Comparing CNNs and ViTs for Brain Tumor Classification of MRI Scans

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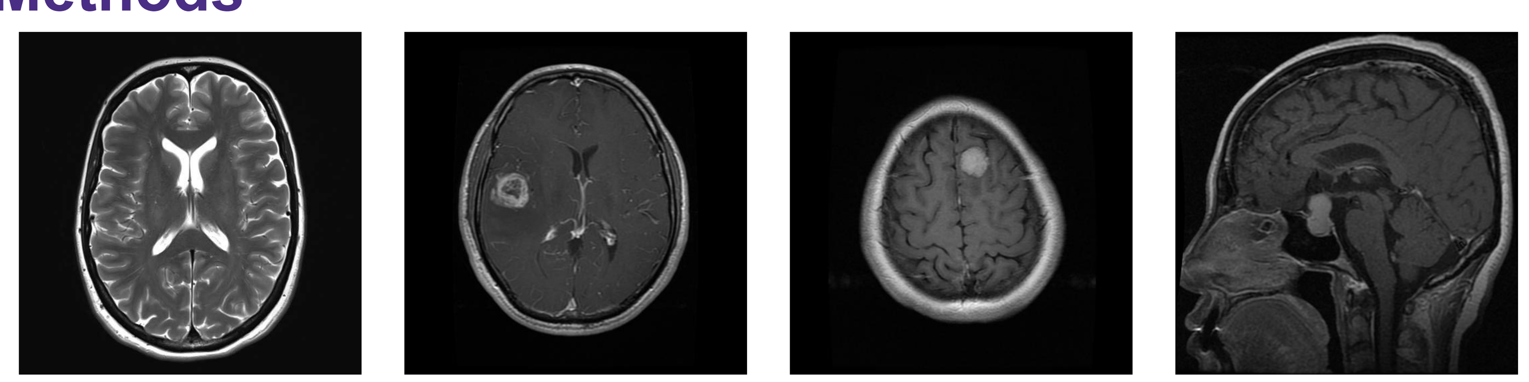
Background

Brain tumors are a debilitating medical diagnosis that alters the anatomy of the brain to accommodate the lesion. Even upon removal, any structural changes to the brain as a result of the lesion are permanent. This is often why patients who undergo a successful craniotomy still will have lingering symptoms for life. Quick and rapid diagnosis of MRI scans will help raise the accessibility of this procedure and make it a viable preventative screening option as opposed to a later stage diagnostic tool in medicine. We seek to compare the performance of a custom CNN model alongside fine-tuning existing pre-trained models towards identification of the existing of a brain tumor from MRI scans.

Objective

- Classify various types of brain tumors (or not) from MRI scans.
- Demonstrate the robustness of different deep learning architectures for classification.

