Brain Tumor Classification in MRI with Deep Learning

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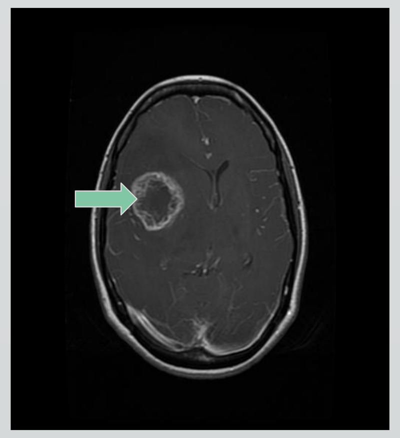
Abstract

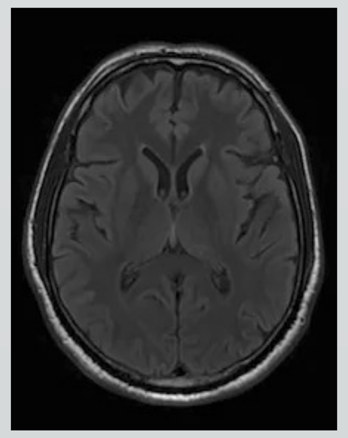
MRI (Magnetic Resonance Imaging) is a widely used, non-invasive diagnostic tool for the detection of tumors. This project compares the performance of various machine and deep learning models in classifying brain tumors in MRI scans (Glioma, Meningioma, Pituitary, and no tumors) in comparison to standards set by trained radiologists. The models deployed include Convolutional Neural Network (CNN), Source Vector Machine (SVM), Random Forest Classifier (RFC), several Transfer-Learning models, as well as a Hybrid model of MobleNetV2 into SVM. Each model is trained off the same train-test split of the pre-processed and standardized data. Appropriate hyperparameter tuning and model-specific optimizations are employed to achieve the highest accuracies and also maintain robustness. Accuracy metrics and confusion matrices were generated to assess validity of the models. Additionally, a separate test dataset is artificially degraded to simulate low-field MRI scans in order to evaluate model robustness. The models' performances are evaluated with and without data augmentation, which includes random degradations, rotations, flips, and zoom profiles to the training set. Considering research showing that radiologists had an overall diagnostic accuracy of 87%: RFC had a 94% accuracy, SVM 95% accuracy, VGG16 (most accurate transfer-learning model) 97.9% accuracy, hybrid MobileNetV2/SVM 98.2% accuracy, and CNN 97.6% accuracy. All models were more accurate radiologists on average, with the hybrid model performing the best. When testing on a degraded dataset to simulate low-field MRI, augmentation drastically improved results for both SVM and RFC models; however, the CNN model accuracy was minimally affected when tested on degraded images, with augmentation being ineffective.

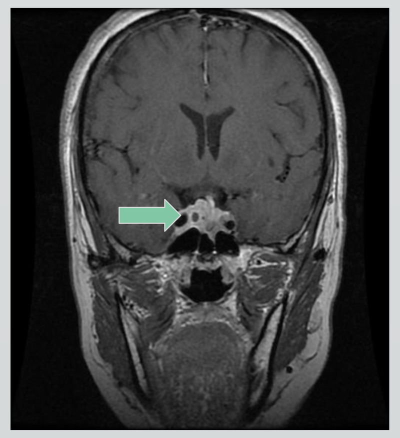
Background

- An MRI machine is able to use a series of magnetic fields and radio waves to create scans of various internal organs in the body. The course of treatment for different types of brain tumors can vary so early detection and accurate identification is paramount to prevent metastasis and poor prognosis.
- It can take anywhere from one to two weeks on average to receive MRI scan results, due to the fact that radiologists have backlogs of scans to interpret.
- MRI machines differ in field strength (0.5T - 3T) which directly correlates to the quality of scan produced.
- Additionally, studies show that radiologists have a 87% accuracy when classifying Brain Tumors in MRI scans.
- There are three types of tumors in the dataset: Meningioma occurring on the meninges layer of the brain, Glioma occurring in the deeper structural cells of the brain, and Pituitary tumors occurring on the pituitary gland in the middle of the brain. The dataset also contains scans with no brain tumors.


Glioma


Meningioma


No Tumor


Pituitary

Methods

<u>Dataset</u>: 7023 Images across four classes: Meningioma, Glioma, Pituitary, and No-Tumor. 80-20 Train-Test split, with each image being preprocessed to be 180x180px and grayscale.

