Assessing the impact of image quality on brain MRI diagnosis using deep learning

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Context

- Image quality impairments in brain MRI are widely recognized as a problem that impacts both human experts and ML solutions.
    - Deep Learning solutions may help, but high-quality labeled data (with quality-related info) is costly.
- **Proposed strategy:**
    1. **Select** types of artifacts from literature (to ensure that they are realistic)
    2. **Simulate** those common types of noise/blur/artifacts
    3. **Demonstrate** that noisy images **impact** the accuracy of CNN-based classification (**this work**)
    4. **Demonstrate** that quantitative figures of merit (PSNR, NIQE, etc.) **correlate** well with loss of accuracy in CNN-based classifiers
    5. Build and train a **regression CNN** for estimating the amount of noise/blur (supervised learning)
    6. **Demonstrate** that the resulting CNN can **predict the amount of image degradation** with great accuracy (using standard image quality measures as ground truth)
    7. **Explore** how the approach can be **extended** to other impairments and quality metrics
    8. **Close the loop**

Introduction

- Medical image analysis tasks can lead to erroneous results when the original images are of lower quality.

- MRI image quality has long been a challenging issue as they are unlikely to be artifact-free.
    - Studies have shown that lower image quality (e.g. motion/noise blur) increases potential for errors by radiologists on brain MRI.

Goal and Objectives

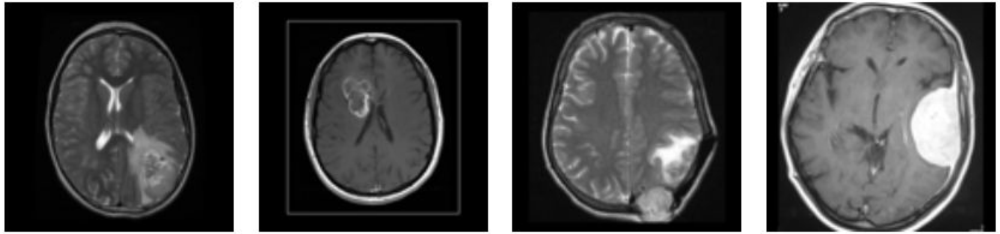
- Overall goal:
    - Determine the impact of image quality on machine/deep learning algorithm performance

- Objectives:
    - To evaluate a series of image quality measures on a publicly available brain MRI dataset.
    - To demonstrate the impact of image quality on results produced by a deep learning algorithm for binary brain tumor classification, indicating the presence or absence of tumor on individual brain MRI image slices.
    - To establish the correlation between low-quality MRI images and decreased CNN accuracy in the binary classification of brain tumors.

Hypothesis

The accuracy of a Convolutional Neural Network (CNN)-based binary brain tumor classifier decreases as the degree of image quality degradation on brain MRI images increases.

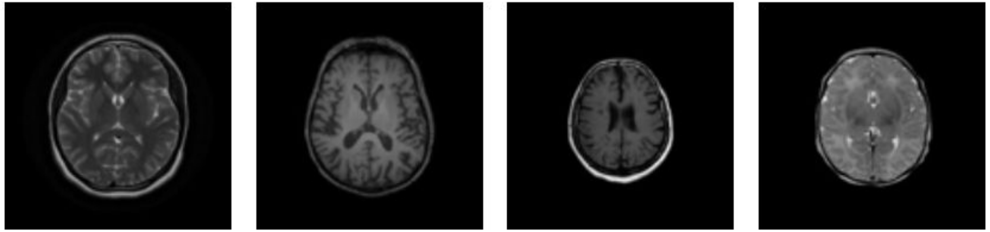
Dataset



Tumorous brains

253 images (155 tumorous, 98 non-tumorous) from Kaggle's *Brain MRI Images for Brain Tumor Detection* dataset.

