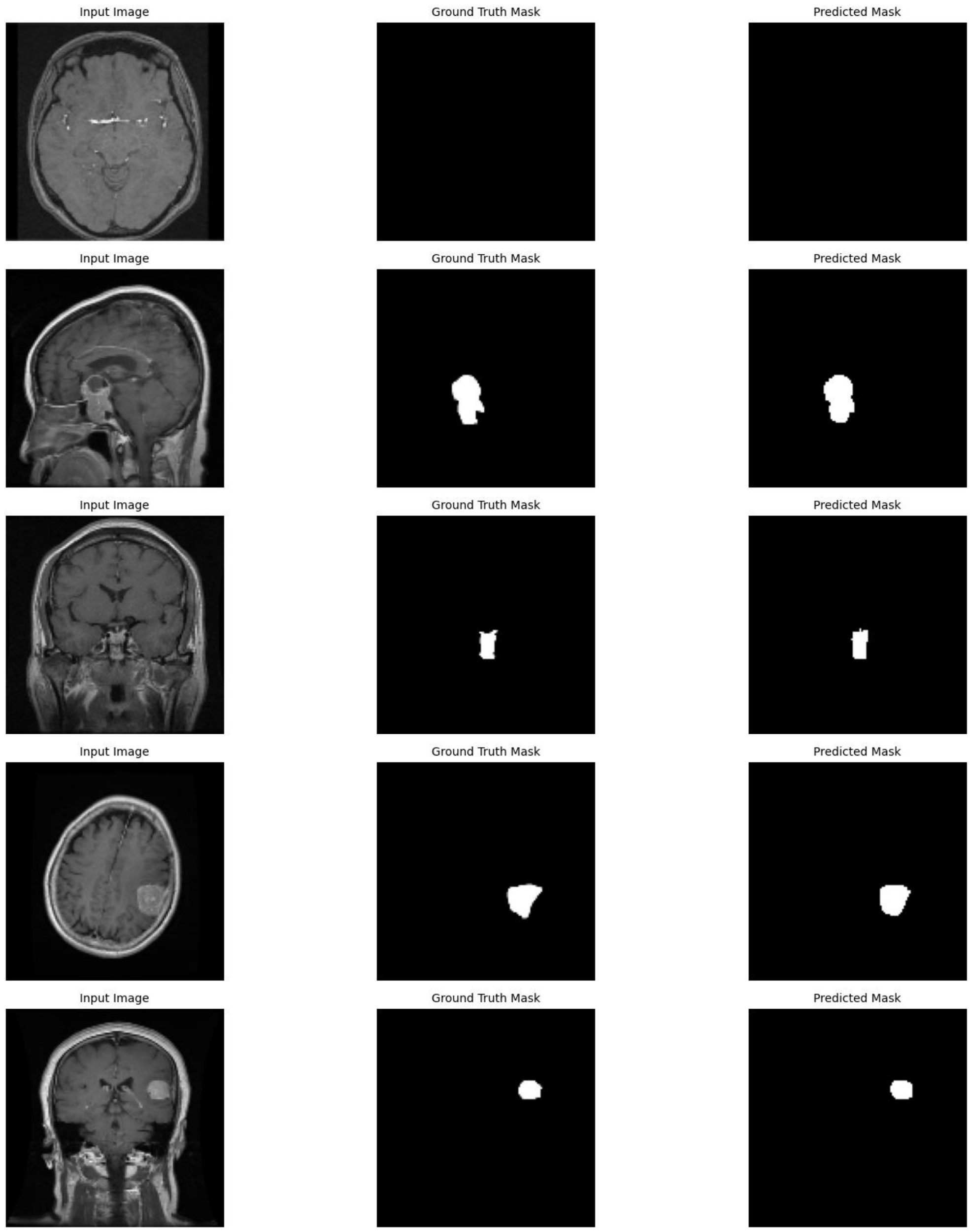

Figure 2: Ground-truth masks vs. predicted masks for tumor segmentation on the validation set.