<u>Non Neural Network Models.</u>

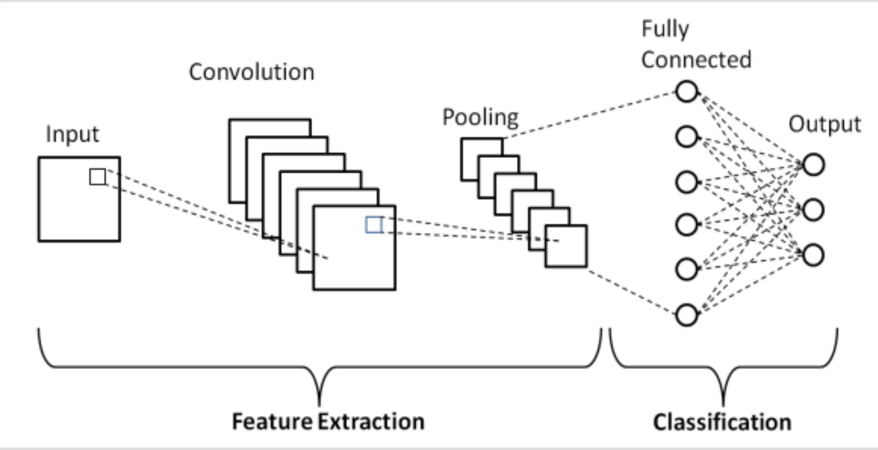
Support Vector Machine Classifier and Random Forest Classifier. Both are hyperparameter-optimized via a gridsearch, a Python library called Optuna, and cross-validation.

<u>Neural Networks</u>

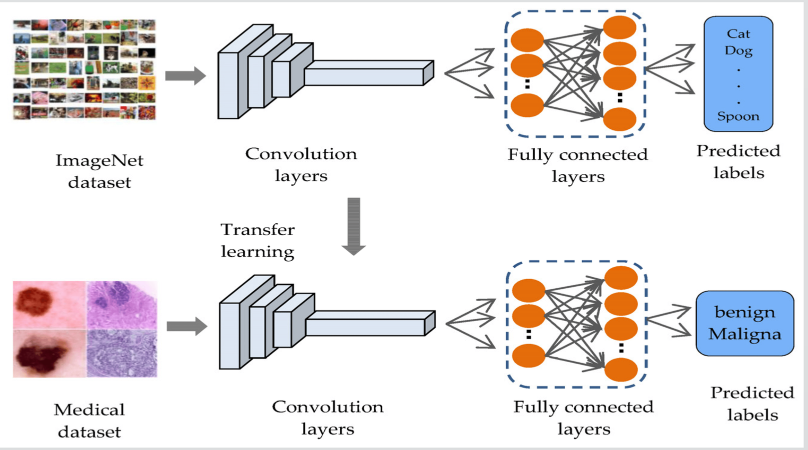
- Convolutional Neural Network: four convolutional and max-pooling layers (filters increasing 16 - 32 - 64 - 128) with ReLu activation, a flattening layer, a hidden dense layer (200 nodes) with 30% dropout, and a final dense classifying layer. Nadam optimizer was utilized due to having the highest accuracy and efficiency in comparison to other tested optimizers.
- Transfer Learning Models: VGG16, MobileNetV2, InceptionV3, and Xception trained on ImageNet. Top layers were removed and replaced with a Global 2D pooling layer, 2 dense hidden layers of sizes 1024 and 512, and final 'Softmax' layer. The final classifying layers were converged first with model layers initially frozen, and then fine-tuned by unfreezing layers at beginning and end of model as validation set performance plateaued. The most accurate model is shown in the results.
- Hybrid model: light-weight MobleNetV2 (top layers replaced as before) as a feature extractor, reducing feature space from 32400 to 1280, feeding into a SVM classifier.

<u>Degradation and Augmentation tests</u>

Ground-truth test dataset is degraded with Gaussian noise, resolution reduction (nearest-neighbors estimation), and random contrast/brightness adjustments. A portion of the training images are randomly degraded, flipped, zoomed, and rotated to augment dataset.