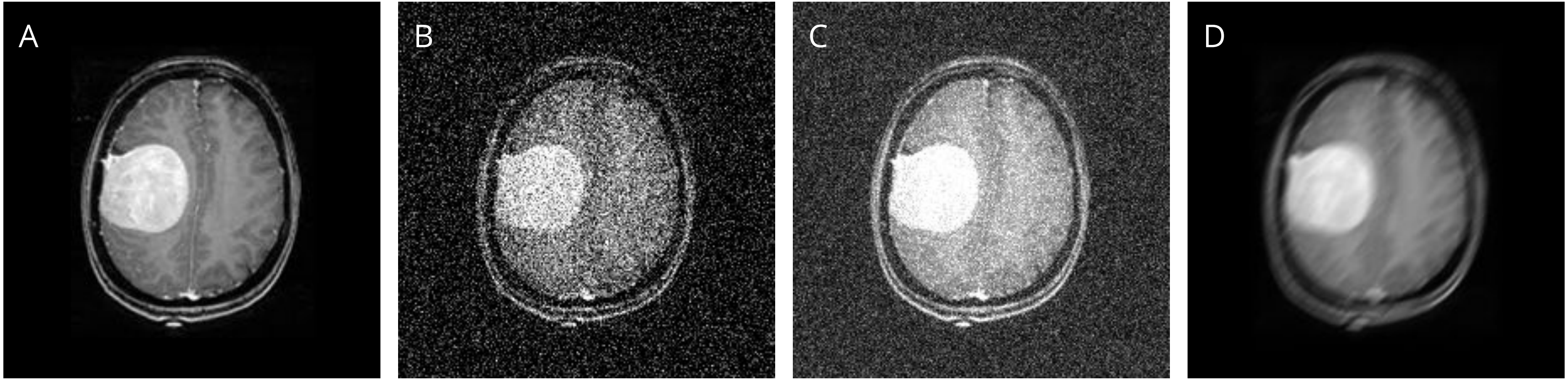
Healthy brains



Methods

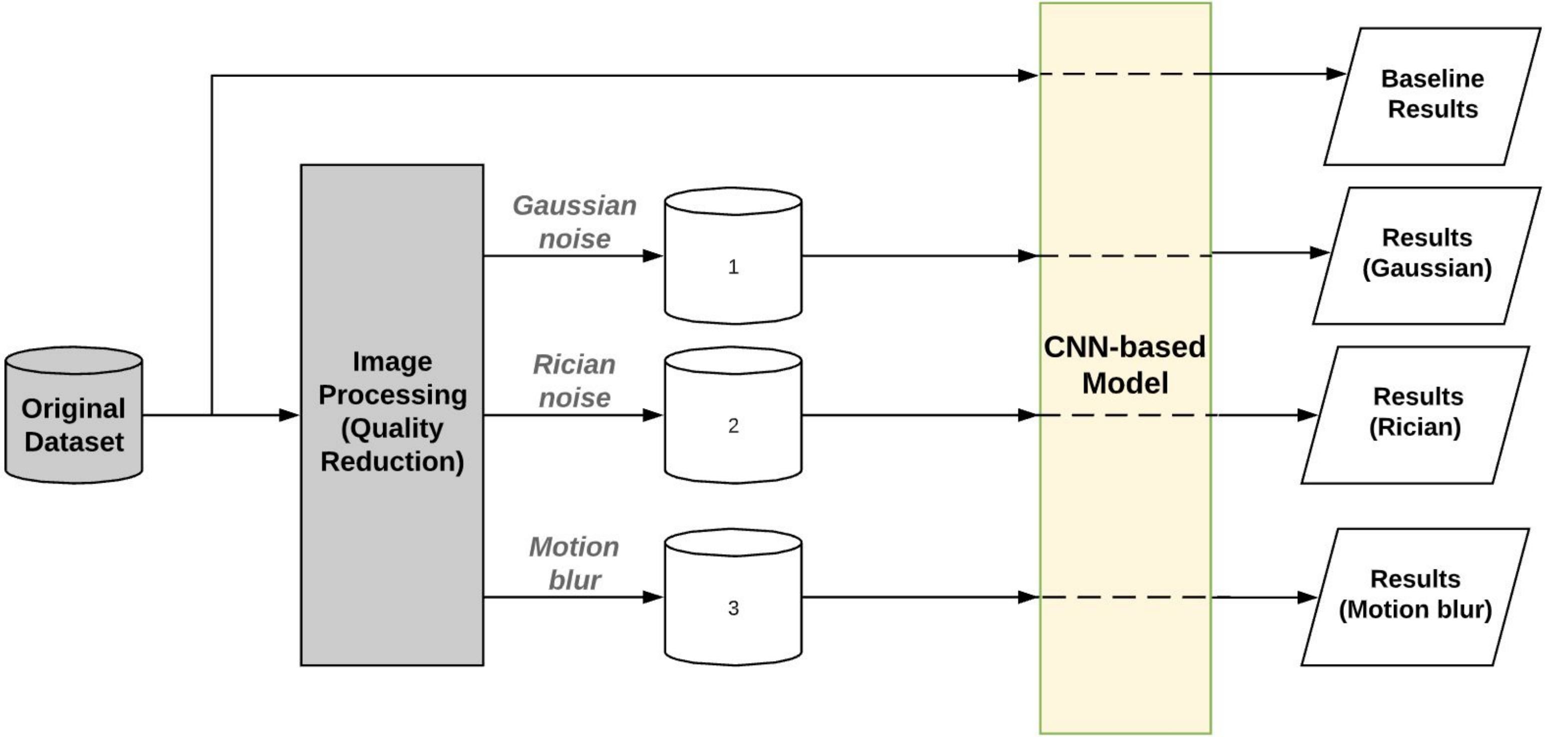
- We use MATLAB to process the original images with 3 types of image quality degradation algorithms:
  - **Gaussian noise** (zero-mean) for multiple values of sigma
  - **Rician noise** for several parameter combinations
  - **Motion blur** for different combinations of length and angle
- The resulting images are then used as separate test datasets to evaluate the performance of a previously trained, fine-tuned, and validated CNN-based classifier.