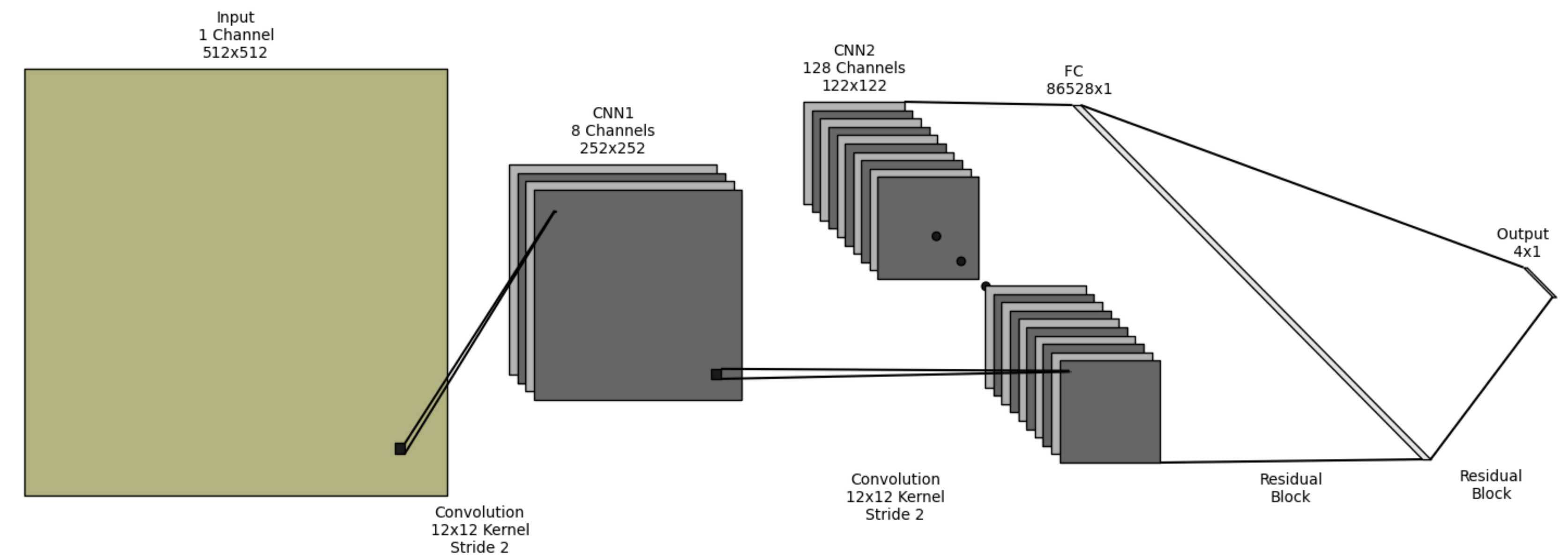
Methods

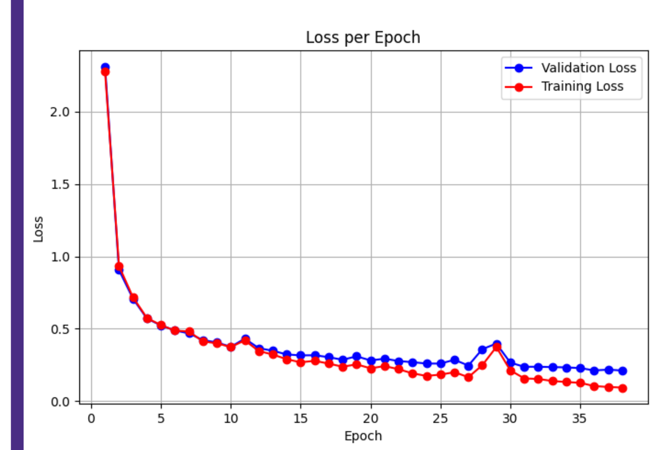


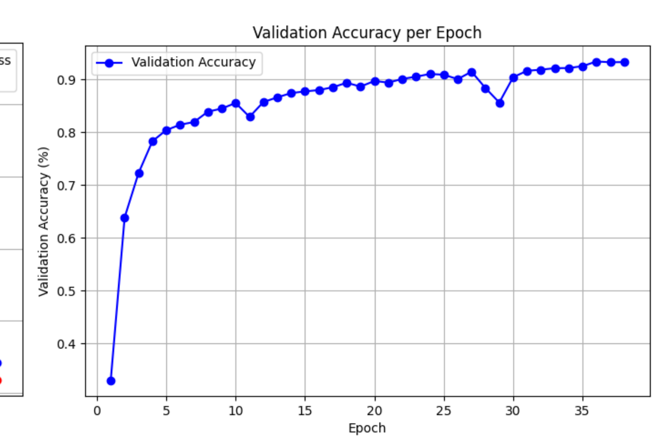
No Tumor	Glioma	Meningioma	Pituitary
1,595 Train	1,321 Train	1,339 Train	1,457 Train
405 Test	300 Test	306 Test	300 Test

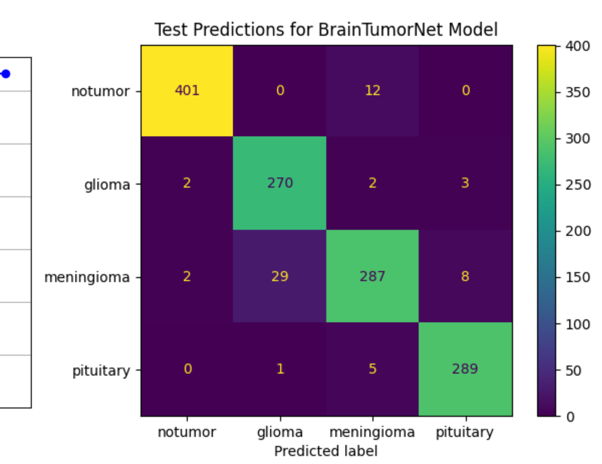
- Create a custom PyTorch **`Dataset`** class for the Kaggle MRI data set.
- Standardize MRI scans to a single channel **`float32`** image **`512 x 512`** in size.
- Use the PyTorch **`DataLoader`** class to help with batch creation and shuffling of images during training.
- Use an 80-20 training-validation split and perform hyper parameter tuning until sufficient performance is achieved.
- Test a custom CNN model in addition to a vision transformer (ViT) model for comparison.
- Report metrics for evaluation of performance quantitatively.

