A Comparative Assessment of CNN and Machine Learning Models on MRI Brain Tumor Images

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Abstract

Brain tumors, ranking as the 10th leading cause of mortality according to Cancer.net, constitute a critical health concern necessitating early detection and precise classification for effective intervention.

This study draws upon a comprehensive compilation of diverse datasets, comprising 7,023 human brain MRI images sourced from figshare, SARTAJ dataset, and Br35H, categorized into glioma, meningioma, no tumor, and pituitary groups. The primary objective is to harness the collective power of these datasets to develop a robust predictive tool aimed at early brain tumor detection and lifesaving interventions. This diverse dataset, coupled with machine-learning methodologies, offers a pivotal resource for optimizing brain tumor diagnosis and treatment by facilitating early detection.

To achieve this, this study initially employed random forest and support vector machine algorithms to enhance accurate classifications and diagnostic precision. Furthermore, Convolutional Neural Networks (CNNs) were used for multi-task classification, concurrently addressing tumor detection, classification, and localization within MRI scans. This research aspires to advance brain tumor diagnosis and improve patient outcomes through the integration of deep learning techniques.

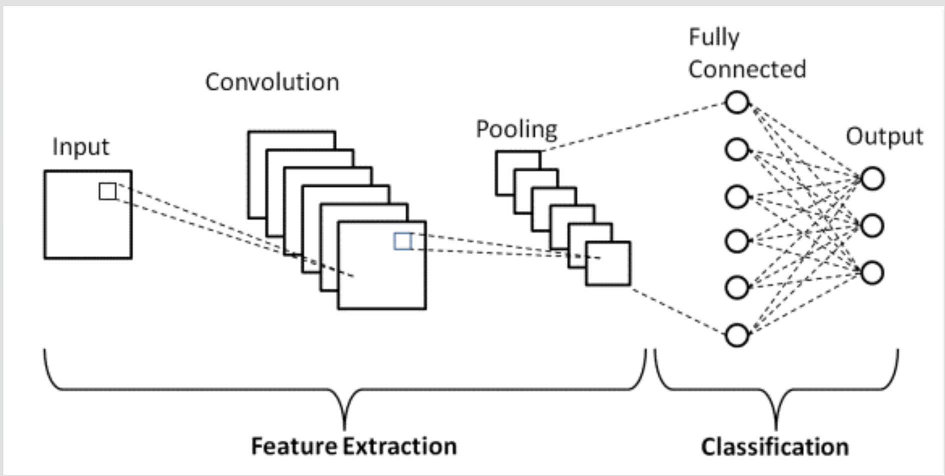
Background

- A paper titled "Accurate brain tumor detection using deep convolutional neural network" published in the National Library of Medicine used a CNN architecture of 23 layers as well as VGG16 in order to classify brain tumors.
- That study had a 97% classification accuracy. This study aims to set that accuracy as a goal to surpass and ultimately provide a better model.
- Machine learning, particularly advanced techniques such as CNNs, has revolutionized brain tumor detection, enabling precise analysis of complex MRI and CT scan data. A comprehensive review encompassing 1747 studies from 2019 to 2023 pinpoints a focus on multiclass classification and efficient models for small datasets, with glioma being a primary concern. This global research effort, with substantial contributions from countries like India, China, and the United States, underscores a concerted drive towards innovation in medical imaging.
- This study aims to build upon these global efforts, seeking to refine and advance the existing machine learning methodologies for brain tumor detection. By engaging in a comparative analysis with previous works and targeting the challenges they faced, we aspire to enhance the detection accuracy, particularly in tumor segmentation and classification. This endeavor not only furthers the technological frontier but also holds the promise of improving patient survival rates and preserving the quality of life.

