Brain Tumor Detection Project Report

Project Overview

This project focuses on the detection of brain tumors from MRI images using deep learning techniques. The workflow includes data augmentation, model training, evaluation, and interpretability using visualization methods such as Grad-CAM. Two main models were compared: a custom convolutional neural network (CNN) and a ResNet-based transfer learning model.

Data Preparation and Augmentation

- Dataset: Brain MRI images, categorized as 'tumor' and 'no tumor'.
- Preprocessing: All images were resized to 240x240 pixels and converted to grayscale (for custom CNN) or RGB (for ResNet).
- Augmentation: Mild augmentations (rotation, flip, brightness/contrast jitter) were applied to increase dataset diversity and balance classes.
- Combination: Original and augmented images were merged into a single dataset for training and evaluation.

Model Architectures

1. CustomBrainTumorCNN:

- Four convolutional blocks (Conv2d, BatchNorm, ReLU, MaxPool)
- Global average pooling
- Fully connected layer and sigmoid activation for binary classification
- Designed for grayscale input
- Outputs both the predicted probability and the last feature map for interpretability

2. ResNetCAM (Transfer Learning):

- Based on pretrained ResNet-18 (ImageNet weights)
- Final fully connected layer replaced for binary classification
- Uses global average pooling and sigmoid activation
- Designed for RGB input
- Supports Grad-CAM for localization
- Outputs both the predicted probability and the last convolutional feature map

Training and Evaluation

- Loss Function: Binary Cross-Entropy (BCELoss)
- Optimizer: Adam with learning rate scheduling
- Metrics:
    - Accuracy: Proportion of correct predictions out of all predictions.
    - Precision: Proportion of positive identifications that were actually correct (TP / (TP + FP)).
    - Recall (Sensitivity): Proportion of actual positives that were correctly identified (TP / (TP + FN)).
    - Specificity: Proportion of actual negatives that were correctly identified (TN / (TN + FP)).
    - F1-score: Harmonic mean of precision and recall (2 * (Precision * Recall) / (Precision + Recall)).
    - Confusion Matrix: Table showing counts of true positives, true negatives, false positives, and false negatives.
    - Classification Report: Detailed breakdown of precision, recall, f1-score, and support for each class.
- Hardware: Training and inference performed on GPU (NVIDIA RTX 4060)

Results

Custom CNN

- Best Validation Accuracy: 95.45%
- Test Accuracy: 96.22%
- Test Loss: 0.0848
- F1 Score: 0.9615

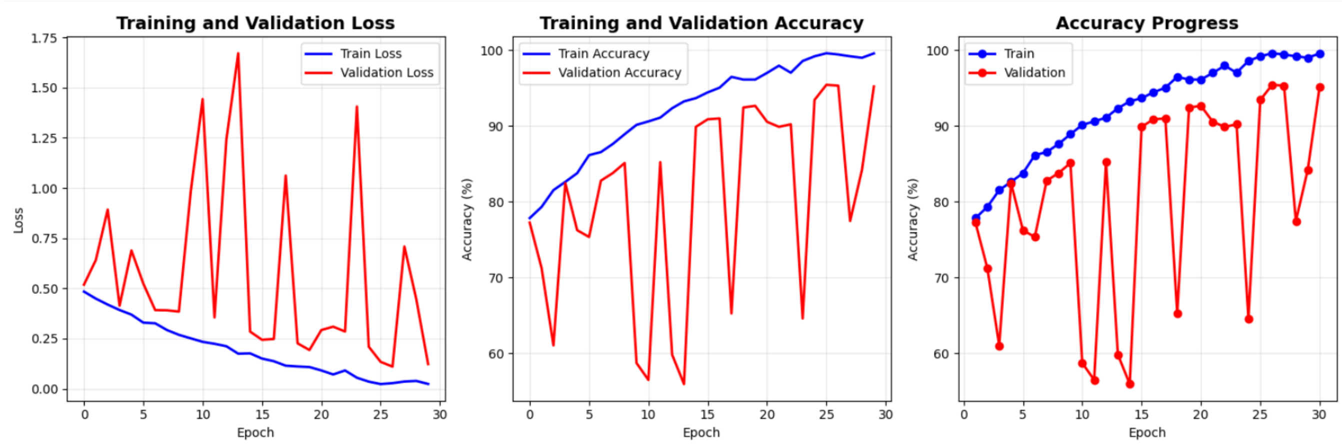
Confusion Matrix

- True Negatives (No Tumor): 441
- False Positives: 9
- False Negatives: 25
- True Positives (Tumor): 425
- Sensitivity (Recall): 0.9444
- Specificity: 0.9800
- Precision: 0.9793

