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Feature analysis and extraction for post aphasia recovery prediction

Feature Analysis and Extraction for Post Aphasia Recovery Prediction

Chennuri S.[2], Billot A.[1], Lai S.[2], Ishwar P.[3], Betke M.[2], Kiran S.[1]
[1]Department of Speech, Language, & Hearing Sciences, Sargent college, Boston University [2]Computer Science Department, Boston University [3]College of Engineering, Boston University

Introduction

Aphasia affects approximately 1/3 of stroke survivors and severely impacts their quality of life as well as their ability to return to work.[1,2]

Predicting recovery is essential to provide a personalized prognosis and help patients and family plan for the future.

A few studies have used machine learning models to predict language recovery after stroke using neuroimaging and behavioral data. However, these studies present different limitations: variable period of recovery across participants, no control of the amount of therapy received, and/or only one type of imaging data investigated.[3-5]

Aim of this study: Building upon our previous study[6], we here aim to investigate the importance of the features extracted (lesion information) from stationary MRI along with demographic information in prediction of recovery scores.

Hypothesis: Model accuracy will be improved by the newly explored combination of features extracted from structural MRI images, behavioral and demographic variables to predict treatment response group compared to models using single feature sets.

Methods

Participants

55 individuals with aphasia (18F / 37M, age = 58.8 +/- 10.6, months post stroke = 59.0 +/- 47.2) resulting from a single left-hemisphere stroke were recruited in 3 research sites (Boston, Johns Hopkins, and Northwestern Universities)

Input features: Demographics, Behavioral and Imaging data

Demographics

- Age
- Months post-stroke onset
- Education

(DM)

Behavior

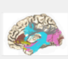
Ling	Cog
✓	X
X	✓

- Aphasia severity: WAB-R aphasia quotient (AQ)
- Cognitive composite scores (CS): visuo-spatial processing + verbal working memory components
  PCA using Doors and People, Corsi, Raven's matrices, SRTT, WAIS Digit span tests

Lesion information

- Lesion size (LES)
  Semi-automated lesion drawing on T1-weighted images
- Percentage of spared tissue in **gray** matter regions (PSg)
  N = 69 left-hemisphere regions
  AAL atlas, preprocessed with fmriprep
- Percentage of spared tissue in **white** matter regions (PSw)
  N = 36 left-hemisphere white matter regions
  BCBtoolkit, Rojkova et al. 2015

Lesion connectivity



- Lesion Adjacency Matrix (CN)
  Existence of lesion in two different brain regions is considered as one connection. This has been repeated for multiple brain regions giving rise to a network of connections represented as an adjacency matrix

Target: Treatment response

- **12 weeks** of site-specific treatment (BU: Semantic Feature Analysis, JHU: Spell-Study-Spell paradigm, NU : Treatment of Underlying Forms), + **site-specific probes** related to treatment at baseline and post-treatment.
- **Responsiveness to treatment** = **percent change in accuracy** (i.e. average post-treatment accuracy score minus average pre-treatment accuracy score in percentages).
- **Classification** in two groups: **responders** (percent change ≥ 0.25) and **non responders** (percent change < 0.25)

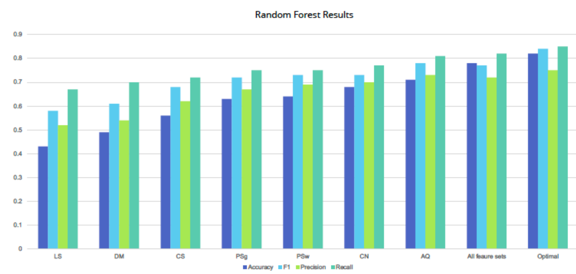
Method

- **Algorithm app:** Given the patient's MRI scan, the algorithm automatically extracts the white matter and grey matter content remaining in the patient's brain after the stroke and creates new derived features from the extracted data.
- **Training and validation:** Random Forest (RF) and Support Vector Machine (SVM) were used to classify participants into responders and non responders. All feature sets combinations were tested. For each feature sets combination, leave-one-out round-robin was used to train and test the model. Hyper-parameters were tuned on the training set using leave-one-out cross-validation.
- **Model performance metrics:** Accuracy, F1 (harmony mean between precision and recall), precision (positive predictive value) and recall (sensitivity)

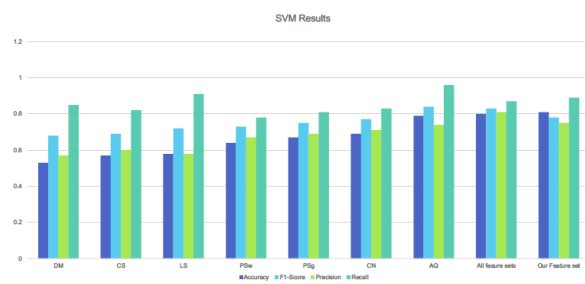
Results

RF and SVM models performance

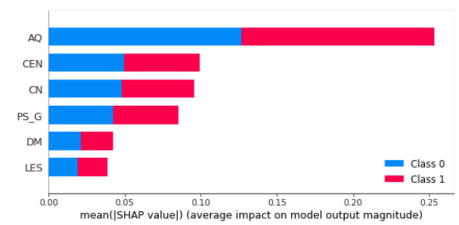
Comparison of models including a single feature set, all feature sets and the optimal model that resulted in the best F1 score.



→ Optimal model = Aphasia Quotient + Demographics + Lesion Connectivity + Percentage of Grey Matter per Region
→ Highest F1 score: 0.82
→ Method = Random Forrest



Feature Set Importance in the Best Predictive Model



Class 0: Contribution of attribute in prediction of recovery

Class 1: Contribution of attribute in prediction of a patient not being recovered

→ It is observed that the Aphasia Quotient has the highest impact on prediction of a person being recovered or not, which aligns with the theory.
→It is also observed that the existence of a lesion in the brain, interpreted as an adjacency matrix, also has an impact on this prediction.

Conclusion

- Random Forest and Support Vector Machine models can **predict with high accuracy** if an individual with chronic aphasia may show some **improvement after language treatment** or not.
- Across models, **resting-state structural MRI data** is also a good predictor of responsiveness.
- It is observed via SHAP analysis that the Aphasia Quotient and the analysis of brain regions represented as a connected graph play important roles in predicting the recovery of the patient
- Since the proposed approach using Structural MRI attains a similar accuracy as the prior approach that used resting state data, this proposed approach provides an alternative to predicting the recovery of a patient when the resting state fMRI data is not available.

Acknowledgements

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Corresponding author: Saurav Chennuri
saurav07@bu.edu