Predicting Language Outcomes from MRI Post-Stroke: A Machine Learning Approach

Deepa Tilwani[1], Christian O'Reilly[1], Raxitkumar Goswami[1], Nicholas Riccardi[2], Xuan Yang[2], Valerie L. Shalin[3], Vignesh Narayanan[1], Svetlana Shinkareva[2], Amit Sheth[1], Rutvik Harshad Desai[2]

1. Artificial Intelligence Institute, University of South Carolina, Columbia, SC
2. Department of Psychology, University of South Carolina, Columbia, SC
3. Department of Psychology, Wright State University, Fairborn, OH

1. INTRODUCTION

- Decades of research have focused on understanding language impairment after a stroke and its neuroanatomical correlates.
- Traditional approaches in lesion-symptom mapping use mass-univariate statistics, overlooking complex relationships between variables [1, 2].
- Advanced machine learning (ML) techniques have the potential to be more effective in improving the prognosis for language outcome measures post-stroke and revealing novel insights regarding the neural underpinnings of language comprehension and production.
- By training ML models on MRI modalities, we can identify patterns and relationships that contribute to predicting aphasia severity, language impairments, and recovery potential.

2. METHODS

- Subjects: 238 left-hemisphere (LH) stroke survivors (> six months post-stroke) underwent MRI scanning. Participants were administered the WAB (Western Aphasia Battery) by a licensed speech-language pathologist (Philadelphia Naming Test (PNT) N = 191).
- Machine Learning: The percentage of damaged voxels was calculated for 90 LH regions in the Johns Hopkins University atlas. These voxel damage values were input data for machine learning (ML) models to predict AQ (Aphasia Quotient) from WAB and PNT scores. Regression models were used, with and without an auto-encoder (AE), for dimensionality reduction, feature extraction, and representation learning.
- After training the AE on MRI data, the middle-layer activation of AE was extracted as the feature representation. We used several ML regression methods (Random Forest (RF), Linear Regression (LR), Support Vector Regression (SVR), Gradient Boosting (GB), Decision Tree (DT), and K Nearest Neighbours (KNN) regression) with the extracted features as input. Nested Cross-Validation was employed to identify the best-performing model for estimating PNT/AQ scores.
- The RF model with Lesion modality consistently demonstrated the highest Pearson's coefficient of correlation (r).

