CSE472

Machine Learning Project:

Brain Tumor Detection and Classification

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Introduction

This report outlines the methodologies and results of our machine learning project focused on brain tumor detection and classification. The project consists of two main objectives:

- Detection: Determining whether a brain tumor exists.
- Classification: Identifying the type of brain tumor among four classes: glioma tumor, meningioma tumor, pituitary tumor, and no tumor.

Detection

The goal of the detection task was to determine the presence of a brain tumor.

Methodology

We employed a Vision Transformer (ViT-google/vit-base-patch16-224) for image classification for this task.

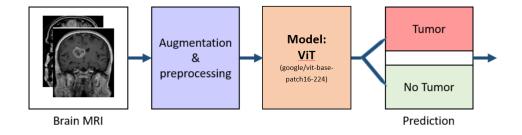


Figure 1: Methodology for Brain Tumor Detection

Dataset Augmentation: We did not apply any form of augmentation, as the testing accuracy was satisfactory without it.

Optimizer: Adam

Loss Function: Cross entropy loss

Results

Hyperparameters

The following hyperparameters were used in our experiments:

• Learning rate: 10^{-4}

• Number of epochs: 2

• Batch size: 32

The model achieved the following performance metrics during training, validation, and testing:

• Epoch 1: Training accuracy = 97%, Validation accuracy = 99%

• Epoch 2: Training accuracy = 98%, Validation accuracy = 99%

• Testing accuracy: 97%

Classification

The classification task involved identifying the type of brain tumor. We considered four categories:

- 1. Glioma tumor
- 2. Meningioma tumor
- 3. Pituitary tumor
- 4. No tumor

Methodology

Dataset Augmentation

To improve the robustness of our model, we augmented the dataset using the following techniques:

- Random horizontal flip
- Random vertical flip
- Combined horizontal and vertical flip
- Random rotation

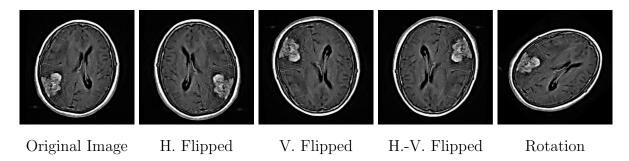


Figure 2: Examples of Dataset Augmentation Techniques

Models

For this task, we utilized three models:

- Vision Transformer (ViT-google/vit-base-patch16-224)
- EfficientNet (efficientnet_b0)
- YOLO (yolov8n-cls)

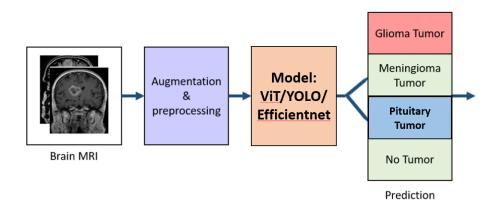


Figure 3: Methodology for Brain Tumor Classification

Results from Vision Transformer (ViT)

Dataset Augmentation

- Random horizontal flip
- Random vertical flip
- Combined horizontal and vertical flip
- Random rotation

Hyperparameters

- Learning rate: 10^{-4}
- Number of epochs: 4
- Batch size: 32

Performance

- Epoch 1: Train Accuracy = 95%
- Epoch 2: Train Accuracy = 97%
- Epoch 3: Train Accuracy = 98%
- Epoch 4: Train Accuracy = 98%
- Test Accuracy = 77%

Results from EfficientNet

Dataset Augmentation

- Random horizontal flip
- Random vertical flip
- Combined horizontal and vertical flip

Hyperparameters

- Learning rate: 10^{-4}
- Number of epochs: 22
- Batch size: 32

Performance

- Epoch 1: Train Accuracy = 89%, Loss = 0.362
- Epoch 2: Train Accuracy = 94%, Loss = 0.394
- Epoch 3: Train Accuracy = 96%, Loss = 0.409
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- Epoch 22: Train Accuracy = 99%, Loss = 0.585
- Test Accuracy = 79%

Results from YOLO

Hyperparameters

• Batch size: 16

• Learning rate: 10^{-4}

• Number of epochs: 30

• Training settings:

```
model.train(
    data=dataset_dir, # Dataset folder organized by class
    epochs=30, # Training epochs
    batch=16, # Batch size
    imgsz=224 # Image size (224x224)
)
```

