Towards AI-powered Language Assessment Tools for Dementia

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Abstract
The main objective of this paper is to propose an approach for developing an Artificial Intelligence (AI)-powered Language Assessment (LA) tool. Such tools can be used to assess language impairments associated with dementia in older adults. The Machine Learning (ML) classifiers are the main parts of our proposed approach, therefore to develop an accurate tool with high sensitivity and specificity, we consider different binary classifiers and evaluate their performances. We also assess the reliability and validity of our approach by comparing the impact of different types of language tasks, features, and recording media on the performance of ML classifiers. Our approach includes the following steps: 1) Collecting language datasets or getting access to available language datasets; 2) Extracting linguistic and acoustic features from subjects’ speeches which have been collected from subjects with dementia (N=9) and subjects without dementia (N=13); 3) Selecting most informative features and using them to train ML classifiers; and 4) Evaluating the performance of classifiers on distinguishing subjects with dementia from subjects without dementia and select the most accurate classifier to be the basis of the AI tool. Our results indicate that 1) we can find more predictive linguistic markers to distinguish language impairment associated with dementia from participants’ speech produced during the Picture Description (PD) language task than the Story Recall (SR) task; and 2) phone-based recording interfaces provide more high-quality language datasets than the web-based recording systems. Our results verify that the tree-based classifiers, which have been trained using the linguistic and acoustic features extracted from interviews’ transcript and audio, can be used to develop an AI-powered language assessment tool for detecting language impairment associated with dementia.

Keywords Alzheimer’s Disease · Acoustic Features · Dementia · Language Impairments · Linguistic Features · Machine Learning · Mild Cognitive Impairment
1 Introduction

More than 50 million people worldwide are living with different types of neurodegenerative dementias including Alzheimer’s Disease (AD), Vascular Dementia, Lewy Body Dementia, and Frontotemporal Lobar Dementia [1]. These are among the leading global neurodegenerative diseases and have notable economic impacts on individuals and societies [2]. To mitigate the impact of neurodegenerative dementias on older adults and help them plan for the future [3], early detection of dementia is necessary. It would help older adults at the early stages of the disease seek out different intervention programs [4], including psycho-social interventions (e.g., walking programs and art therapy) [5], non-pharmaceutical intervention programs (e.g., music interventions [6]) as well as clinical interventions so that they can maintain their quality of life [7] at the normal level and slow down disease progression.

There is no single test to diagnose dementia; clinicians run different tests, including cognitive [8, 9, 10], neuropsychological, neurological, brain-imaging, laboratory tests, and psychiatric evaluation to detect cognitive impairment associated with dementia [11]. Two well-known cognitive assessment tools are Montreal Cognitive Assessment (MoCA) and the Mini-Mental State Examination (MMSE) [12, 13]. The MoCA test consists of a 30-points scale to identify subjects with AD and Mild Cognitive Impairment (MCI) [13]; while, the MMSE includes 11 questions to assess impairments related to five cognitive functions such as orientation, attention, memory, language and visual-spatial skills [8]. The MoCA and MMSE assessment tools are quick and cost-effective, and widely used by clinicians and psychiatrists [15]. However, these tests cannot diagnose dementia with high sensitivity and specificity [17, 12]. This can be problematic since the false results of such tests can significantly impact health insurance and some social rights of the individuals [18]. Therefore, to detect dementia quickly and effectively, it has been suggested that such tests be considered as the beginning steps in early detection programs and can be combined with the Language Assessment (LA) tools [19, 17].

Clinical services and psychiatrists can detect dementia patients using LA tools, which have been recognized as low-cost and effective tools with high specificity and sensitivity of diagnosis [20] at the earliest stage of the disease. These tools can detect language impairments, which are signs of the first cognitive manifestations of any types of dementia, specifically the onset of AD [21] and MCI. LA tools can also be useful to identify different types of language impairment including difficulties with finding a relative expression, naming, and word comprehension and various level of language impairments [21]. For example, the tools can identify 1) lexical-semantic language problems such as naming the things or being vague in what they want to say [21]; 2) signs of empty speech (e.g., “The thing is over there, you know”); 3) phonological, morphological, syntactical problems and the lack of verbal fluency; which are patients’ language problems at the mild, moderate and severe stage of AD respectively. Thus, the tools make possible to clinicians to detect different types of dementia and its various stages.

Furthermore, these tools can detect language disorders, incoherent speech, tangentiality and grammatical error, lexical retrieval difficulties, auditory comprehension difficulties, grammatical and spelling failures in the subjects. These signs are associated to Language and Communication Impairment in patients with dementia. In particular, LA tools that analyze spontaneous speech, produced during the completion of cognitive tasks can recognize linguistic features associated with language performance deficits in elderly individuals [26]. Therefore, they are efficient methods to diagnose AD/MCI in elderly adults [27].

