SynapSpeech

Artificial Intelligence for Cognitive Screening

Early detection of Alzheimer's disease through the analysis of spontaneous speech.

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Dementia: An Urgent Global Challenge

Dementia represents one of the greatest public health crises of the 21st century, affecting millions of lives and imposing a colossal socioeconomic burden (WHO, 2023). The numbers are alarming:

55M

People currently affected

Living with dementia worldwide (WHO, 2023).

139M

Projection for 2050

The number of people with dementia may triple (Alzheimer's Disease International, 2023).

$1.3T

Annual global cost

Massive economic impact, surpassing many national economies (ADI, 2023).

Every 3 seconds, a new person develops dementia. It is a global imperative to act now (Alzheimer's Association, 2023).

The Challenge of Early Diagnosis

Current Context

- Late diagnosis compromises treatment (Gomes et al., 2021)
- Traditional tests are expensive and, in most cases, inaccessible (Martins & Souza, 2020)
- Language changes appear before clinical symptoms (Pereira et al., 2022)

70%

Undiagnosed cases (Silva & Costa, 2023)

10M

New cases per year (Global Health Institute, 2023)

SynapSpeech: Our Proposal

Spontaneous Speech Analysis

Captures linguistic markers through oral narratives.

Use of Artificial Intelligence

Automatic extraction of cognitive patterns with machine learning.

Accessible Screening

Digital platform for remote and inclusive assessment.

Objective: Differentiate healthy individuals, those with mild cognitive impairment (MCI), and those with Alzheimer's disease through computational language analysis.

SynapSpeech: The Differentiator That Transforms

The cognitive screening market lacks solutions that combine accessibility, precision, and cultural relevance. Current tools often fail to meet the specific needs of the Brazilian population.

Broad Accessibility

Low cost and high scalability make cognitive screening viable across diverse healthcare settings, removing financial barriers.

Exclusive Brazilian Data

Developed and validated with a corpus of spontaneous Brazilian speech, ensuring unique precision and cultural relevance.

Cultural and Linguistic Adaptation

Unlike generic tools, SynapSpeech understands and interprets the nuances of Brazilian Portuguese, optimizing diagnosis.

Filling the Gap

There is no other solution on the market that combines AI, spontaneous speech analysis, and Brazilian data for effective cognitive screening.

Methodology and Data Foundation

DNLT-BP Dataset

Oral narratives in Brazilian Portuguese with:

- **4 narrative tasks:**
  - Cinderella
  - Dog
  - Lucia
  - Wallet
- **Categorized participants:**
  - Healthy
  - MCI
  - Alzheimer's
- **Features:**
  - Standardized transcriptions

Methodological Process

1. **Pre-processing**

   Text cleaning and normalization

2. **Feature Extraction**

   Linguistic embeddings

3. **Training**

   Classification models

4. **Validation**

   Performance metrics

Technological Tools

We used a robust set of tools for analysis:

