A Convolutional Neural Network (CNN) approach for Brain Tumor Classification

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Introduction

Medical professionals face the ongoing challenge of accurately and efficiently classifying diverse brain tumors through medical imaging.

Manual classification can be time-consuming and subjective, necessitating the development of advanced, automated solutions.

Our methodology incorporates cutting-edge models such as U-Net and pre-trained AlexNet to streamline the feature extraction and classification processes.

pandas

NumPy

Motivation

- ✓ Provide valuable support to radiologists and clinicians in their efforts to identify and classify diverse types of brain tumors.
- ✓ Feature selection plays a role in machine learning since it boosts model performance but Traditional ML requires manual feature engineering, in which domain experts select suitable features.
- ✓ Recognize the challenge of overfitting in medical image analysis.

Contribution

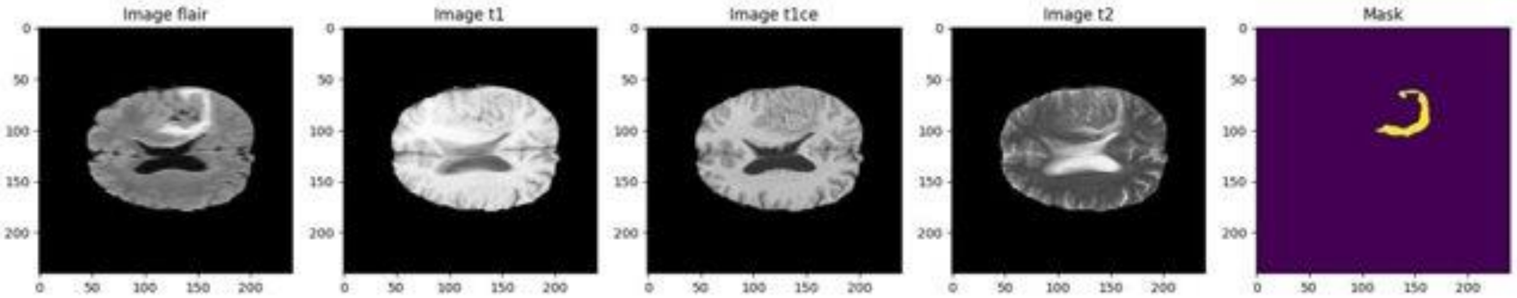
- We use revolutionary deep learning models like U-Net to automate feature extraction and image segmentation, without requiring extensive manual intervention.
- We also use pre-trained AlexNet to detect complex patterns in medical images not only tackles the issue of overfitting but also improves training efficiency.
- We use BraTS-2019 dataset, which evaluates such as loss, dice coefficient, accuracy, precision, recall, and intersection over union (IOU) utilized to evaluate the performance of both models.

Dataset

The BraTS-2019 (Brain Tumor Segmentation) dataset is commonly used for brain tumors.
We have details about the classes and the types of images available for each subject.

Given the dataset characteristics:

- **Classes:**
  - Class 0: No tumor
  - Class 1: Necrotic/Core
  - Class 2: Edema
  - Class 3: Enhancing



- **Images for Each Subject:**
  - Native (T1)
  - Post-contrast T1-weighted (T1Gd)
  - T2-weighted (T2)
  - T2 Fluid Attenuated Inversion Recovery (T2-FLAIR)

Data Preprocessing

Data Preprocessing

1. Data Normalization: Image matrix normalization ensures equal feature contribution
2. One-Hot Encoding: Encode categorical class labels into binary vectors, facilitating compatibility with classification models
3. Data Resizing: Resize images to a uniform dimension, addressing input size variations and ensuring model training consistency

$$X_{rescaled} = \frac{x}{max(|x|)}$$

Evaluation Metric {Categorical Cross Entropy}

It serves as the loss function for a multi-class classification model. The function computes the difference between the actual-value labels and the expected labels under conditions where actual-value labels are one-hot encoded. This encoding method represents the data's true class, with the label vector indicating the true class with a value of 1 and assigning 0 to the rest elements