Example brain MRI images from Kaggle dataset



(A) original, (B) Gaussian noise, (C) Rician noise, (D) motion blur

Experimental setup



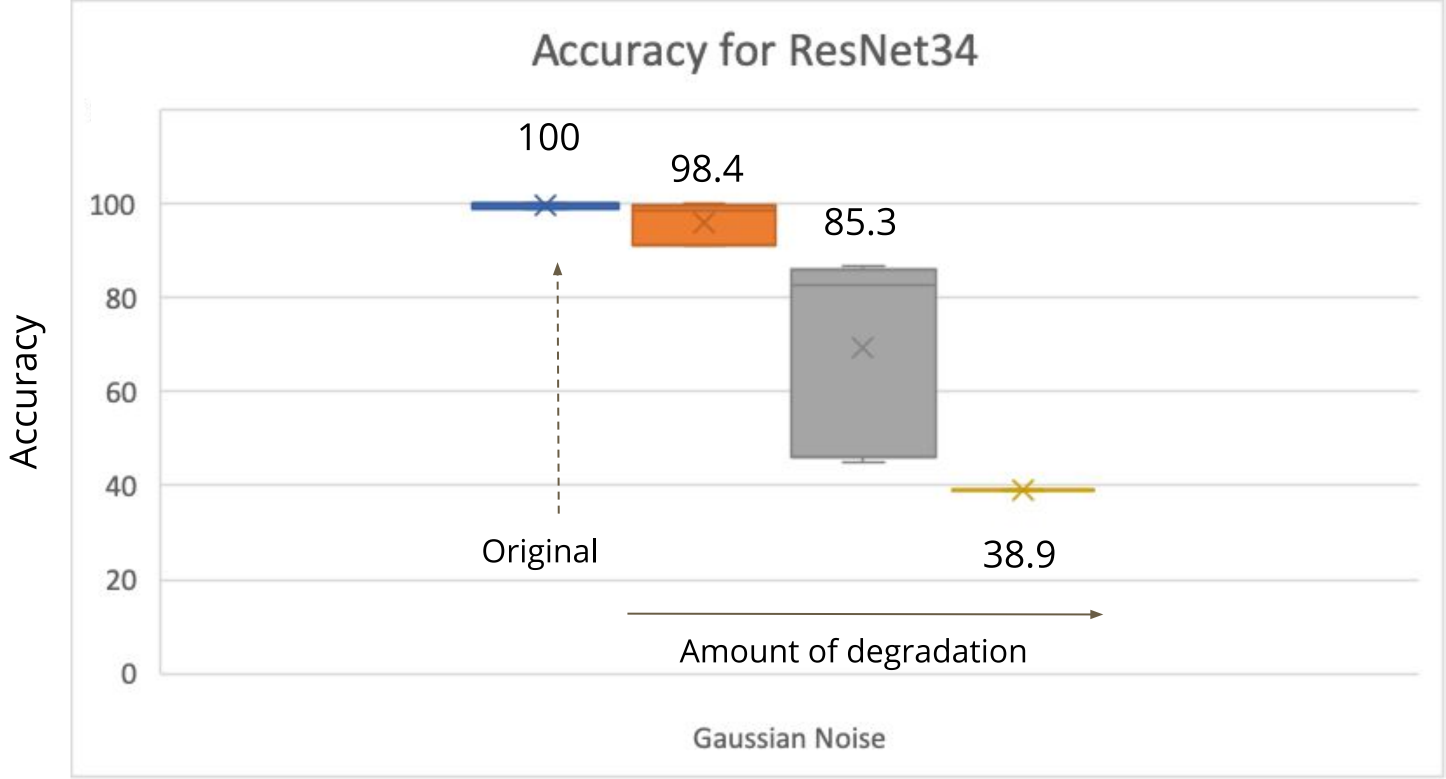
Experiments

- Two architectures were used to test the performance for each dataset:
  - **AlexNet**
  - **Resnet-34**
- The Adam optimizer was used with an initial learning rate of 0.001.
- The experiments were performed using Python version 3.7 and PyTorch.

