Quality Control and Topological Analysis of MRI Segmentation Data

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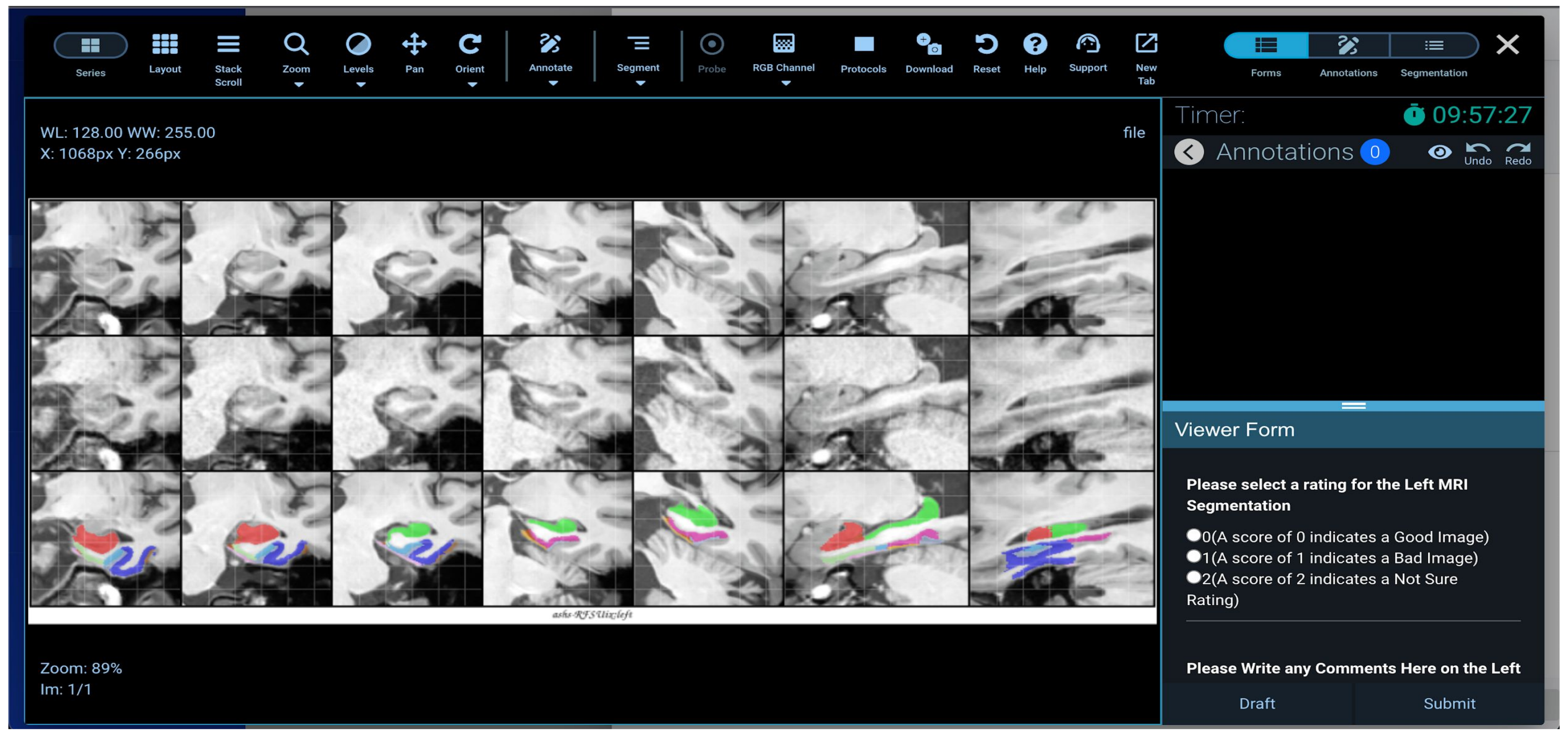
Abstract