$$J_{cee} := -\sum_{q=1}^{l} \sum_{k=1}^{p} d_{qk} \log(y_{qk})$$

Evaluation Metric {Accuracy}

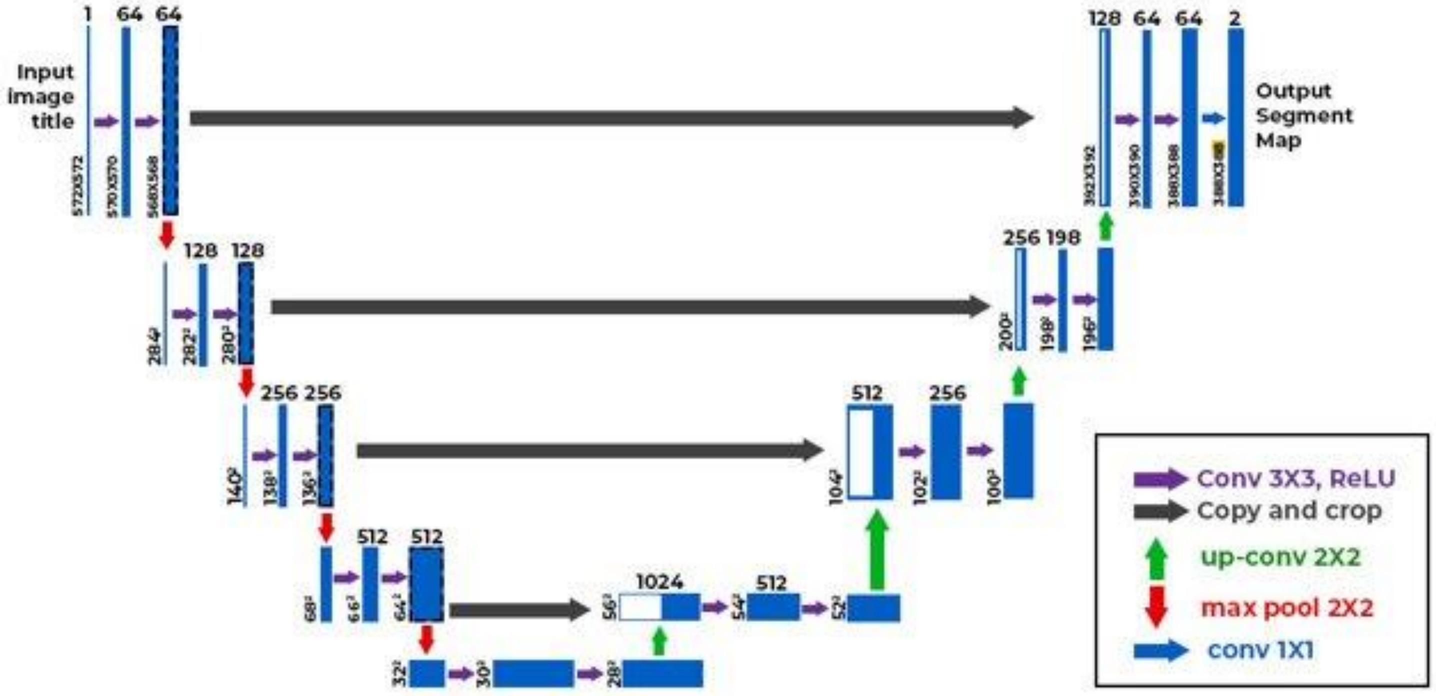
It is calculated by adding the total number of True Positive (TP) and True Negative (TN) samples and then dividing the total number of samples by the total number of samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Evaluation Metric {Dice Loss}

It is used to compare the similarity of two images, which is often used in image segmentation tasks. The loss is obtained by subtracting one from the ratio of twice the intersection over the sum of the pixels in the two images, which is derived from the Dice coefficient

$$DiceLoss(y, \underline{p}) = 1 - \frac{(2y\underline{p} + 1)}{(y + \underline{p} + 1)}$$

