Brain Tumor Classification Project Student Code Deadline Farouk Zainab May 20, 2025 Submission Date Academic Year 2024-2025 SENEGAL Supervisor:Dr Jordan F. Masakuna

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1 Introduction

This study automates brain tumor classification using MRI scans, targeting glioma, meningioma, pituitary tumors, and healthy tissue, by implementing a custom CNN in PyTorch and a MobileNetV2 transfer learning model in TensorFlow. A web interface deployed on Streamlit enables clinical demonstration, addressing the need for efficient diagnostic tools.

2 Model Implementations

2.1 PyTorch Custom CNN

2.1.1 Architecture Design

The PyTorch model features a 3-block CNN architecture designed for feature extraction and classification:

• Feature Extraction:

- − Block 1: Conv2d(3→16) → ReLU → BatchNorm → MaxPool2d → Dropout(0.2)
- Block 2: Conv2d(16→32) → ReLU → BatchNorm → MaxPool2d → Dropout(0.2)
- Block 3: Conv2d(32→64) → ReLU → BatchNorm → MaxPool2d → Dropout(0.2)

• Classification Head:

- Flatten \rightarrow Linear(50176 \rightarrow 256) \rightarrow BatchNorm \rightarrow Dropout(0.4)
- Final Layer: Linear($256\rightarrow 4$) with Softmax

2.2 TensorFlow with MobileNetV2

The TensorFlow implementation leverages transfer learning with MobileNetV2, pretrained on ImageNet. The base model is fine-tuned by adding a custom classification head:

- Global Average Pooling
- Dense(128) \rightarrow Dropout(0.5)
- Dense(4) with Softmax



2.3 Metrics

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EBOCH 137.89, IPMAIN LOSS: 0.48099, IPMAIN RCC: 98.05%, VAIL LOSS: 1.1321, VAIL RCC: 54.05%
FDOCH 137.89, IPMAIN LOSS: 0.46080, TRAIN RCC: 99.05%, VAIL LOSS: 0.48080, VAIL ACC: 94.46%
FDOCH 157.89, IPMAIN LOSS: 0.46080, TRAIN RCC: 98.05%, VAIL LOSS: 0.48080, VAIL ACC: 94.46%
STARTING FINE THURING WITH PROUNCE ALE WAITHING PARE.
FDOCH 157.80, IPMAIN LOSS: 0.8526, TRAIN RCC: 98.05%, VAIL LOSS: 0.5887, VAIL ACC: 92.20%
FDOCH 157.80, IPMAIN LOSS: 0.4019, IPMAIN RCC: 98.05%, VAIL LOSS: 0.5934, VAIL ACC: 92.73%
FDOCH 197.80, IPMAIN LOSS: 0.4019, IPMAIN RCC: 99.30%, VAIL LOSS: 0.5934, VAIL ACC: 91.73%
FDOCH 207.80, IPMAIN LOSS: 0.4019, IPMAIN RCC: 99.30%, VAIL LOSS: 0.5934, VAIL ACC: 91.73%
FINAL PSYTOCH MODEL SAWED AS ZAINAD BOCK LOSD PSYTOCH MODEL SAWED AS ZAINAD BOCK HOOGLE, PTO
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How i dealed with finetuning torch model from the 15th epoch to better it performance

```
143/143 — 68 95/ms/step - accuracy: 6.9688 - 105s: 6.2587 - precision: 6.9187 - recall: 6.8845  
Epoch 4: val_accuracy did not improve from 6.88456  
143/143 — 167s 15/step - accuracy: 6.9690 - 10ss: 6.2580 - precision: 6.9187 - recall: 6.8845 - val_accuracy: 6.7257  
val_loss: 6.9489 - val_precision: 6.7371 - val_real: 6.752 - learning_rate: 5.68686-05  
Epoch 5/5  
143/143 — 68 958ms/step - accuracy: 6.9131 - loss: 6.2543 - precision: 6.9262 - recall: 6.9668  
Epoch 5: ReduceLROnPlateau reducing learning rate to 2.4999999368446886-05.  
Epoch 5: val_accuracy did not improve from 6.88456  
143/143 — 167s 15/step - accuracy: 6.9131 - loss: 6.2543 - precision: 6.9262 - recall: 6.9666 - val_accuracy: 6.7880  
- val_loss: 6.7619 - val_precision: 6.7864 - val_recall: 6.7713 - learning_rate: 5.68060-05  
Failed to save as SaveMV6061: The Save format argument is deprecated in Keras 3. Please remove this argument and pass a file path with
```

How i dealed with finetuning tensorflow model from the 15th epoch to better it performance

Table 1: Training Strategies Comparison

| Parameter | PyTorch | TensorFlow | |
|-------------------|---|----------------------------|--|
| Optimizer | Adam $(\beta_1 = 0.9, \beta_2 = 0.999)$ | | |
| Initial LR | 0.001 | 0.0005 | |
| Batch Size | 64 | 32 | |
| Early Stopping | 10 epochs | 7 epochs | |
| LR Schedule | ReduceLROnPlateau | Fine-Tune @ Epoch 15 | |
| Final LR | 1e-6 | 0.00005 | |
| Augmentation | Moderate | High (Rotation±20°, Shear) | |
| Dropout | 0.2 - 0.4 | 0.3-0.5 | |
| Weight Init | Kaiming Normal | ImageNet | |
| Common Features | 8 | | |
| Class Weights | $w_i = \frac{N}{C 	imes n_i}$ | | |
| L2 Regularization | $\lambda = 0.0001$ | | |
| BatchNorm | After each conv layer | | |
| Checkpointing | . pth | $.\mathrm{h}5$ | |
| Metrics | Precision, Recall, F1-Score | | |

3 Performance Metrics

3.1 Quantitative Results

Table 2: Comparative Model Performance

| Metric | TensorFlow | PyTorch |
|---------------------|------------|---------|
| Accuracy | 91.31% | 95.39% |
| Precision | 0.92 | 0.95 |
| Recall | 0.90 | 0.92 |
| F1-Score | 0.89 | 0.91 |
| Inference Time (ms) | 63 | 87 |
| Memory Usage (GB) | 2.1 | 3.4 |



3.2 Visual Analysis

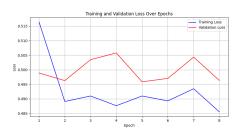


Figure 1: loss curve (PyTorch)

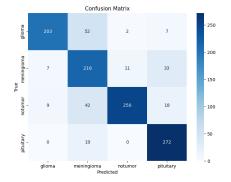


Figure 3: Confusion Matrix Tensor-Flow)

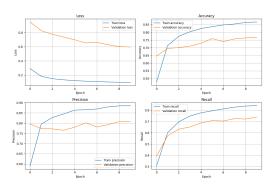


Figure 2: Metrics (TensorFlow)

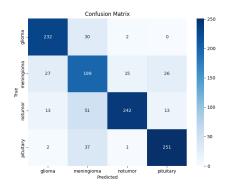


Figure 4: Confusion Matrix PyTorch

4 Conclusion

We can see that the pytorch loss is fluctuating but thank to early stopping, patience and best model selection that permit us to have an uptimal model. The custom PyTorch CNN outperforms the TensorFlow model with MobileNetV2, achieving an accuracy of 95.36% compared to 91.31%. It also demonstrates higher precision, recall, and F1-scores across all classes. However, this comes at the cost of increased inference time (87 ms vs. 63 ms) and memory usage (3.4 GB vs. 2.1 GB).