Development

Python + scikit-learn

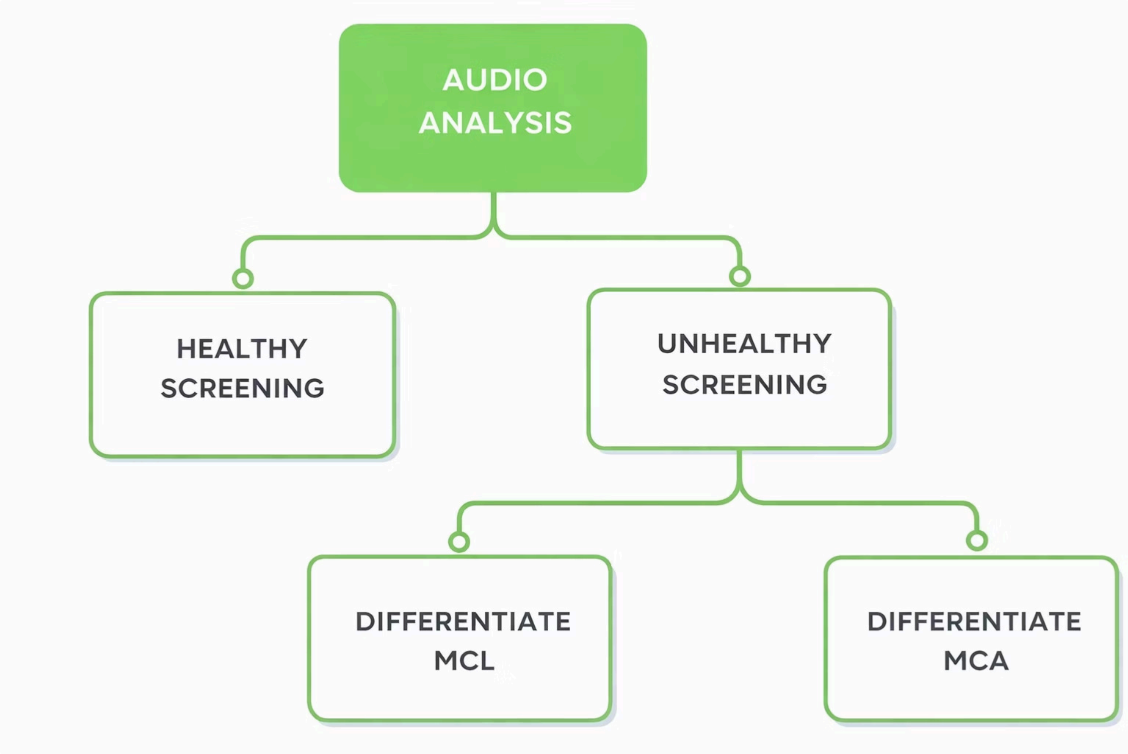
Language Processing

NLTK + Gensim + Transformers

Embeddings

Advanced semantic embeddings

System Architecture



Models Used

- CatBoost
- LightGBM
- XGBoost

Balancing

- SMOTE
- ADASYN
- TomekLinks
- SMOTETomek

Approach

Hierarchical supervised learning with hyperparameter optimization

PHASE 1: Initial Screening (Healthy vs. Non-Healthy)

Current Operational Pipeline

- Ensemble: CatBoost + ExtraTrees
- Member A: BOW (with stopwords) + TF-IDF (without stopwords) + BorderlineSMOTE
- Member B: BOW (without stopwords) + BorderlineSMOTE
- Ensemble Weights: 0.70 / 0.30
- Decision Threshold: 0.54

Conclusion of Phase 1: The ensemble approach demonstrates strong effectiveness for initial screening through spontaneous speech.

86.77%

Accuracy

Overall classification performance across healthy and non-healthy cases.

85.66%

Balanced Accuracy

Robust class balance with consistent sensitivity across groups.

85.72%

F1-macro

Strong average performance across both classes.

89.59%

F1 Healthy

High effectiveness in identifying healthy patients.

81.86%

F1 Non-Healthy

Reliable detection of non-healthy cases.

89.37%

Precision Healthy

Healthy predictions are highly reliable.

82.20%

Precision Non-Healthy

Non-healthy predictions remain solid and clinically useful.

91.20%

AUC

Excellent overall separability between the two groups.

Official Results (Strict Protocol with Stratified Cross-Validation)

PHASE 2: Differentiation Between MCI and Alzheimer's Disease

Current Operational Pipeline

- Member A: LightGBM on BOW (without stopwords) + GloVe (with stopwords), BorderlineSMOTE
- Member B: ComplementNB on BOW (without stopwords), BorderlineSMOTE
- Ensemble Weights: 0.70 / 0.30
- Decision Threshold: 0.57

Conclusion of Phase 2: The ensemble approach shows strong effectiveness for differentiating MCI from Alzheimer's Disease.

Official Results (Strict Protocol with Stratified Cross-Validation)

87.39%

Accuracy

Overall classification performance across MCI and Alzheimer's Disease cases.

86.91%

Balanced Accuracy

Robust class balance with consistent sensitivity across both groups.

86.27%

F1-macro

Strong average performance across both classes.

90.20%

F1-MCI

High effectiveness in identifying MCI cases.

82.35%

F1-AD

Reliable detection of Alzheimer's Disease cases.

92.00%

Precision MCI

MCI predictions are highly reliable.

79.55%

Precision AD

Alzheimer's Disease predictions remain solid and clinically useful.

88.46%

Recall MCI

Strong ability to identify actual MCI cases.

85.37%

Recall AD

Strong ability to identify actual Alzheimer's Disease cases.