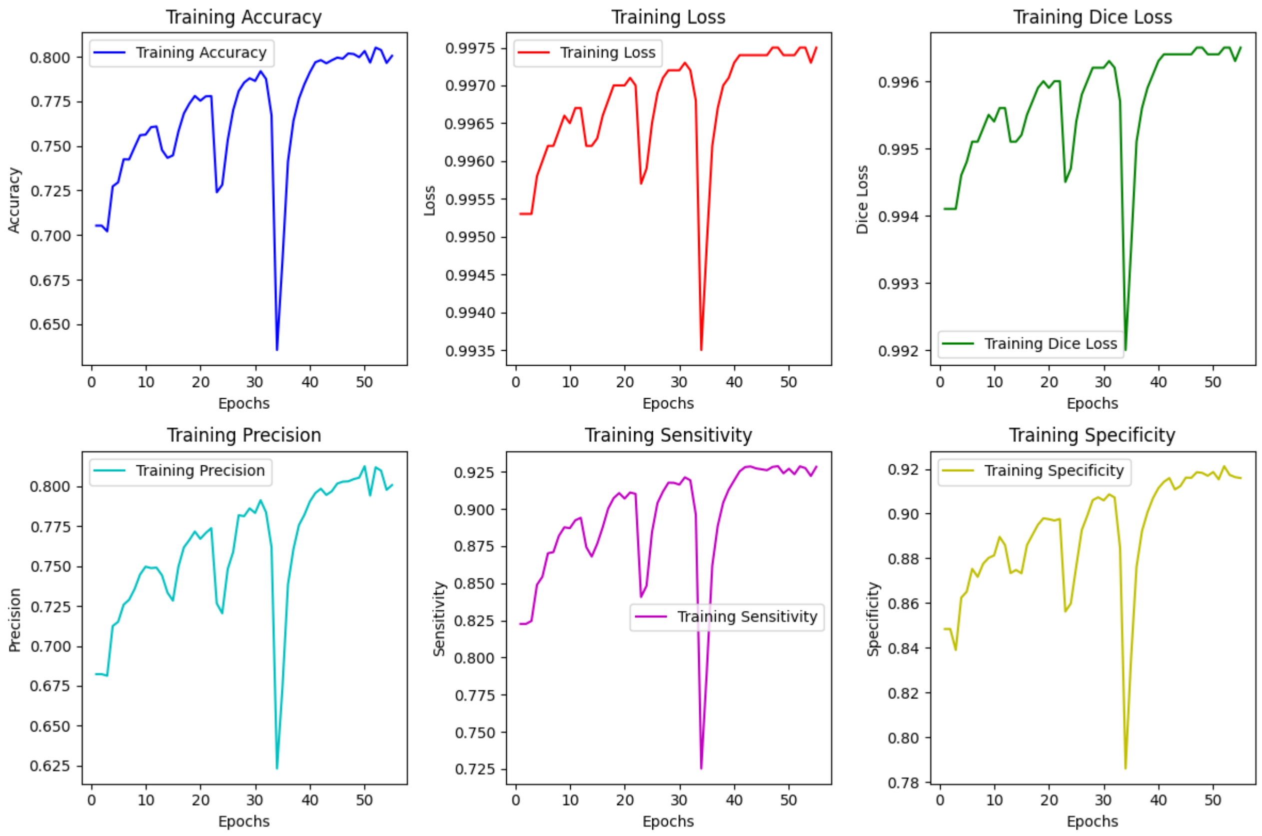


U-Net Architecture

The input image size is 240x240x155, with an output size of 128x128x4. The model co mprises a total of 19 2D convolutional layer s,four 2x2 Max pooling layers, one dropout layer, four 2x2 upsampling layers, and four merged layers.