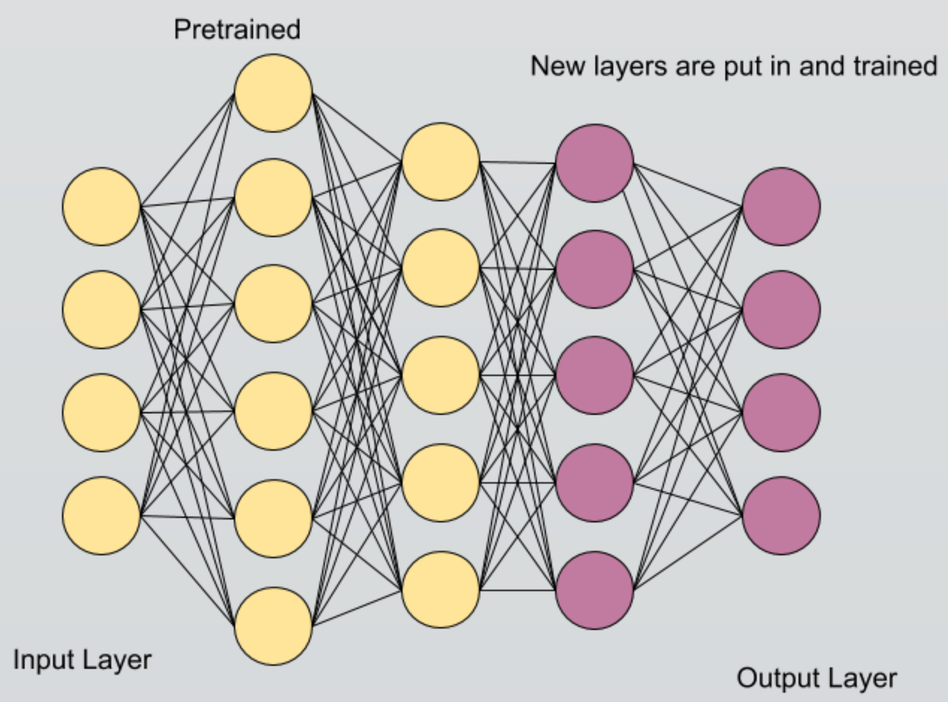
Methods

- Basic CNN Model:
  - Three blocks of a Convolutional layer followed by a MaxPooling layer with ReLU activation
  - Hyperparameter tuning using Keras Tuner to find best learning rate.
  - EarlyStopping feature to prevent model from overfitting without improvement.
- Basic CNN with Dropout:
  - After every MaxPooling layer a dropout layer of 20 percent is added
- The size of the images in the dataset were standardized to 150x150 resolution and converted to grayscale.
- Non-neural network models like Support Vector Classifier (SVC) and Random Forest Classifier (RFC) were used to compare the effectiveness of classification from the CNN models.
- Transfer Learning Models
  - All included a sequential CNN model attached to the classification portion, to specifically classify 4 classes.
  - In addition, all were trained on the 'Imagenet' dataset.
  1. VGG16
  2. InceptionV3
  3. Xception
  4. ResNet50