92.59%

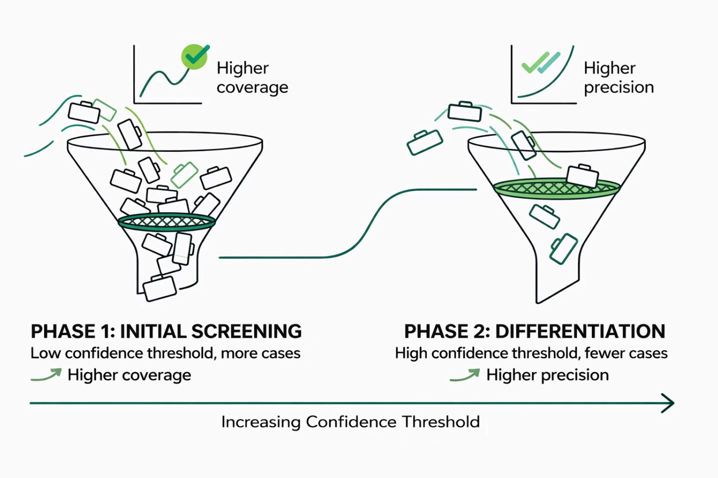
AUC

Excellent overall separability between the two groups.

Official Results (Strict Protocol with Stratified Cross-Validation)

Confidence Levels: How Many Cases Are Correctly Identified?

Understand the relationship between the model's required confidence level and the accuracy of its predictions.



PHASE 1: Initial Screening (Total: 325 samples)

Threshold ≥ 80%

- Out of 325 patients, the model selects 163 (50% of the total)
- Among these 163, it correctly classifies 154 (94.48% accuracy)

When the model is reasonably confident, it is correct in about 94 out of 100 cases

Threshold ≥ 90%

- Out of 325 patients, the model selects 78 (24% of the total)
- Among these 78, it correctly classifies 77 (98.72% accuracy)

When the model is highly confident, it is correct in about 99 out of 100 cases

Threshold ≥ 95%

- Out of 325 patients, the model selects 33 (10% of the total)
- Among these 33, it correctly classifies 32 (96.97% accuracy)

When the model is extremely confident, it is correct in about 97 out of 100 cases

PHASE 2: Differentiation Between MCI and Alzheimer's Disease (Total: 119 Samples)

Threshold ≥ 80%

- Out of 119 patients, the model selects 92 (77% of the total)
- Among these 92, it correctly classifies 85 (92.39% accuracy)

When the model is reasonably confident, it is correct in about 92 out of 100 cases

Threshold ≥ 90%

- Out of 119 patients, the model selects 74 (62% of the total)
- Among these 74, it correctly classifies 70 (94.59% accuracy)

When the model is highly confident, it is correct in about 95 out of 100 cases

Threshold ≥ 95%

- Out of 119 patients, the model selects 67 (56% of the total)
- Among these 67, it correctly classifies 64 (95.52% accuracy)

When the model is extremely confident, it is correct in about 96 out of 100 cases

The higher the required confidence, the fewer cases the model selects, but the higher the accuracy among those selected cases. This allows the system to be adjusted according to clinical needs.

What You Need to Know

Performance in Simple Numbers

PHASE 1 (Initial Screening)

Out of every 100 patients analyzed:

- **The model is correct:** 87
- **The model is incorrect:** 13

PHASE 2 (Differentiation)

Out of every 100 non-healthy patients:

- **The model is correct:** 87
- **The model is incorrect:** 13

Key Points

✓ SynapSpeech is correct in about 9 out of 10 cases during initial screening

✓ In disease differentiation, it is correct in about 87 out of 100 cases

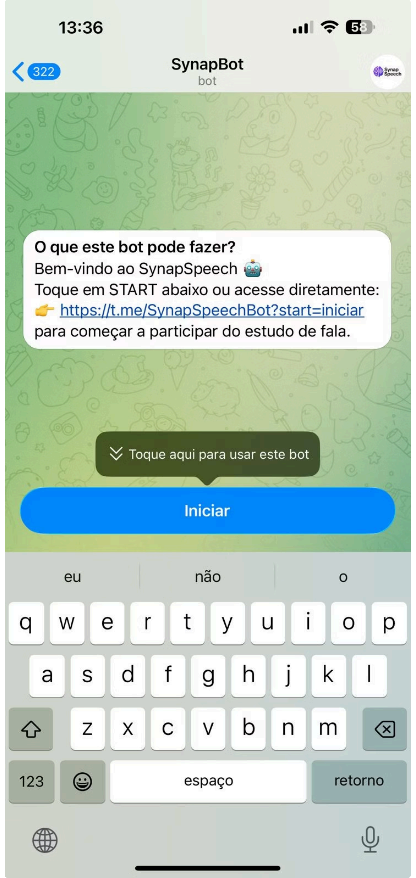
✓ When the model is highly confident, its accuracy increases