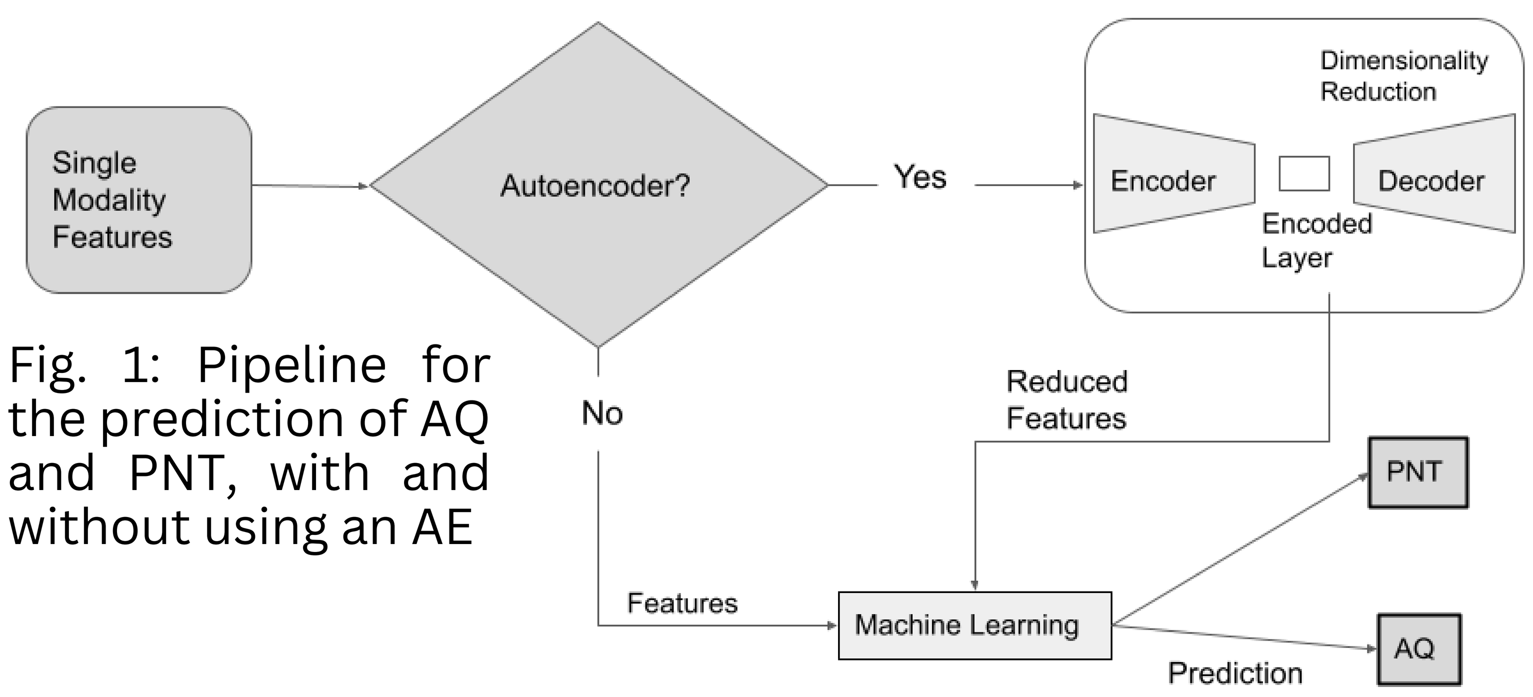

Fig. 1: Pipeline for the prediction of AQ and PNT, with and without using an AE

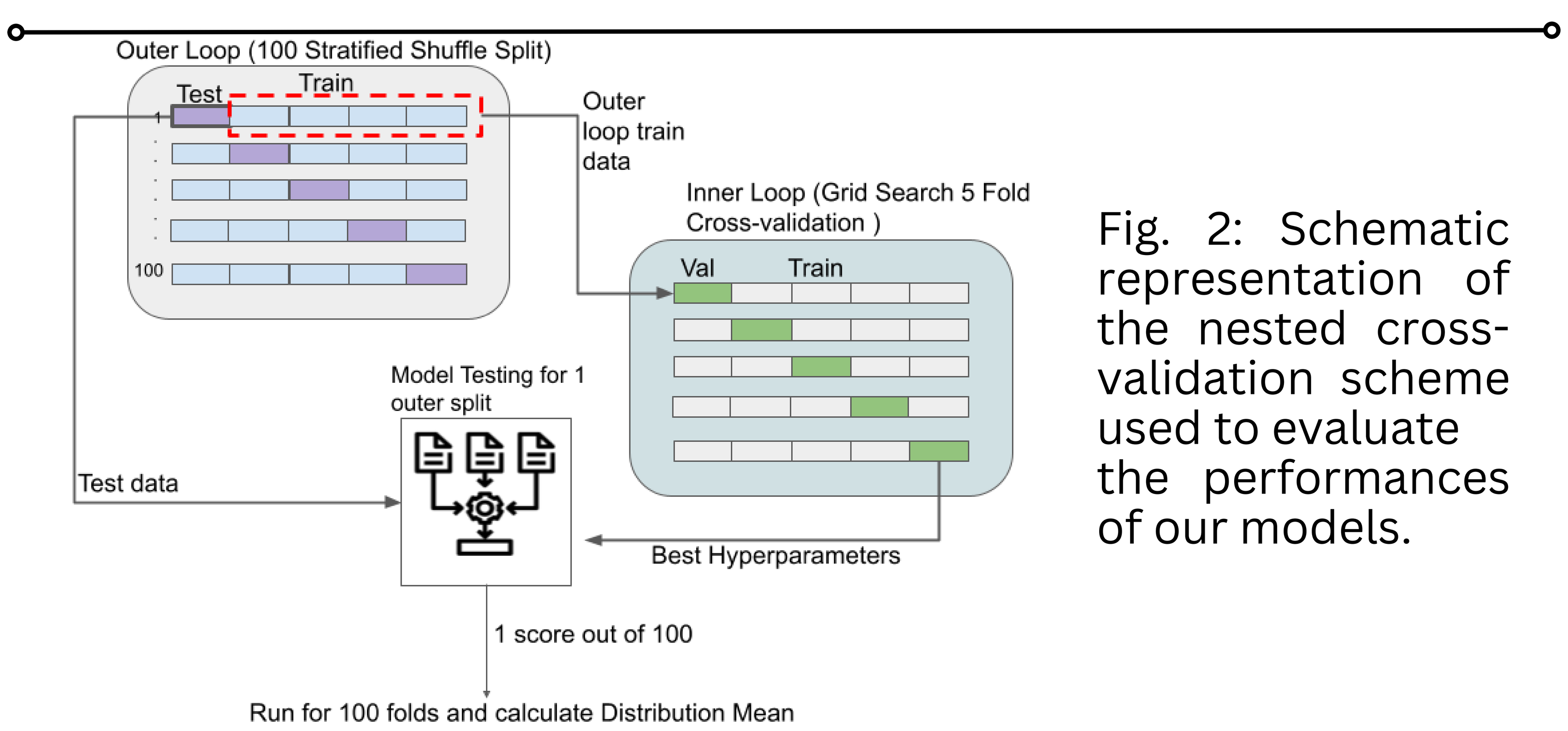

Fig. 2: Schematic representation of the nested cross-validation scheme used to evaluate the performances of our models.

3. GENERAL VISUALIZATION RESULTS

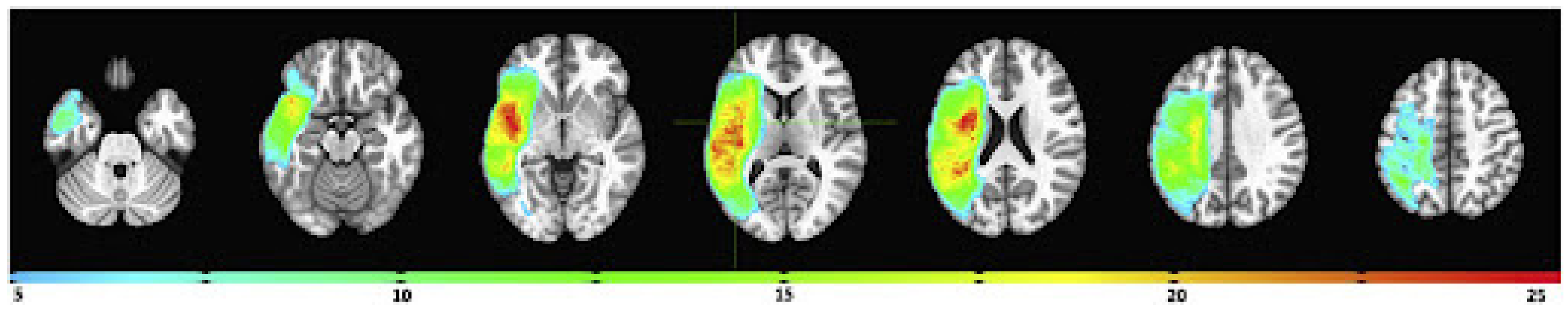

Fig. 3: This figure display the distribution of the lesions across participants (in numbers of participants, color-coded as shown by the color bar). The highest overlap was around the perisylvian fissure.

4. MODALITY-SPECIFIC RESULTS

- Out of seven ML models, we found the RF model performed best for PNT (r mean±std: 0.46±0.14; p < 0.0001) and for AQ (0.61±0.14; p < 0.0001) using Lesions without AE.
- We performed the AE for dimensionality reduction an obtained 0.64±0.014 (p < 0.0001) for predicting AQ with AE+RF, and increase of 3% compared to RF alone.
- Also, AE+SVR, showed 6% of improvement in predicting AQ.

Fig. 4: Results of the nested cross-validation scheme with and without AE for ML models on Lesion Modality (N=191).