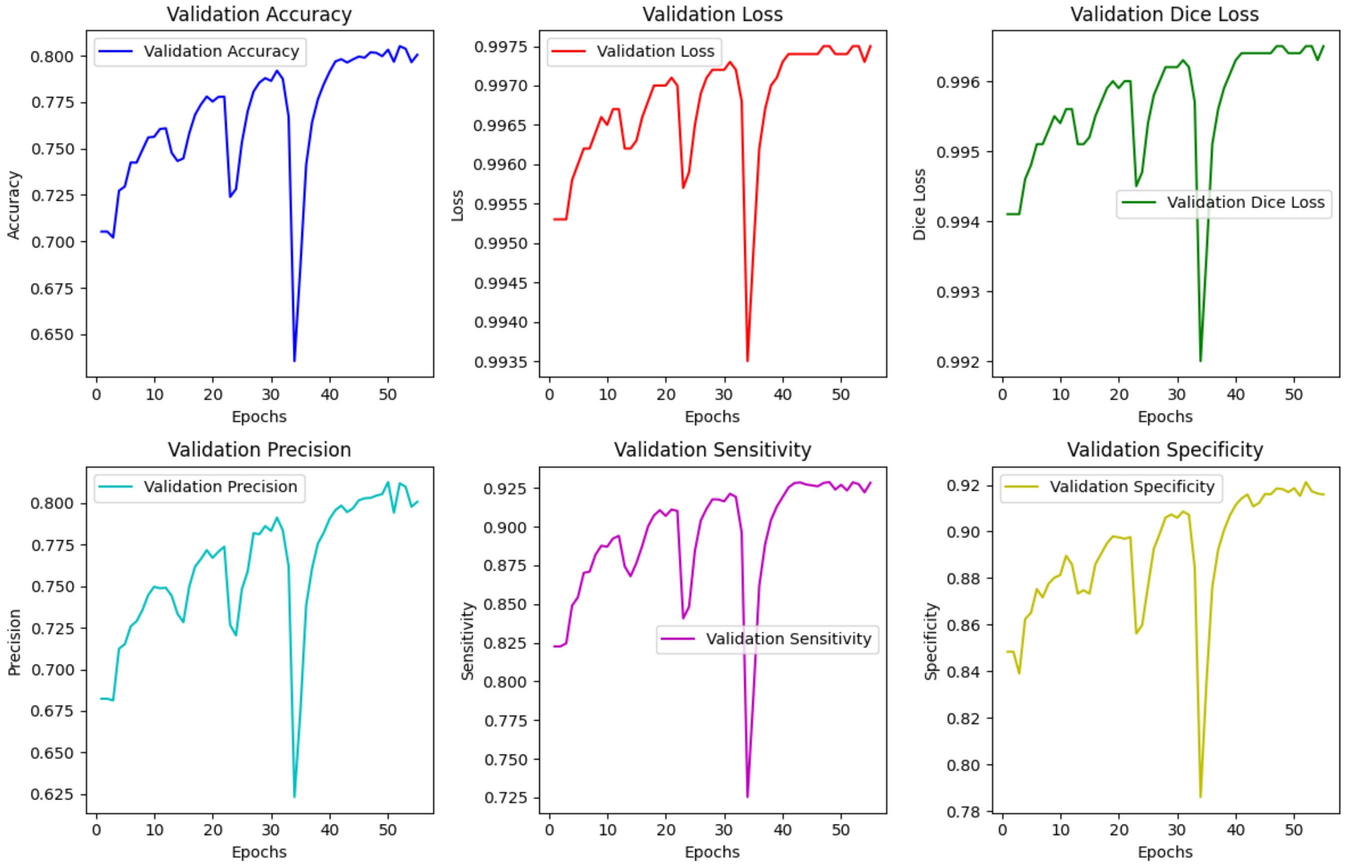
Activation functions include Softmax in the output layer and ReLU throughout other layers. Weight initialization utilizes the He_Normal initializer for optimal performa-nce.