Performance

• Train Accuracy: 82.70%

• Test Accuracy: 83.50%

Graphs

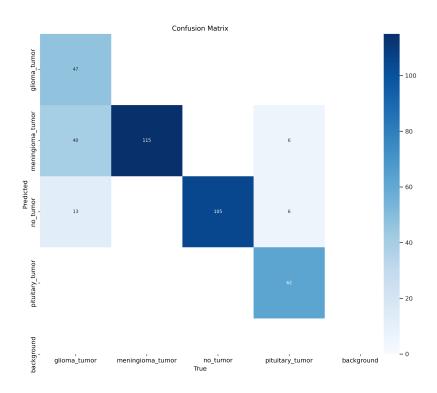


Figure 4: Confusion matrix for Classification

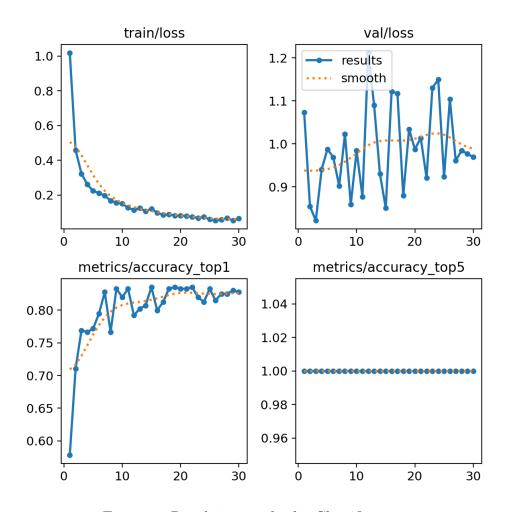


Figure 5: Resulting graphs for Classification

Challenges and Refinements

While the models performed well for *no tumor*, *meningioma tumor* and *pituitary tumor*, they struggled to classify *glioma tumor*.

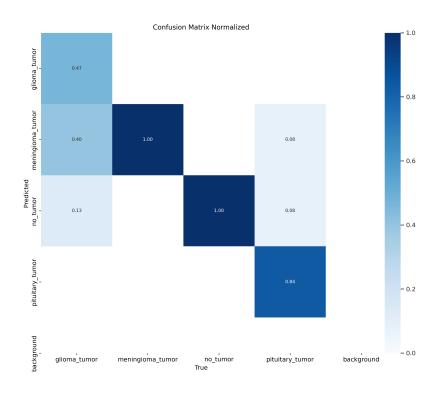


Figure 6: Confusion matrix for Classification

To address this, we conducted a secondary classification focusing solely on the *meningioma tumor* and *glioma tumor* categories, using Vit and YOLO, as glioma tumors are often misclassified as meningioma tumors.

Additional preprocessing steps, such as contour detection and clipping, were employed.

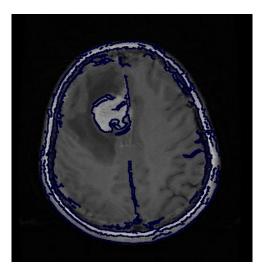


Figure 7: Finding contour of Image Data

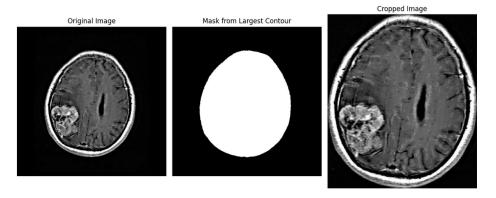


Figure 8: Clipping of Image Data

Summary of Results

Initial Results:

• Prediction accuracy: 79.07%

• Precision: 0.55

• Recall: 1

• Specificity: 0.718

• F1-score: 0.71

After applying additional augmentation:

