Automated Macrolinguistic Discourse Analysis for Transdiagnostic Detection of Language Impairment

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Introduction

Discourse Analysis in Neurological Conditions

- Discourse analysis provides insight into language abilities beyond the sentence level, often assessed through storytelling.
- While traditional analyses often focus on microlinguistic features, like mean length of utterance and type-token ratio, they often do not assess macrolinguistic features, such as Main Concept Analysis (MCA)[1] and topic coherence, which are important for comprehensive evaluation of language impairments.
- Macrolinguistic analysis remains largely manual[2-3].

Study Aims

Overarching goal: Automate microlinguistic and macrolinguistic discourse analysis for clinical detection of neurogenic communication disorders.

Aim 1: Develop an NLP-based pipeline that automatically extracts main concept (MC), coherence, and sequencing features from retellings of the Cinderella story.

Aim 2: Apply machine learning (ML) to evaluate the diagnostic potential of automated macrolinguistic features in distinguishing healthy controls (HC), people with dementia (PWD), and people with aphasia (PWA).

Methods

Variable	HC (n = 113)	PWD (n = 94)	PWA (n = 102)
Age	67.21 (33-88)	72.41 (58-91)	60.09 (26-88)
Sex (F)	84	53	51
WAB-R AQ (/100)	NA	NA	78.23 (40.5-99.6)
MOCA (/30)	NA	25.44 (14–30)	NA

1. DATA ACQUISITION
Extract Cinderella story retelling audio samples from the public AphasiaBank[4] and DementiaBank[5] corpora

2. AUTOMATED TRANSCRIPTION & SEGMENTATION
Transcribe audio with Amazon Transcribe and segment utterances by terminators and conjunctions.

3. SEMANTIC EMBEDDINGS
Generate vector representations of utterances and MCs[3] using the all-mpnet-base-v2 Sentence-Transformers model[6]

4. CENTROID & MC MATCH
MC semantic embeddings are averaged to get the centroid. Utterances within 1 SD of the centroid are matched as MCs.

5. AUTOMATED FEATURE EXTRACTION PIPELINE
Extract 23 features, including distance to centroid, coherence error types[7], MC metrics, and sequence score[8].

6. ML CLASSIFICATION
Conduct a 3-way multinomial logistic regression classification among PWA, HC, and PWD, as well as one-vs-one pairwise classifications. Identify the most discriminative features based on coefficient magnitudes.

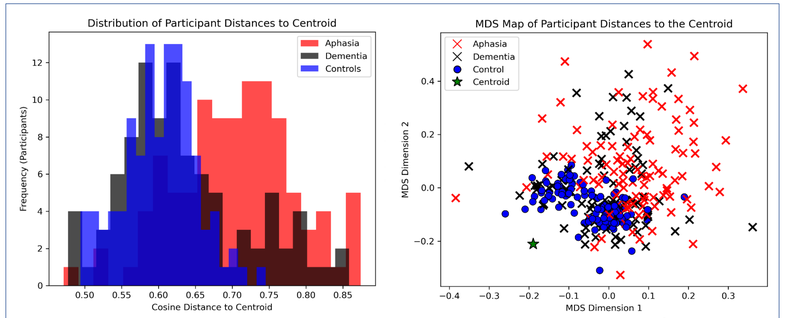
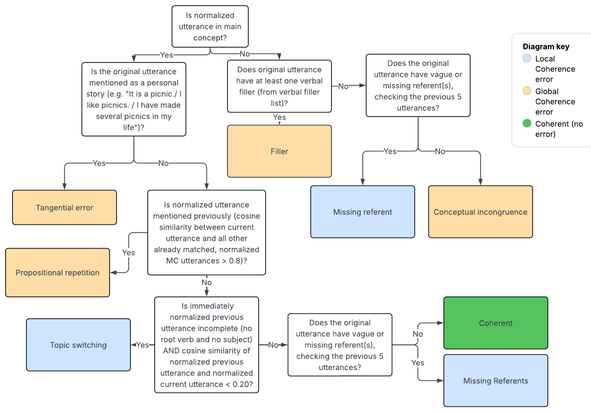
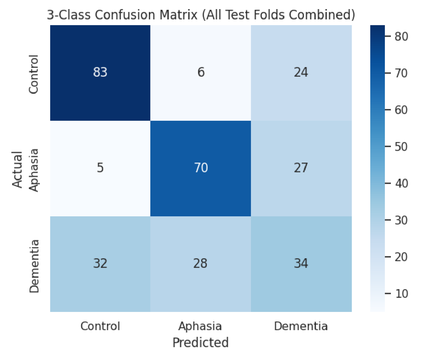