Evaluation of U-Net on Training Set



plotting of evaluation metrics of Training dataset

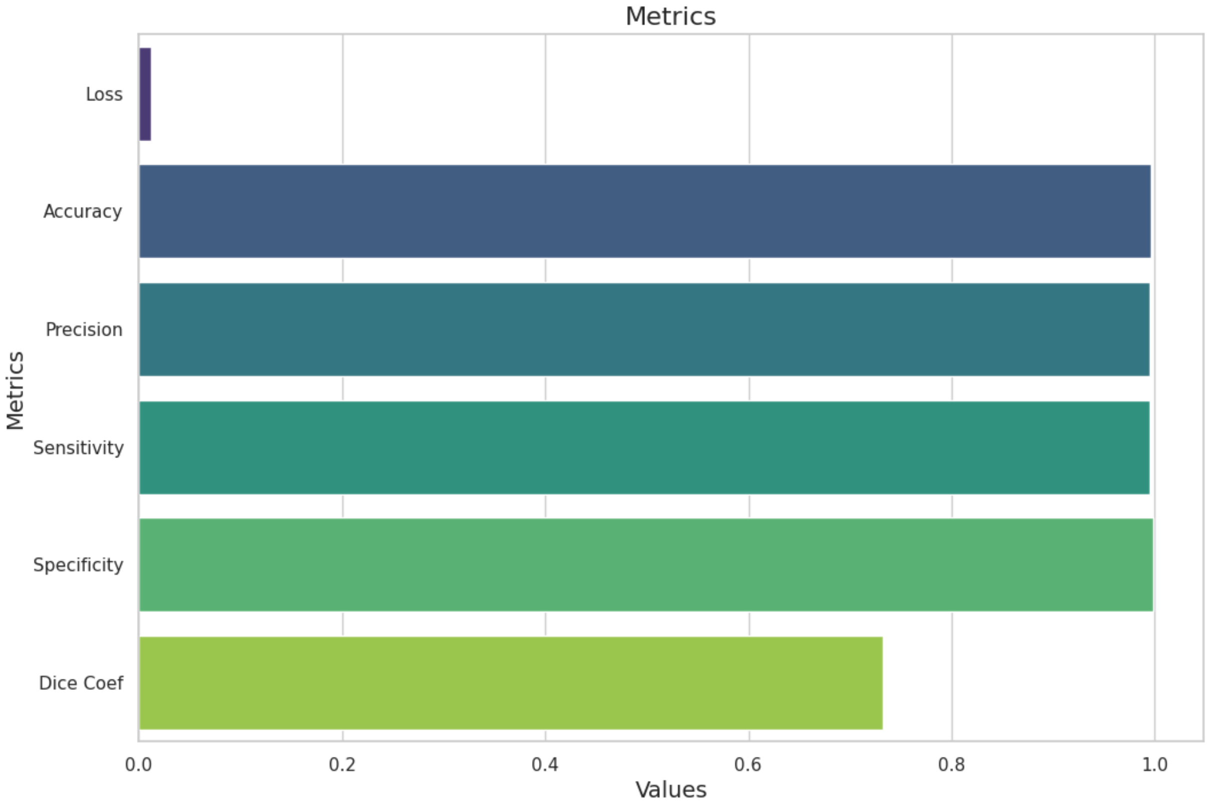
Evaluation of U-Net on Validation Set



plotting of evaluation metrics of Validation dataset

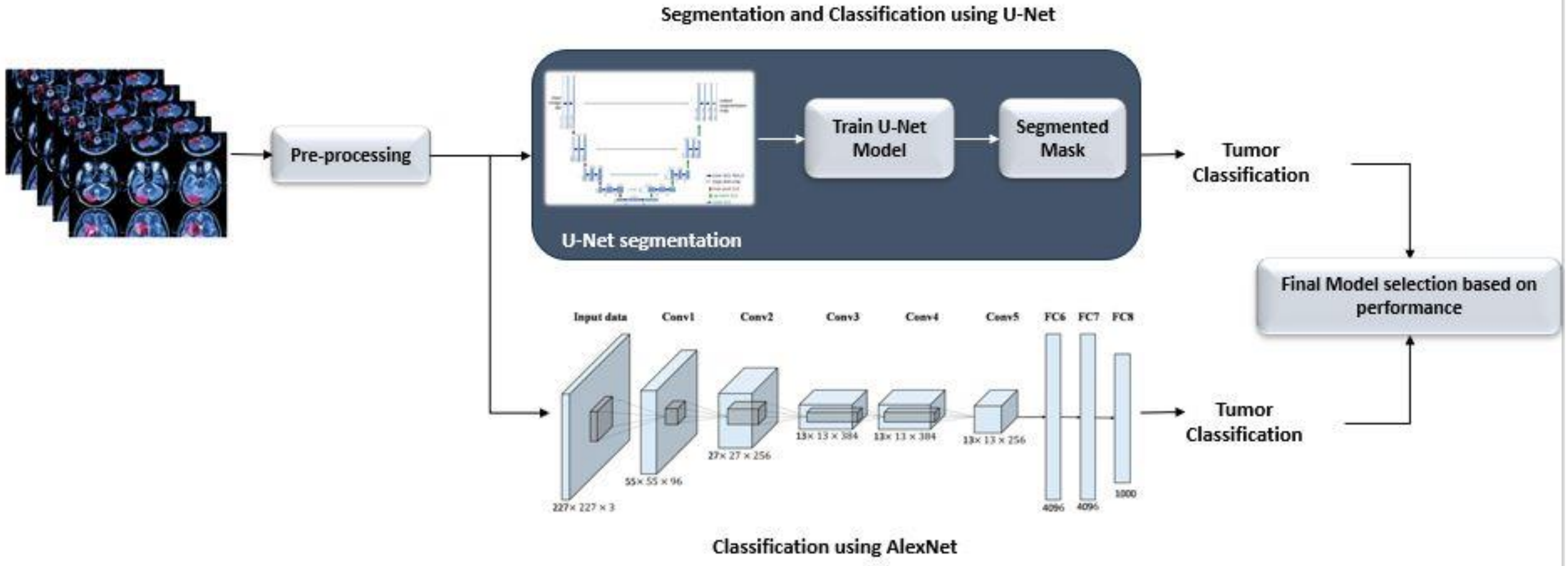
Evaluation of U-Net on Test Set

A low training loss of 0.0089 indicating that the model is effectively learning the patterns in the training data.