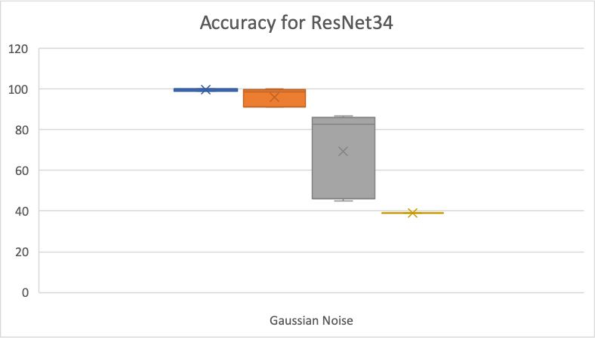
Results

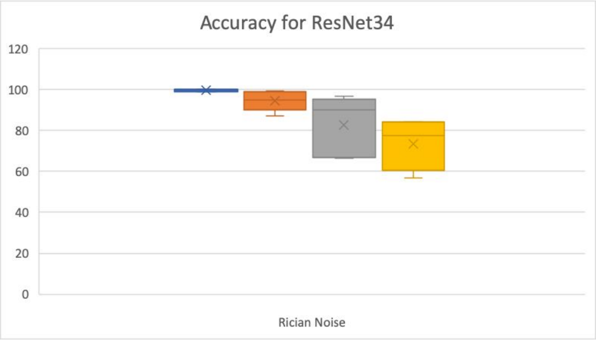
- We computed the average accuracy after 5 runs for each combination of classifier and image quality level.
- For the baseline case (artifact-free test images), the accuracy of our CNN classifier was nearly 100%.
- The impact of the different types of artifacts on accuracy depends on the type (and amount) of noise/blur and the CNN architecture.
    - ResNet is more robust to modest amounts of noise/blur than AlexNet for the same amount of quality loss.

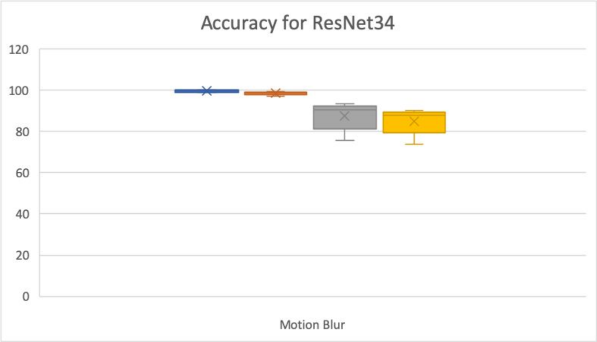
Experimental results: example

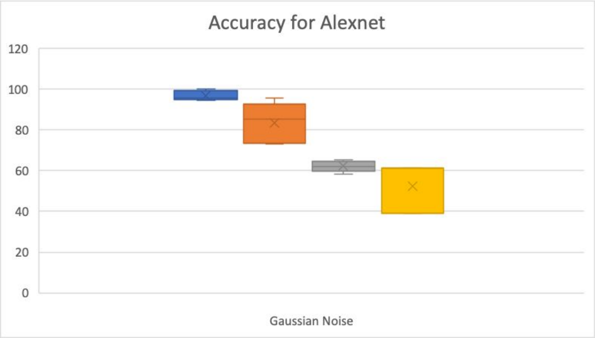


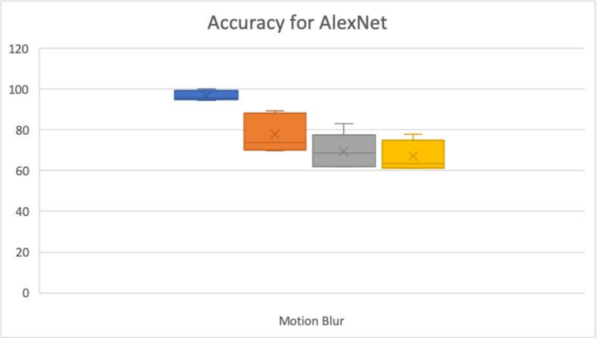
Experimental results











Limitations

- Choice of dataset (e.g. Kaggle)
  - Dataset size
  - Inherent bias
  - Use of pre-selected MRI slices, not volumes
  - No metadata
  - Simplistic take on brain tumor detection/classification
- Self-generated artifacts to create test dataset
  - May not be fully representative of actual artifacts
- Choice of CNN architectures

Ongoing and future work

- Build and train a regression CNN for estimating the amount of noise/blur (in a supervised learning setting)
- Demonstrate that the resulting CNN can predict the amount of image degradation with great accuracy (using standard image quality measures as ground truth)
- Demonstrate that the approach can be extended to other impairments (and quality metrics)
- Expand the testing setup to larger, more challenging/realistic datasets
- Publish!

Conclusion

- We quantitatively demonstrate the impact of three image quality degradation measures on the accuracy of a binary CNN classifier for brain lesions on MRI.
    - ResNet is more robust than AlexNet for an equivalent amount of image quality loss.

- This work can be extended to other brain MRI datasets, additional types of image artifacts, as well as different deep learning architectures and tasks (e.g., lesion segmentation and detection).