Figure 1. Increasing distance to centroid (representing semantic alignment to MCs) from controls → with dementia → aphasia demonstrates its ability to capture narrative informativeness across groups

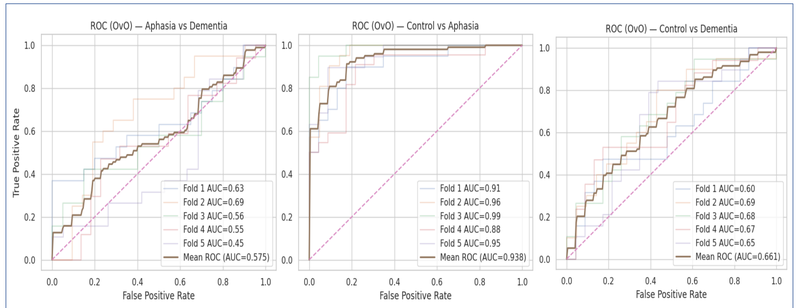
Coherence Error Classification Algorithm



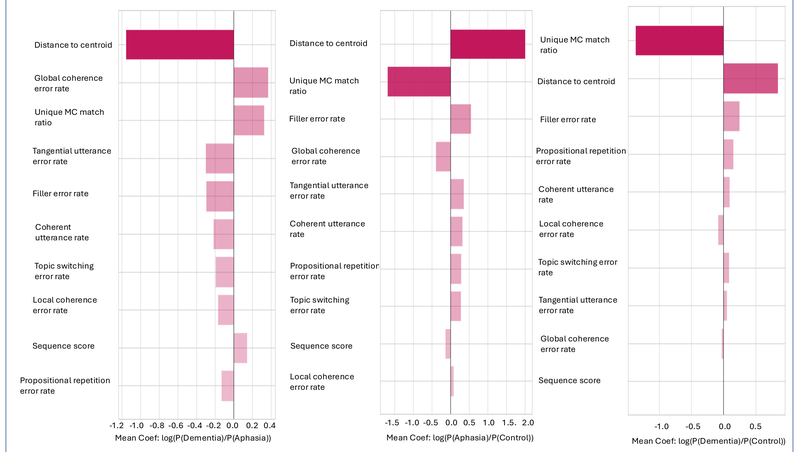
Results



- Most accurate classification for HC, followed by PWA, then PWD.
- PWD are misclassified roughly equally as HC and PWA → dementia occupies an intermediate position in macrolinguistic abilities relative to other groups.



- Excellent PWA and HC discrimination (mean AUC = 0.938)
- Moderate performance for PWD vs. HC (mean AUC = 0.661) and poor for PWD vs PWA (mean AUC = 0.575) → macrolinguistic features alone insufficient for dementia differential diagnosis.



- Distance to centroid was the strongest predictor.
- Greater semantic deviation from narrative core characterized both clinical groups vs HC, and aphasia vs dementia→ consistent, interpretable marker of discourse-level impairment

Conclusions

Fully automated extraction of macrolinguistic features from narrative speech is feasible.

The automated pipeline captured clinically meaningful group differences.

Automated discourse analysis is a scalable, objective, and clinically relevant approach for detecting linguistic impairment.

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