✓ These results come from rigorous testing on data the model has never seen

✓ The system is a support tool, not a definitive diagnosis

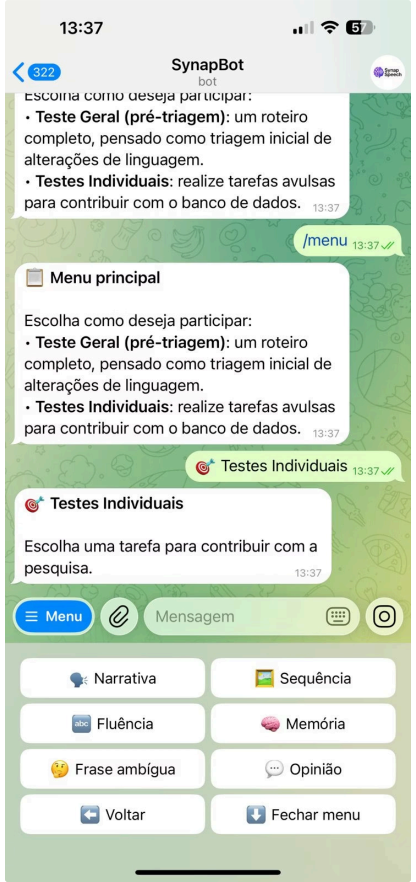
Practical Application and Accessibility

Telegram Prototype



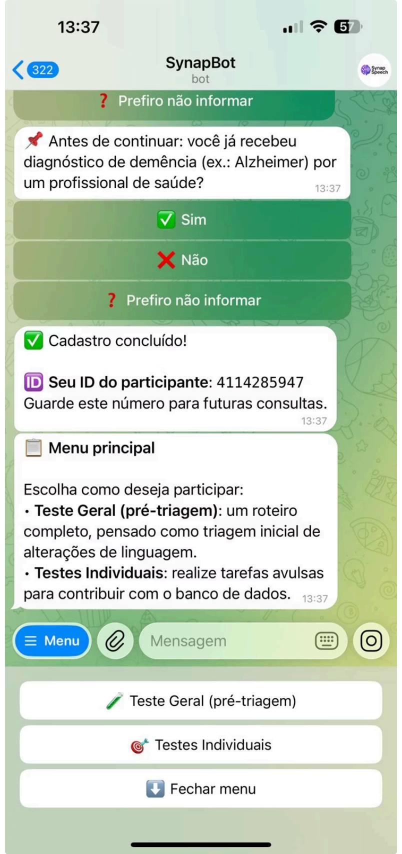
Narrative Recording

The user tells a guided story.



Automated Analysis

The AI processes linguistic patterns, applying tests.



Registration

Completes registration to carry out the activities.

Social Impact and Ethical Considerations

Democratizing Access

Bringing cognitive screening to remote regions and underserved communities, reducing inequalities in healthcare.

Early Detection

Identification of cognitive decline in its early stages, when interventions are more effective (Smith et al., 2021).

Privacy and Security

Strict protection of sensitive data in compliance with the LGPD and international ethical standards (ANPD, 2020; ISO/IEC, 2022).

Bias Mitigation

Continuous validation across diverse populations to ensure fairness and representativeness (AI Ethics Council, 2023).

Clinical Complement

A support tool, not a substitute for specialized medical diagnosis.

Transparency

Clear communication about the limitations and reliability of results to users (Responsible AI Guidelines, 2020).

Limitations and Next Steps

Current Challenges

Database

Need to expand with more diverse samples.

Clinical Validation

Longitudinal studies in real clinical environments.

Linguistic Variability

Adaptation to different accents and variants of Portuguese.

Ethics Committee

Approval process for making the tool available to the public.

Future Development

Data Expansion

Include multiple regions and sociodemographic profiles.

Deep Learning

Implement deep neural network architectures.

Clinical Validation

Partnership with healthcare institutions for pilot testing.

Science + Empathy + Technology

> SynapSpeech demonstrates how Artificial Intelligence can make cognitive care more accessible, humane, and effective.

Scalability

Social Inclusion

Thank you for your attention!

ICMC - Institute of Mathematical and Computer Sciences • InteliGente Research Group

Acknowledgments

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SÃO CARLOS

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