- Reliable MRI (Magnetic Resonance Imaging) segmentation data is crucial to the development of new techniques that detect conditions, such as Alzheimer's, using MRI data.
- This research is intended to replace traditional methods that involve a human manually reviewing original MRI images along with their segmentation. This method is problematic because it is:
  - Time-intensive
  - Labor-intensive
  - Prone to human judgement
- Data was sourced from the Alzheimer's Disease Neuroimaging Initiative (ADNI) as well as the Penn Image Computing and Science Laboratory (PICSL)

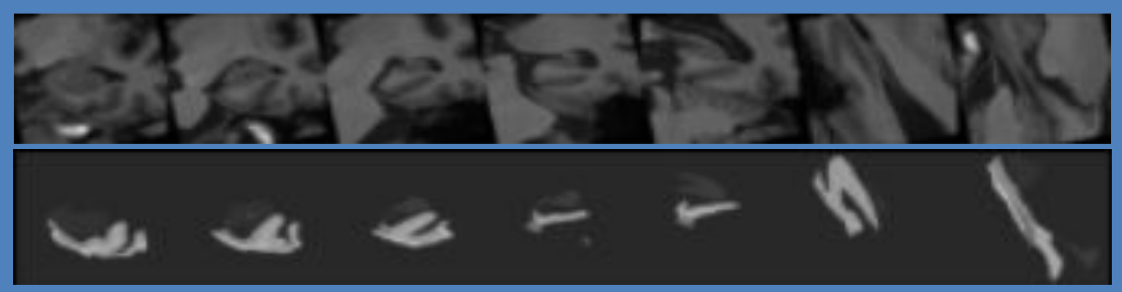
Objectives

- Build a new QC workflow for MRI segmentations that leverages AI through a neural network as well as topological data

Materials and Methods

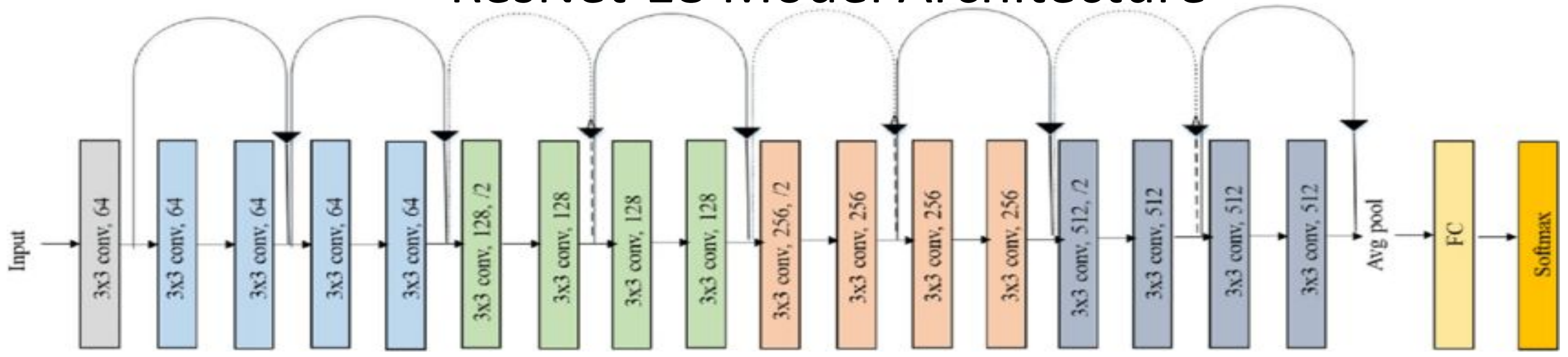


(A sample of the original QC process)



- Training data includes the original super resolution MRI as well as its segmentation, to mimic human QC process

ResNet-18 Model Architecture



The neural network employs a ResNet-18 model

Results

- The neural network showed reasonable accuracy
- The topological analysis successfully processed over 10,000 MRI segmentation data points

Conclusions

- The resulting integration of the QC system into Flywheel enhances user engagement
- Contributes to improved data quality, ensuring the reliability of MRI segmentation data for medical applications
- We would like to express our sincere gratitude to Dr. Sandhistu Das, Emily McGrew, Yue Li, Mengjin Dong, and Dr. Paul Yushkevich for their invaluable support and guidance throughout this research journey.

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