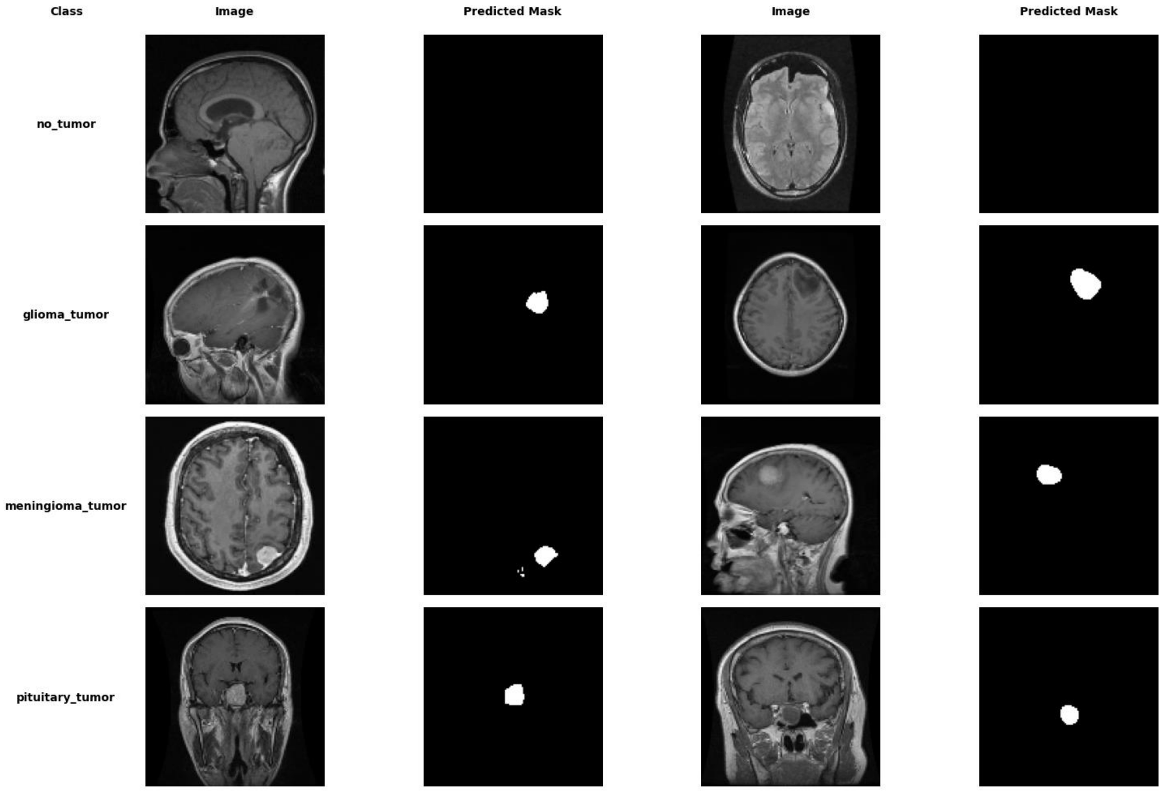

Figure 3: Predicted segmentation masks on the test dataset, demonstrating the model's ability to generalize across various tumor types (glioma, meningioma, pituitary) and non-tumor cases.

3. Discussion

The proposed U-Net model achieved high precision for boundary-sensitive segmentation tasks, as evidenced by the high Dice and IoU coefficients across training and validation datasets. These metrics affirm the model's suitability for clinical use. Additionally, the qualitative results highlight the model's ability to segment tumors of varying sizes and shapes, making it robust for real-world scenarios.

However, some limitations are noted:

- Slight variations in IoU and Dice values for the validation dataset suggest that further hyperparameter tuning or data augmentation techniques could improve generalization.
- Post-processing steps, such as morphological operations, could further refine the predicted masks, particularly at boundary edges.

In summary, the proposed U-Net architecture achieves high accuracy and segmentation quality, providing a promising approach for brain tumor segmentation. Future work could extend the model to include multi-class tumor type classification and testing on larger datasets to evaluate its scalability.