Classification Report

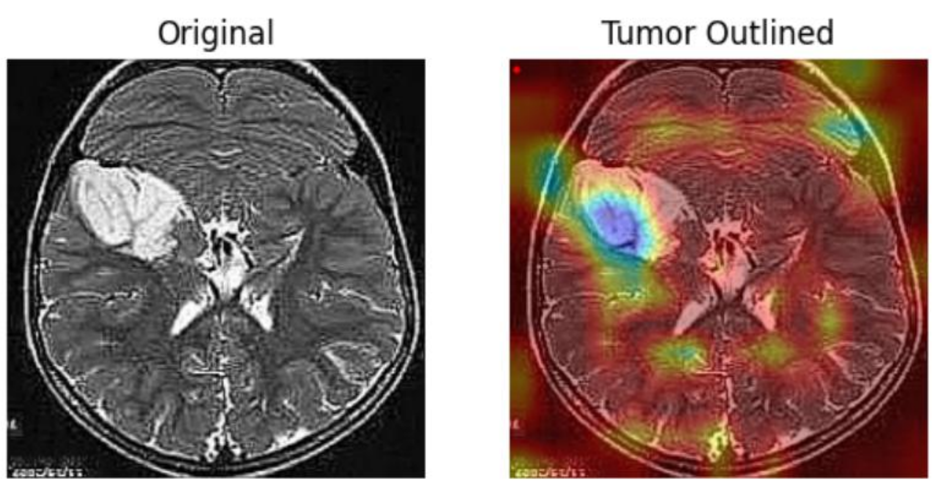
```
Classification Report:
              precision    recall  f1-score   support

    No Tumor       0.95      0.98      0.96       450
       Tumor       0.98      0.94      0.96       450

    accuracy                           0.96       900
   macro avg       0.96      0.96      0.96       900
weighted avg       0.96      0.96      0.96       900
```

Training and Validation Curves




```
Best validation accuracy: 95.45%
```

Grad-CAM Visualization




```
Predicted Tumor Probability: 1.00
```

ResNetCAM

- Best Validation Accuracy: 98.44%
- Test Accuracy: 98.67%
- F1 Score: 0.9870

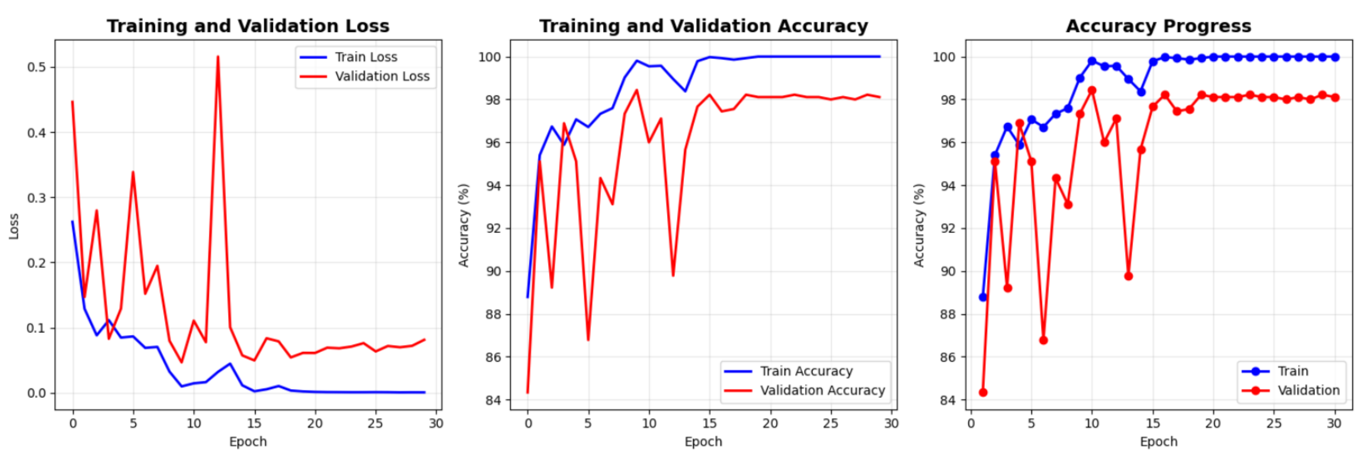
Confusion Matrix

- True Negatives (No Tumor): 433
- False Positives: 6
- False Negatives: 6
- True Positives (Tumor): 455
- Sensitivity (Recall): 0.9870
- Specificity: 0.9863
- Precision: 0.9870