Evaluation of the U-Net model on Test set

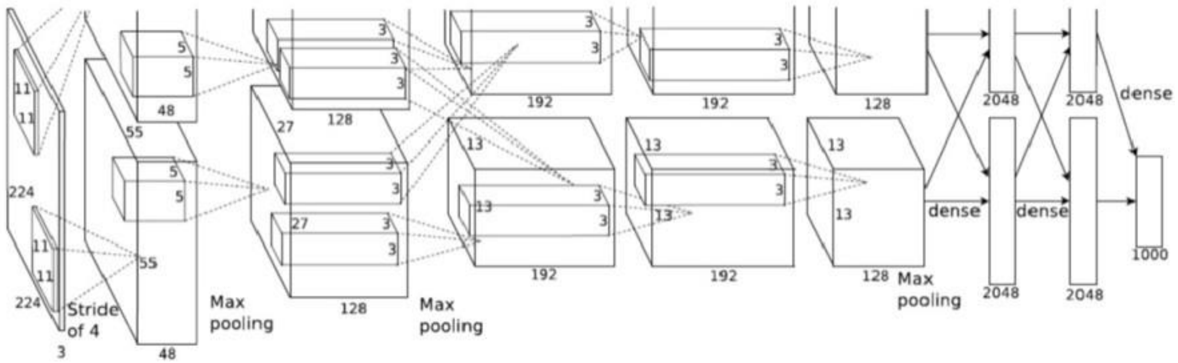
AlexNet Architecture



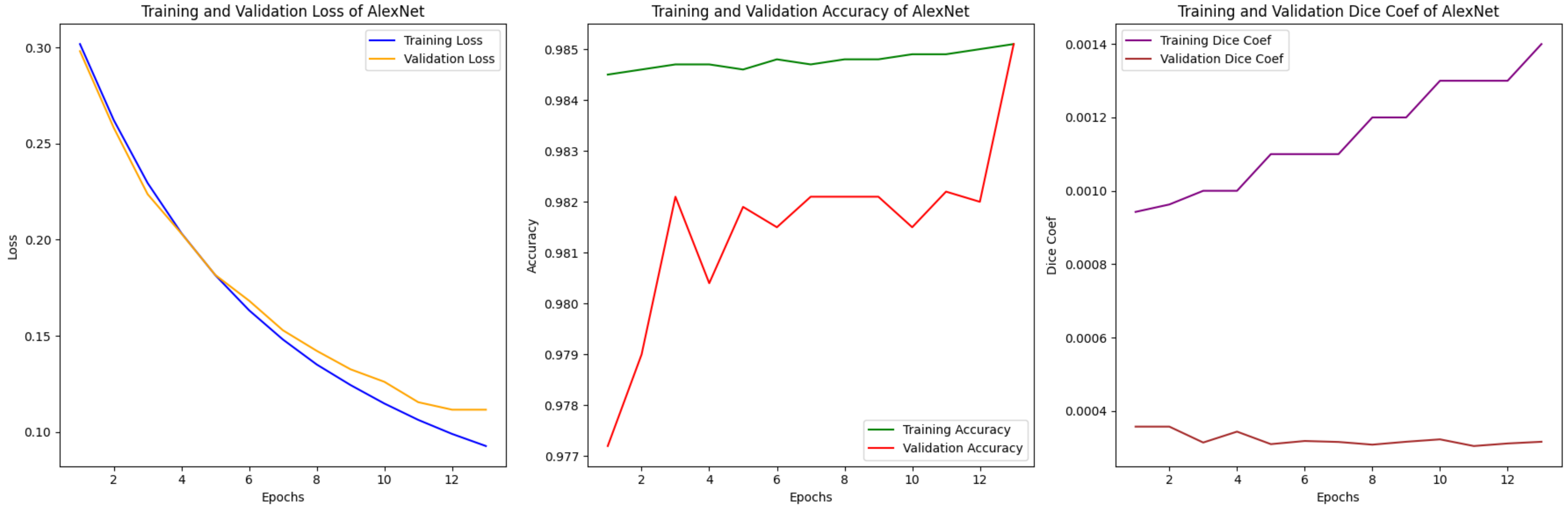
Overview of Proposed Methodology

AlexNet Architecture

AlexNet includes 5 convolutional layers, 7 Batch Normalization layers, three 2x2 Max Pooling layers, 3 dropout layers, one flatten layer, three dense layers, and one reshape layer. Activation functions include Softmax in the output layer and ReLU throughout the other layers, mirroring the U-Net model. For a visual representation of the AlexNet structure, refer to the accompanying image.