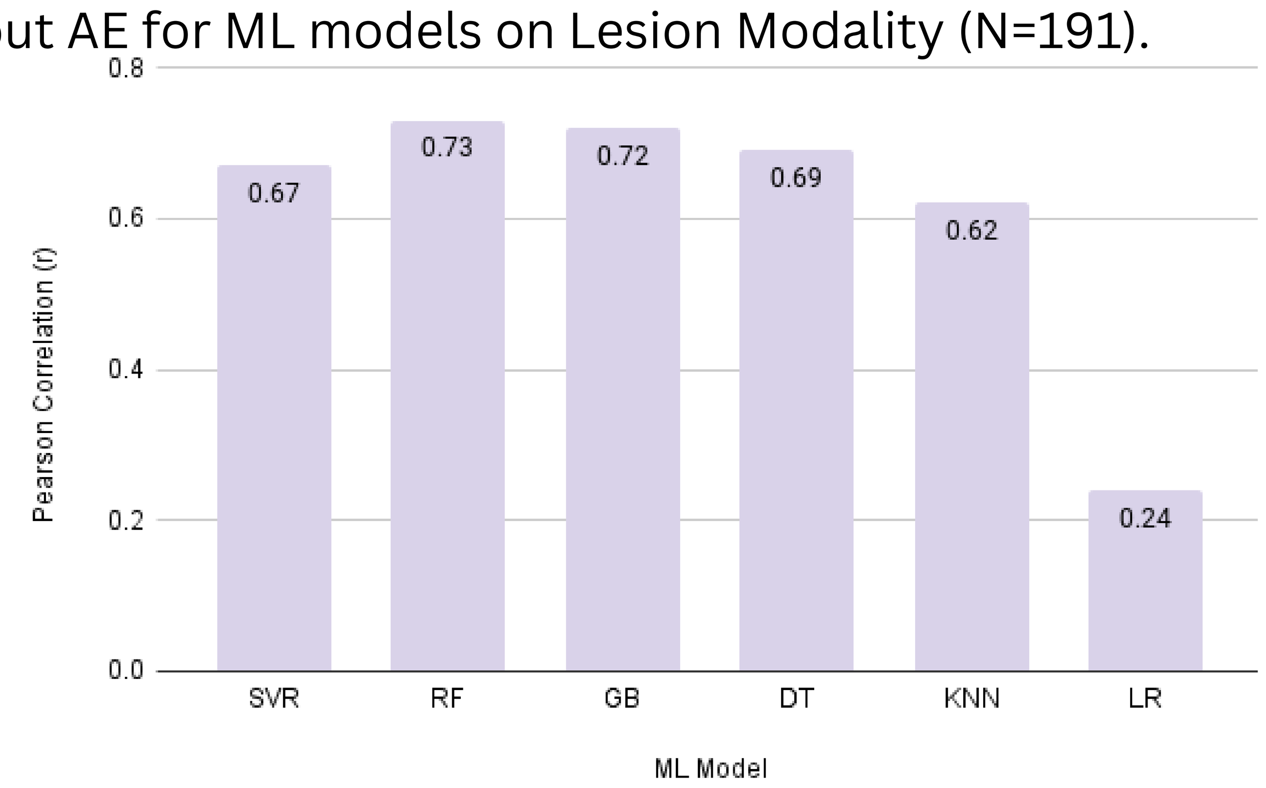

Fig. 5: Results of ML models with the addition of 74 additional participants for AQ, using JHU Atlas and Extracted Lesions as Features (N=238)

5. CONCLUSIONS

The results indicate that ML models are promising for the prediction of language outcomes in stroke survivors using only T1 images.While both AQ and PNT scores could be predicted, the prediction of AQ was more accurate, and RF appears to be the most promising ML model in this domain and SVR with dimensionality reduction using AE. Such methods can be applied in longitudinal studies to predict improvement from therapy. Future directions also include incorporating other imaging modalities such as resting state functional imaging or diffusion tensor imaging to further improve predictions.

REFERENCES

1. Forkel SJ, Catani M. Lesion mapping in acute stroke aphasia and its implications for recovery. Neuropsychologia. 2018 Jul 1;115:88-100. doi: 10.1016/j.neuropsychologia.2018.03.036. Epub 2018 Mar 30. PMID: 29605593; PMCID: PMC6018610.
2. Kristinsson S, Zhang W, Rorden C, Newman-Norlund R, Basilakos A, Bonilha L, Yourganov G, Xiao F, Hillis A, Fridriksson J. Machine learning-based multimodal prediction of language outcomes in chronic aphasia. Hum Brain Mapp. 2021 Apr 15;42(6):1682-1698. doi: 10.1002/hbm.25321. Epub 2020 Dec 30. PMID: 33377592; PMCID: PMC7978124.