• Prediction accuracy: 82.79%

• Precision: 0.64

• Recall: 0.9846

• Specificity: 0.76

• F1-score: 0.776

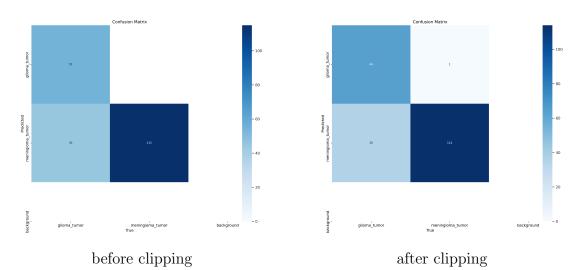


Figure 9: Performance Improvement

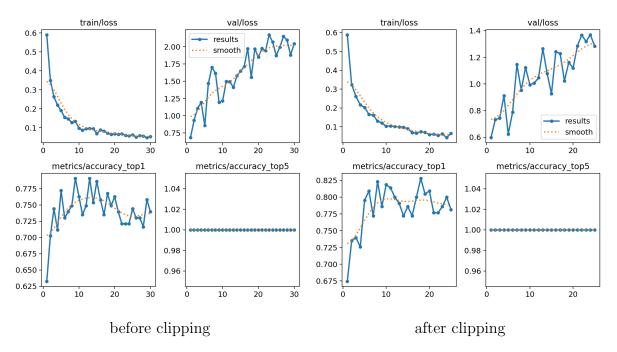


Figure 10: Resulting Graphs

Modified Classification

After applying additional augmentation:

 \bullet Prediction accuracy: 83.50%

• Precision: 0.72

• Recall: 1

• Specificity: 0.83

• F1-score: 0.835

Although the overall accuracy does not increase significantly, the following graphs show that the classification is better than before.

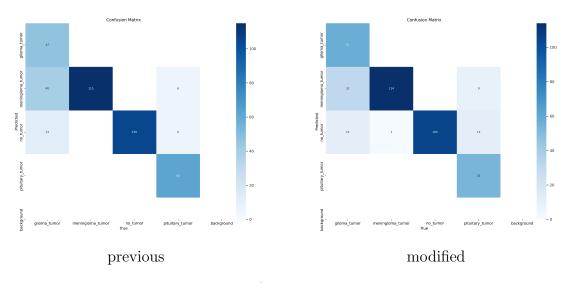


Figure 11: Performance Improvement

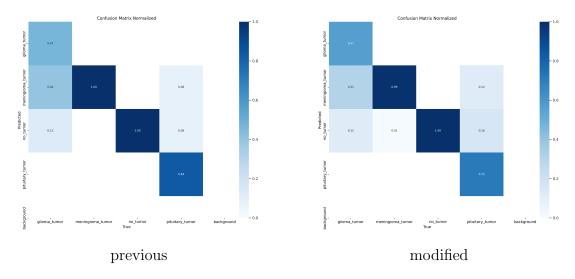


Figure 12: Performance Improvement

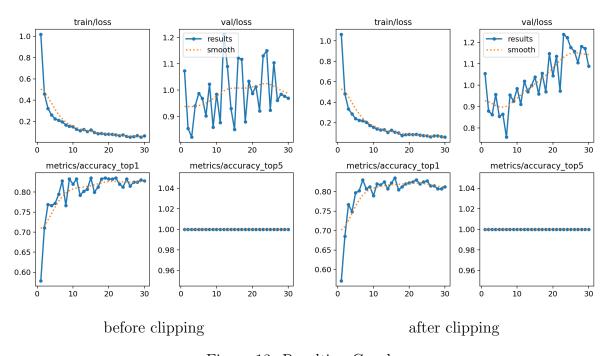


Figure 13: Resulting Graphs

Conclusion

In this project, we successfully implemented models for brain tumor detection and classification. While the detection task achieved high accuracy (97% on test data), the classification task revealed challenges (83.50% on test data), particularly for certain tumor types. Future work will focus on improving the accuracy of glioma tumor classification and exploring additional techniques to enhance overall performance.

References

Literature Insights:

- MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers: This study focuses on brain tumor classification using an ensemble of deep features and machine learning classifiers.
- Brain Tumor Detection Using a Deep CNN Model: This paper presents brain tumor classification using a CNN model with the Adam optimizer.

Dataset:

• Brain Tumor Classification: 3264 brain MRI images with tumor and non-tumor labels, split into test and train sets.

Access Link: Dataset

• Brain Tumor Detection: 3060 brain MRI images with tumor and non-tumor labels, split into test and train sets.

Access Link: Dataset