Classification Report

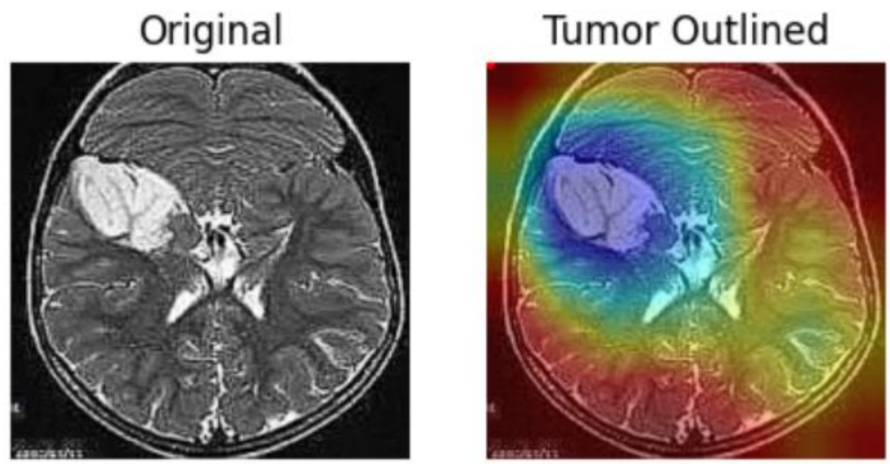
```
Classification Report:
              precision    recall  f1-score   support

    No Tumor       0.99      0.99      0.99       439
       Tumor       0.99      0.99      0.99       461

    accuracy                           0.99       900
   macro avg       0.99      0.99      0.99       900
weighted avg       0.99      0.99      0.99       900
```

Training and Validation Curves




```
Best validation accuracy: 98.44%
```

Grad-CAM Visualization




```
Predicted Tumor Probability: 1.00
```

Model Comparison and Discussion

- Performance:
  - ResNetCAM consistently outperformed the custom CNN in all key metrics (accuracy, F1, precision, recall).
  - Validation and test results for ResNetCAM were more stable and less prone to overfitting.
- Localization:
  - Grad-CAM visualizations showed that ResNetCAM focused more accurately on tumor regions, while the custom CNN's attention was less precise.
  - The deeper architecture and pretrained features of ResNet enable better extraction of relevant spatial patterns, improving both classification and localization.
- Why ResNet Performs Better:
  - Transfer Learning: ResNet leverages features learned from large-scale natural image datasets, providing a strong starting point for medical image analysis.
  - Deeper Architecture: More layers and skip connections allow ResNet to capture complex patterns and avoid vanishing gradients.
  - Robustness: Pretrained models generalize better, especially with limited medical data.
- Why ResNet Localizes Better:
  - Hierarchical Features: ResNet's deep layers capture both low-level and high-level features, making Grad-CAM heatmaps more focused and interpretable.
  - Better Feature Maps: The final convolutional layers in ResNet are more expressive, leading to sharper and more accurate localization of tumor regions.

    - Empirical Evidence: Inference images show that ResNetCAM's Grad-CAM overlays and highlighted regions align more closely with actual tumor locations, while the custom CNN's localization is less precise and sometimes highlights irrelevant regions.

Tools and Libraries Used

- Python 3.10
- PyTorch (torch, torchvision)
- scikit-learn
- OpenCV
- PIL (Pillow)
- Matplotlib, Seaborn
- tqdm

Conclusion

This project demonstrates that transfer learning with ResNet not only improves classification accuracy for brain tumor detection but also provides more reliable and interpretable localization of tumor regions. The combination of data augmentation, robust model architectures, and visualization techniques enables the development of effective and explainable AI tools for medical imaging.

Metric used for Evaluation:

- Accuracy: Proportion of total correct predictions (both tumor and non-tumor) out of all predictions.
- Precision: Proportion of predicted tumors that are actually tumors (TP / (TP + FP)).
- Recall (Sensitivity): Proportion of actual tumors that are correctly identified (TP / (TP + FN)).
- Specificity: Proportion of actual non-tumors that are correctly identified (TN / (TN + FP)).
- F1-score: Harmonic mean of precision and recall, balancing both false positives and false negatives.

Future Work:

- Explore more advanced architectures (e.g., deeper ResNets, EfficientNet, Vision Transformers).

- Incorporate more diverse and larger datasets for improved generalization.
- Investigate semi-supervised or weakly supervised learning for cases with limited labeled data.
- Collaborate with medical professionals for clinical validation and feedback.