As mentioned earlier, the main advantage of using LA tools is their cost-effectiveness and user-friendliness. It is beneficial to patients and clinicians alike to use them. Thus, we propose an approach for developing an AI-powered language assessment tool to detect dementia. Unlike the previous research papers [28, 29, 30, 31, 32], we have not just focused on examining classifiers to distinguish subjects with dementia from subjects without dementia, rather we have defined different experiments to understand the impact of the language tasks, types of features and recording media on the efficiency of the tool. More specifically, we seek to find out the impact of 1) different language tasks, e.g., the picture description and the story recall tasks, 2) recording media, e.g., phone vs web-based interfaces, and 3) linguistic and acoustic features on the efficiency AI-powered language assessment tools.

Another contribution of the paper is that we have introduced four metrics to measure incoherence and tangential speech in elderly individuals.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of using Machine Learning (ML) to develop language assessment tools. Section 3 describes our approach to develop AI-powered LA tools. Section 4 presents our results. Section 5 discusses the data limitation, feature selection, validity, reliability, fairness, and
explainability aspects of LA tools. Finally, Section 6 concludes the article highlighting its main contributions and our future direction.

2 Related Works

Detecting language impairments using ML has captured the attention of researchers in the field of neurodegenerative disease. We generally combine the following steps to develop AI-based LA tools: 1) Collecting language datasets or getting access to available language datasets; 2) Feature Engineering: i) Extracting linguistic and acoustic features; ii) Employing various feature selection methods to select informative features; 3) Training different classifiers using multiple sets of features, and selecting ML algorithms with the highest performance. In this section, we describe the research related to each of the steps.

2.1 Language Datasets

We need labelled language datasets of older adults to develop supervised ML algorithms that can detect language impairments in patients. So far different language datasets, such as Carolina Conversations Collections (CCC) and DementiaBank (DB) have been introduced. The datasets were obtained using various language tests such as the Boston Naming Test (BNT) which is a standard test to assess language performance in participants with aphasia or dementia. Deficits in naming production appear in the first stages of Alzheimer’s disease and boost with time. Thus, BNT is one of the tests that can be used to detect the disease and follow its course. Moreover, it is useful in discriminating healthy elderly persons and those with dementia. The language tests aim to collect data to assess various aspects of language impairment in subjects. For example, the Picture Description (PD) task is usually used to evaluate the semantic knowledge in subjects. Using the Cookie Theft (see Figure 1) or the Picnic Scene (see Figure 2) for the PD task, we can assess the structural language skills of patients and amplify signs of language impairment. On the other hand, the Story Recall (SR) task can help assess impairment in episodic and semantic memory and also global cognition.

2.2 Feature Engineering

One of the main steps to develop AI-based LA tools is to extract linguistic and acoustic features from raw text and audio files. Tables 1 and 2 present the lists of linguistic and acoustic features respectively. These extracted features (or a subset of these features) can directly be used to train ML algorithms.

2.3 ML Classifier

ML algorithms such as k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Decision Trees (DT) and Random Forest (RF) classifiers, emotional learning-inspired ensemble classifier as well as Deep Learning (DL) architectures can analyze language produced by individuals (e.g., patients and healthy subjects) to distinguish healthy subjects from patients with dementia. In more details, the ML algorithms can be trained by linguistic features to identify language performance deficits in elderly individuals. One of the earliest studies to develop such an ML algorithm was proposed using the SVM to detect voice impairments in patients with AD. In another work, an SVM classifier was trained by language features extracted from the DB dataset and could achieve 80% accuracy in predicting probable AD. In an SVM classifier was trained on a dataset that combined DB with Talk2ME (i.e, encompass 167 patients with AD and 187 health controls), and achieved 70% accuracy. Another excellent results obtained from employing an SVM classifier on a dataset that combined DB and CCC with 15 healthy controls and 26 patients with AD. They showed that the SVM can distinguish patients and healthy controls with 75% accuracy. In the authors showed that kNN can distinguish patients with MCI from healthy subjects with 63% accuracy, they also showed that employing Bayesian Network on the CCC dataset, we can achieve 66% accuracy.

This section aims to provide an overview of various ML algorithms and datasets that have been used to identify language impairments associated with AD and MCI. Based on the overview, we believe that AI-powered LA tools can be considered as quick, accurate, cost-effective, user-friendly, reliable and valid tools to detect language impairment in the older adults. Therefore, in the next section, we describe our approach to develop such a tool.

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3The DB dataset has been collected by recording the voice of patients with AD (N=167) and healthy control (N=97) while completing a picture description task.

4During the story recall task, participants are shown a short passage with one of the following options 1) My Grandfather, 2) Rainbow or 3) Limpy that are three well-known passage to assess memory capacity of participants.
Figure 1: The Cookie Theft Picture from the Boston Diagnostic Aphasia Examination. For the PD task, the examiner asks subjects to describe the picture by saying: *Tell me everything you see going on in this picture*. Then subjects might say, "there is a mother who is drying dishes next to the sink in the kitchen. She is not paying attention and has left the tap on. As a result, water is overflowing from the sink. Meanwhile, two children are attempting to make cookies from a jar when their mother is not looking. One of the children, a boy, has climbed onto a stool to get up to the cupboard where the cookie jar is stored. The stool is rocking precariously. The other child, a girl, is standing next to the stool and has her hand outstretched ready to be given cookies."