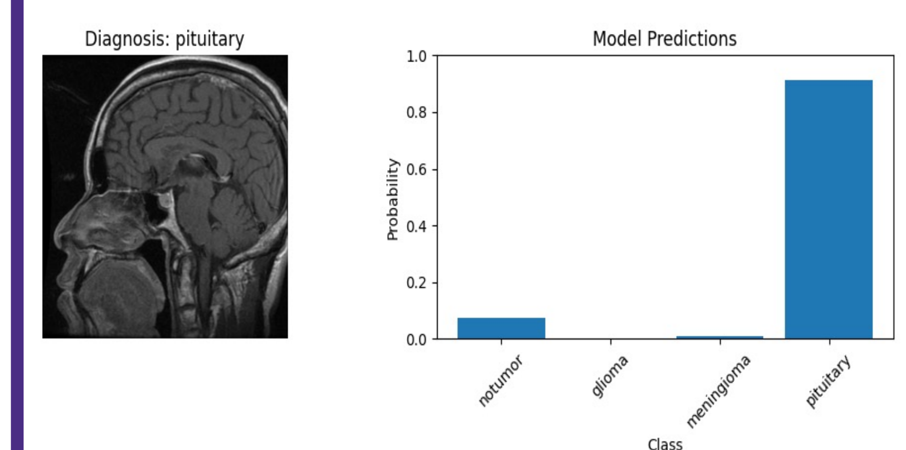
Results: BrainTumorNet-43M

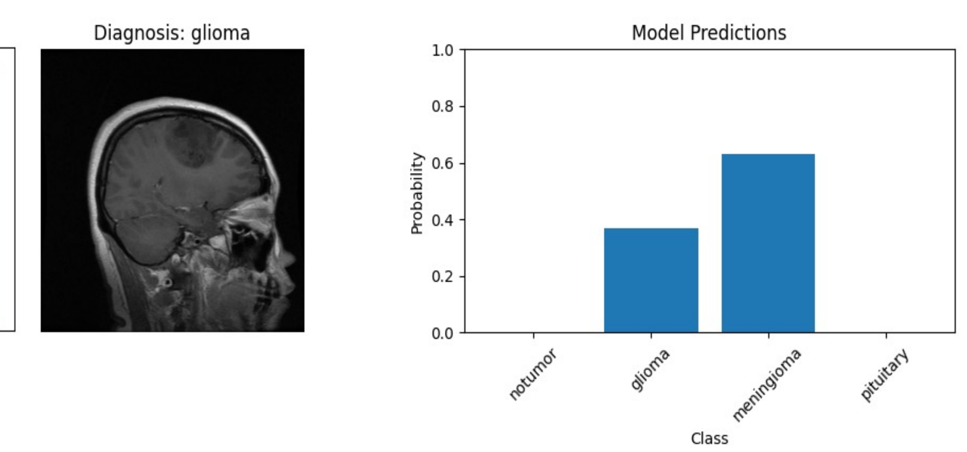










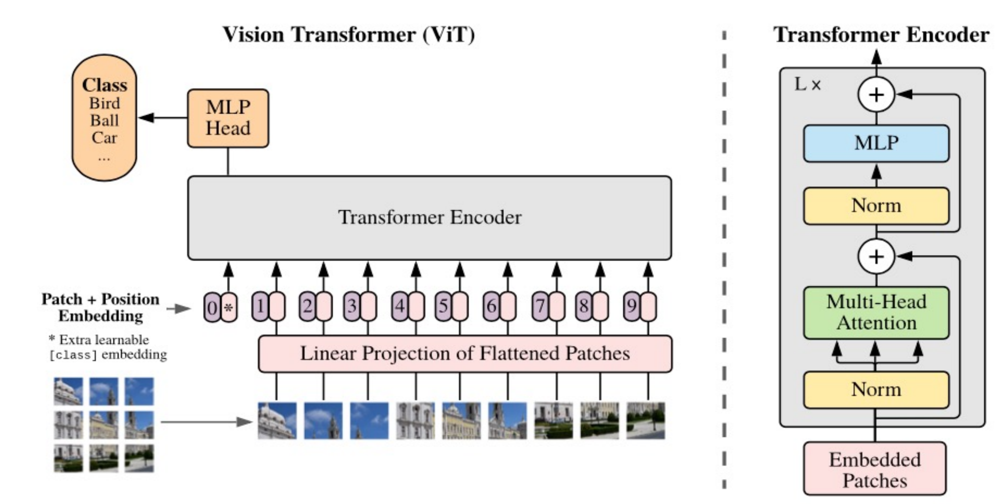


✅ Correct Classification ❌ Incorrect Classification

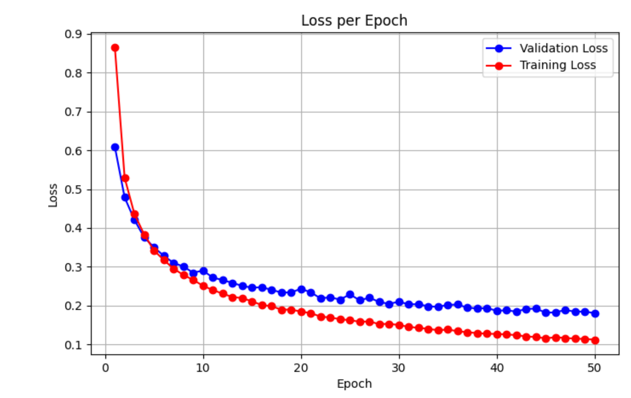
Summary

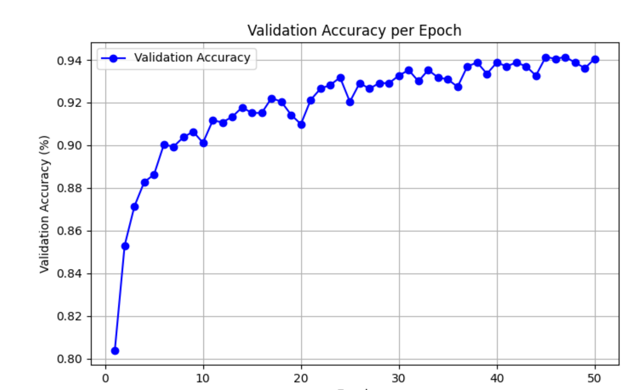
- 256 image batch size with shuffling after each epoch.
- Cross entropy loss.
- ADAM optimizer with 0.001 learning rate and 0.0001 decay.
- 40 training epochs.
- **95.1% accuracy** on testing data.

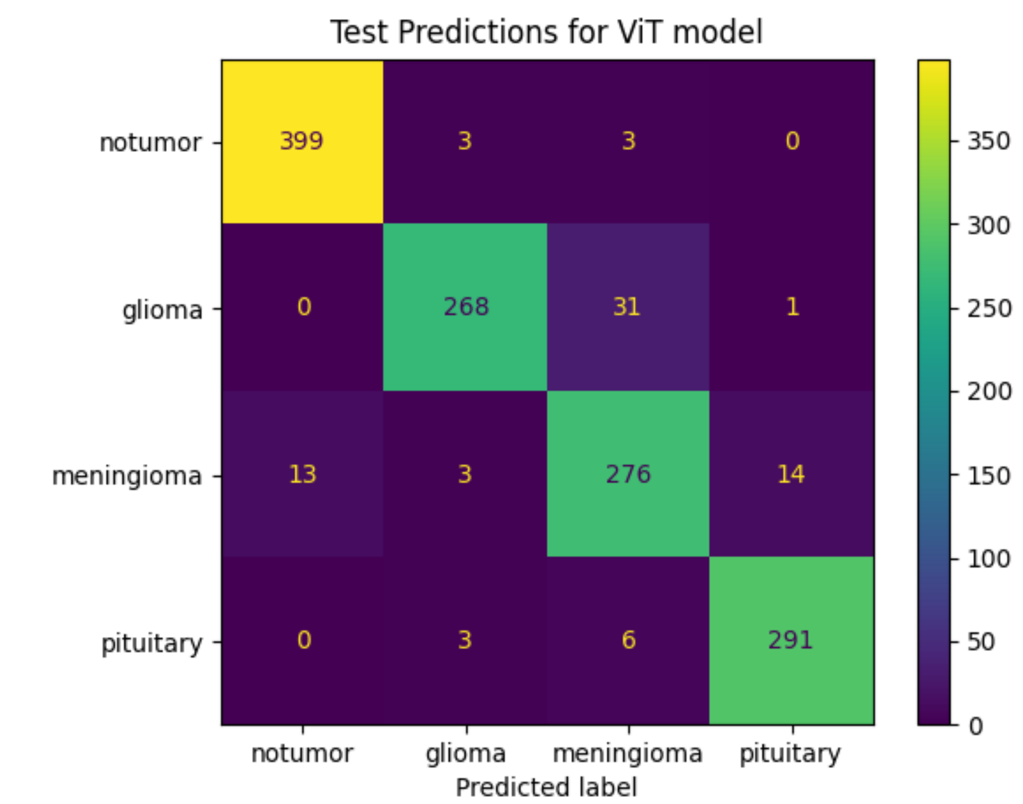
Results: Vision Transformer (ViT)



ViT backbone was pre-trained on 14 million images and 21,842 classes, then fine-tuned on 1 million images from 1,000 classes by Google.







Summary

- 128 image batch size with shuffling after each epoch.
- Cross entropy loss.
- ADAM optimizer with 0.001 learning rate and 0.0001 decay.
- 75 training epochs.
- **94.6% accuracy** on testing data.

Conclusions

- Brain tumor classification from MRI scans is robust and capable of achieving >90% accuracy using a variety of deep learning architectures.
- Additional challenges are required for actual clinical adoption, including a larger training cohort (and larger model parameter sizes).
  - MRI scans should also be sourced from a more diverse range of instrument manufacturers and scanning models.
  - Patient cohorts should be more diverse to help the model better generalize on new out-of-distribution data.

References

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