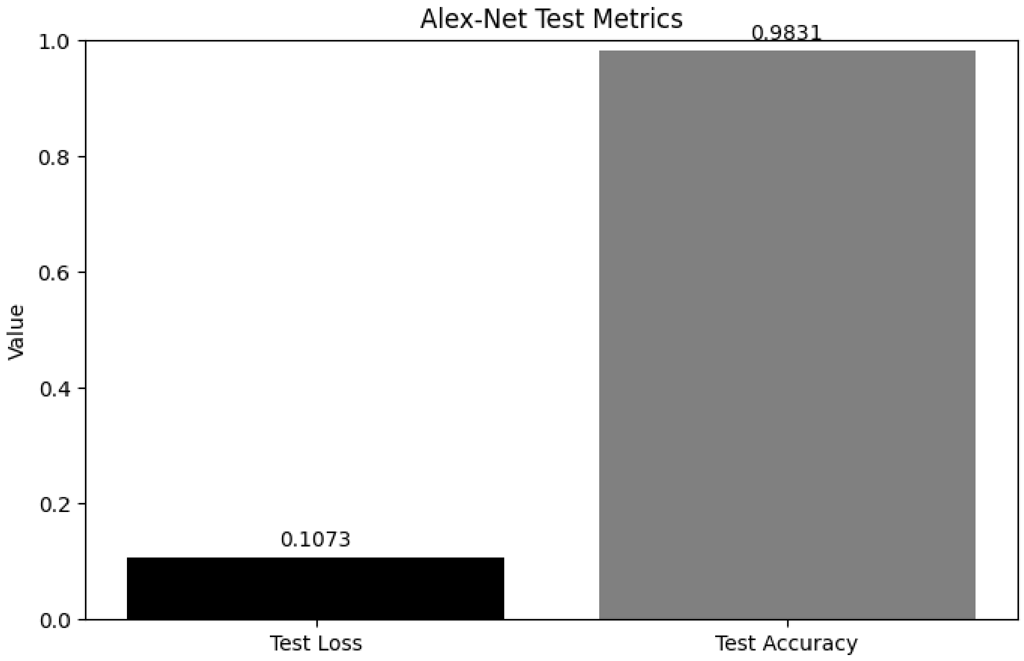
Evaluation of AlexNet on Training and validation set



Visualization of Training and Validation Loss and accuracy of AlexNet, dice loss, precision, and sensitivity of the AlexNet is '0'

Evaluation of AlexNet on Test Set

- AlexNet model performs wonderfully, with a high test accuracy of 98.3%.
- When compared to AlexNet, U-Net clearly goes over it in terms of accuracy, precision, sensitivity, and specificity.



Evaluation of the AlexNet model on Test se

Models Parameters and Evaluation

Model Name	Loss Function	Other Loss Function	Accuracy	Loss Value	Other Loss Value
Customized U-Net	Categorical Cross Entropy	Dice Loss	99.6%	0.0116	Dice Loss: 0.7427
Alex-Net	Categorical Cross Entropy	Dice Loss	98.3%	0.1073	Dice Loss: 0.0010

Model Name	Accuracy	Categorical Cross Entropy Loss	Dice Loss	Precision	Sensitivity	Specificity
U-Net	99.6%	1.2%	74.3%	99.6%	99.5%	99.9%
AlexNet	98.3%	10.7%	0.1%	0.00%	0.00%	100%

Conclusion and Future work

This study addresses the fundamental challenges of precise brain cancer classification through the use of automated tumor classification methods.

The 1st experiment with U-Net demonstrated a significant reduction in loss and an amazing accuracy of 99.58%.

The 2nd experiment with AlexNet improves classification accuracy by 98.3% but with 0 precision. These findings highlight the efficacy of the automated approaches used.

In the future, we can include alternate activation functions such as Leaky ReLU with different deep-learning models

We will also try other techniques such as PCA for dimensionality reduction, image patching,

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