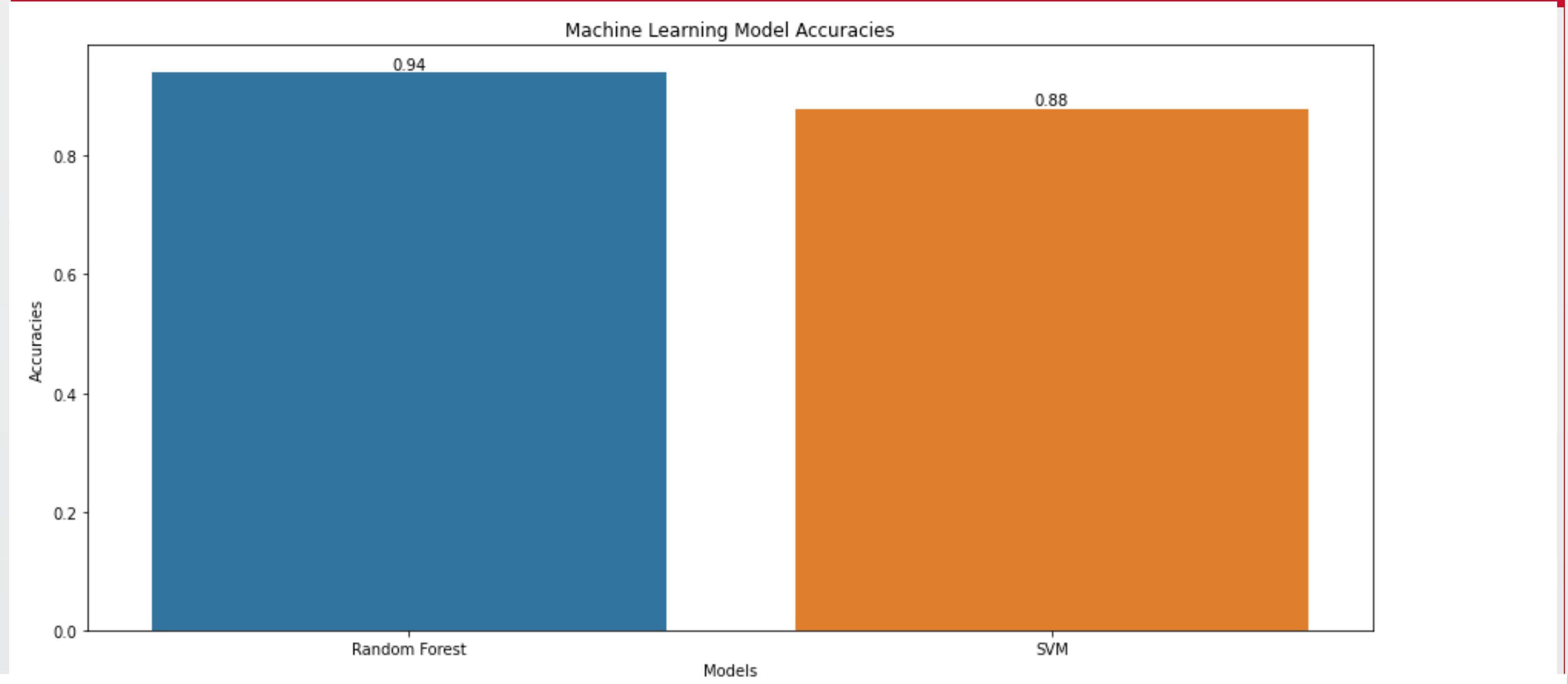
Basic CNN Architecture

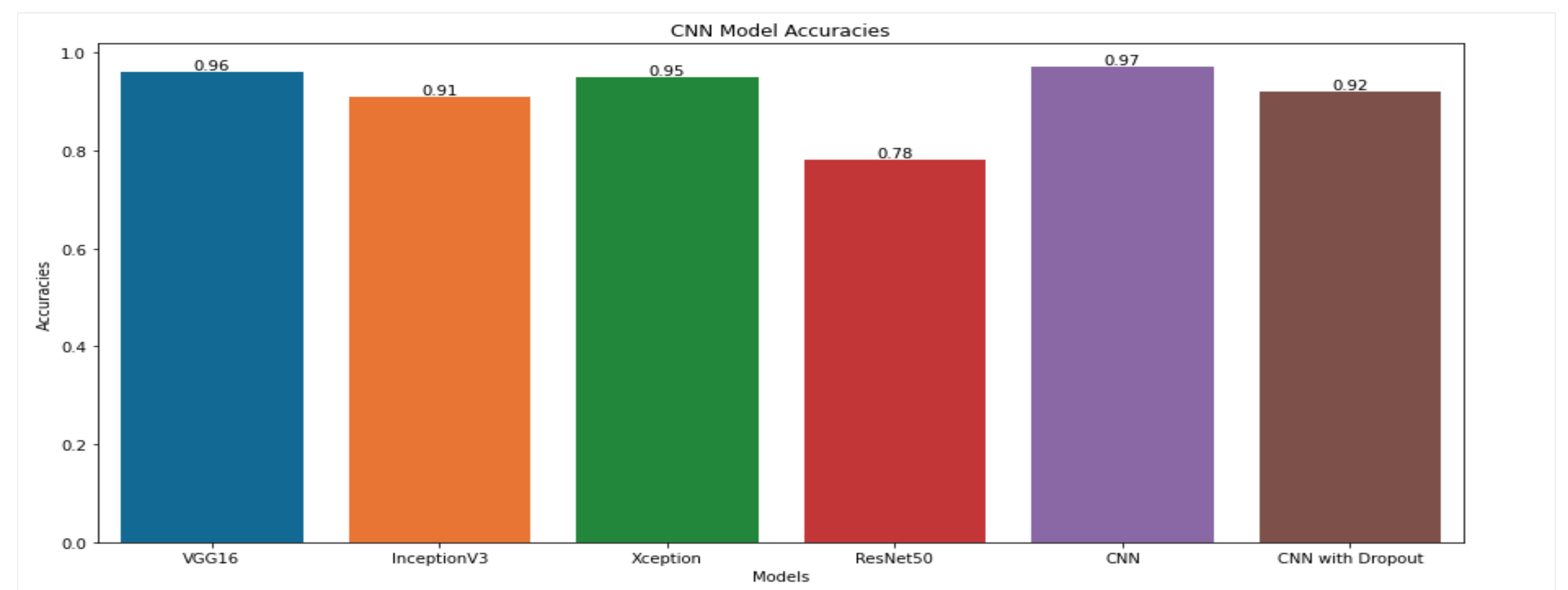


Transfer Learning Architecture



Results





Conclusion

- Across the board, the models did not accurately predict meningioma as well as the other classes.
- VGG16 and Xception performed the best on the dataset among the pre-trained models.
- Adding dropout layers of 20 percent after every max pooling layer did not improve the accuracy of the CNN model.
- All models accurately predicted no tumors, avoiding being told there's a brain tumor when in fact there is not.

Future Direction

- Since the pre-trained models performed very well, having a larger number of images could potentially improve the accuracies.
- Increasing the input image sizes to the default 224x224 for the pre-trained models will allow for better training.
- Using an ImageDataGenerator to prevent overfitting and create more images.
- Specifically targeting meningiomas, as they were the hardest to classify, by creating a model to classify them. Perhaps the presence of the other classes interferes with the performance of the models.

Acknowledgments

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