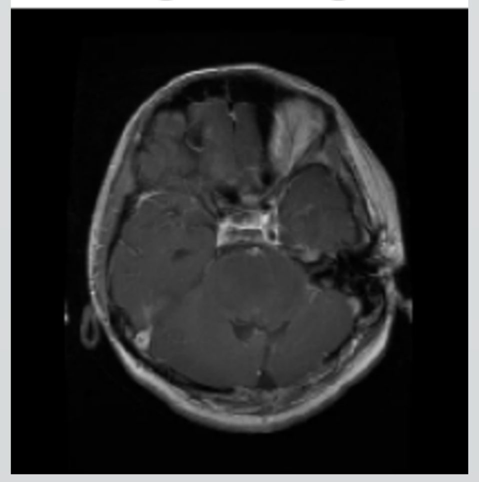


Basic CNN architecture



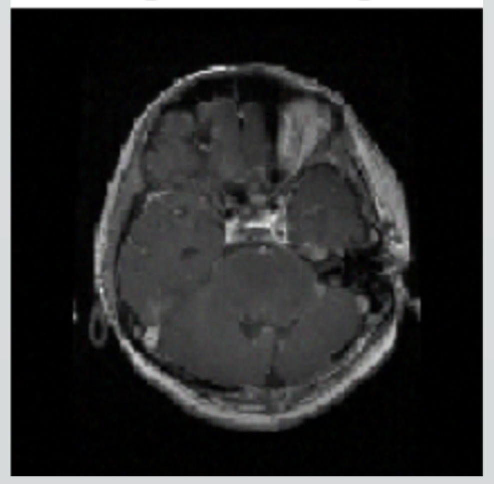
Transfer Learning Method

Original Image



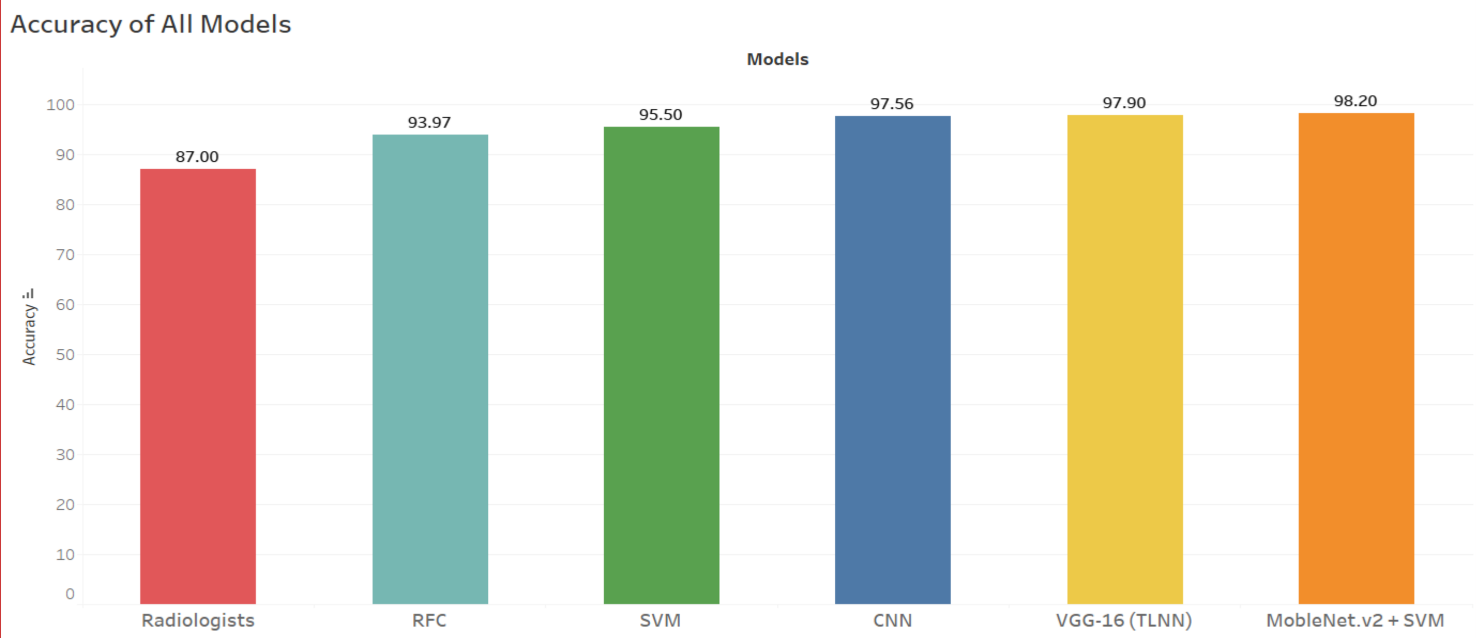
180x180 grayscale brain MRI scan

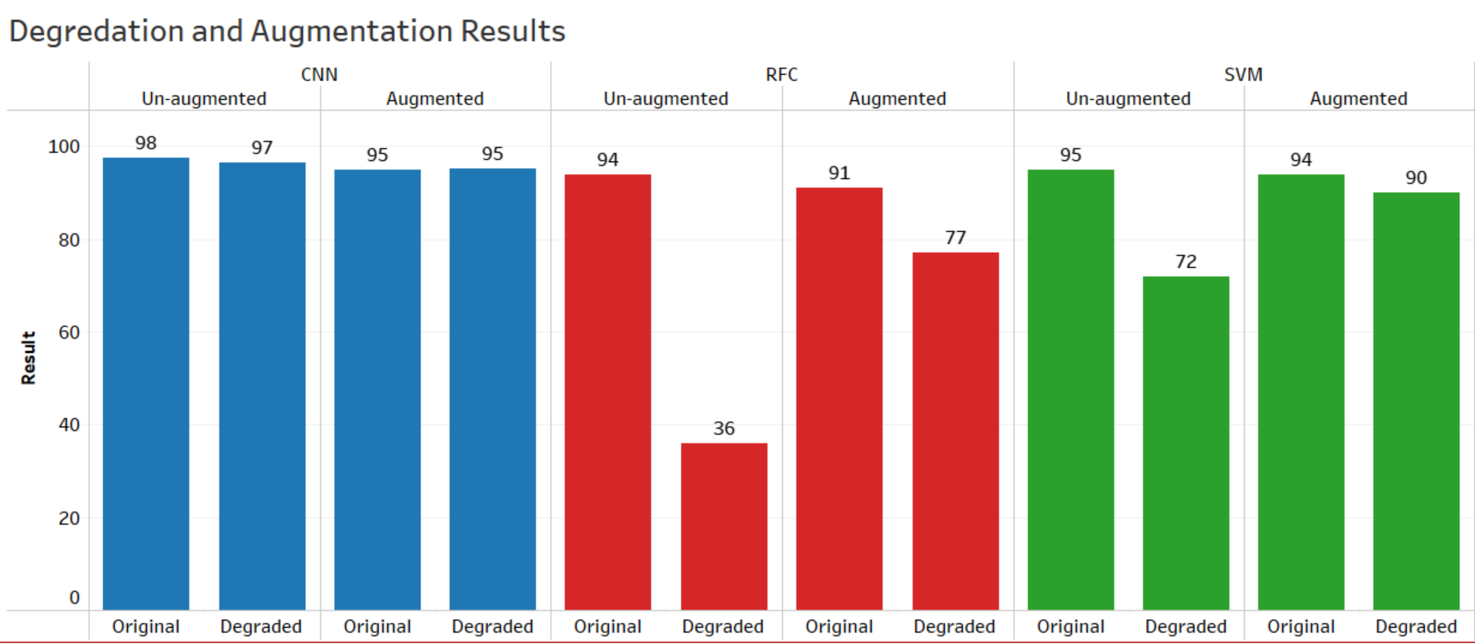
Degraded Image



Gaussian Noise (std=0.1), 20% resolution reduction, random adjustment to pixel brightness up to 50%

Results





Conclusion

- All models were more accurate than radiologists.
- Majority of misclassification across all models were between Meningioma and Glioma. It is suspected that this is due to the main difference in the tumors being depth (meningioma is on outside layer of brain, glioma on inner structure) and so top-down images of the two look similar.
- Neural Networks are more accurate than SVM and RFC.
- Hybrid model proved to be the most accurate at classifying MRI scans.
- Neural Networks are much more robust than traditional machine learning methods, though data augmentation can narrow the gap.

Future Direction

- Test the models on real low-field MRI scans.
- Field testing the models on high-field MRI scans to further analyze validity as brain tumor identification method in a Hospital Setting.
- Test models on different MRI datasets with a specific cross-sectional view of the brain to determine cause of Meningioma/Glioma misclassifications.
- Research if models can identify malignancy of tumors based on MRI scans alone

Acknowledgments

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