Figure 2: The the picnic scene from The Arizona Alzheimer’s Disease Center (ADC). A normal subject might say: A family outing at a lake shore showed people doing several things. Mom and Dad sat on a blanket while dad read a book. Dad was over comfortable without his shoes, while mom listened to the radio and poured herself a cup of coffee. Junior was having fun flying his kite, and the family dog was interested in what all was going on. Another of the family was spending quiet time and fishing, and another was playing in the shallow water. Other friends waved to them as they sailed by. It was a perfect day with just enough wind to move the flag and provide lift for the kite. It must have been comfortable sitting under the shade tree.

3 AI-powered Language Assessment Tool

Our approach to develop an AI-powered language assessment tool uses the same sequential steps that we described in the previous section.
Table 1: List of Linguistic Features reported in the Literature within AD Domain. Different linguistic features, including lexical, syntactic, semantic and pragmatic features can be associated with different types of language deficits in patients with AD and MCI [39].

| Name                              | Type        | Cognitive Function          | References |
|-----------------------------------|-------------|----------------------------|------------|
| Coordinated sentences            | Syntactic   | Syntactic processing       | [40]       |
| Subordinated sentences            | Syntactic   | Syntactic processing       | [40]       |
| Reduced sentences                 | Syntactic   | Syntactic processing       | [40]       |
| Number of predicates              | Syntactic   | Syntactic processing       | [40]       |
| Average number of predicates      | Syntactic   | Syntactic processing       | [40]       |
| Dependency distance               | Syntactic   | Syntactic processing       | [40]       |
| Number of dependencies            | Syntactic   | Syntactic Processing       | [40]       |
| Average dependencies per sentence | Syntactic   | Syntactic processing       | [40]       |
| Production rules                  | Syntactic   | Syntactic processing       | [40]       |
| Noun Rate (NR)                    | Syntactic   | Cognitive strength         | [41, 29]   |
| Pronoun Rate (PR)                 | Syntactic   | Cognitive strength         | [41, 29]   |
| Adjective Rate (AR)               | Syntactic   | Cognitive strength         | [41, 29]   |
| Verbal Rate (VR)                  | Syntactic   | Cognitive strength         | [41, 29]   |
| Utterances                         | Lexical     | the linguistic strength    | [40]       |
| Function words                    | Lexical     | —                          | [40]       |
| Word count                        | Lexical     | —                          | [40]       |
| Character length                  | Lexical     | —                          | [40]       |
| Total sentences                   | Lexical     | —                          | [40]       |
| Unique words                      | Lexical     | language processing        | [40]       |
| Repetitions                       | Lexical     | —                          | [40]       |
| Revisions                         | Lexical     | —                          | [40]       |
| Morphemes                         | Lexical     | —                          | [40]       |
| Trailing off indicator            | Lexical     | —                          | [40]       |
| Word replacement                  | Lexical     | —                          | [40]       |
| Incomplete words                  | Lexical     | —                          | [40]       |
| Filler words                      | Lexical     | —                          | [40]       |
| Type token ration (TTR)           | Semantic    | Vocabulary Richness        | [41, 29]   |
| Brunet’s index (BI)               | Semantic    | Vocabulary Richness        | [41, 29]   |
| Honore’s statistics (HS)          | Semantic    | Vocabulary Richness        | [41, 29]   |
| Fillers                           | Pragmatic   | Cognitive Lapse            | [41, 29]   |
| GoAhead utterances                | Pragmatic   | Cognitive functionality    | [41, 29]   |
| Repetitions                       | Pragmatic   | Cognitive Lapse            | [41, 29]   |
| Incomplete words                  | Pragmatic   | Cognitive lapse            | [41, 29]   |
| Syllables Per Minute              | Pragmatic   | Cognitive impairment       | [41, 29]   |

3.1 Language Dataset

We have extracted audio and text datasets of patients (N=9) with various types of dementia\[^5\] as well as healthy controls (N=13) from a database, named Talk2Me\[^6\]. The Talk2Me database contains speech data recorded using a web or phone interface. In more details, textual and audio responses have been collected from participants using a variety of language tasks such as the PD and SR tasks.

3.2 Feature Engineering

3.2.1 Linguistic Features

We extract different linguistic features (e.g., the lexical diversity) from textual data using the Natural Language Toolkit\[^52\]. The linguistic features of this paper can be divided into three categories: 1) Lexical features (e.g., lexical richness); 2) Syntactic features (e.g., Part-of-Speech (POS)); and 3) Semantic features.

\[^5\]patients have been diagnosed by physician from three hospitals in Toronto

\[^6\]each subject has signed a consent form that has been provided approved by the Research Ethics Board protocol 31127 of the University of Toronto
Table 2: List of Acoustic Features reported in the Literature within AD Domain.

| Type                     | Name                                      | References |
|--------------------------|-------------------------------------------|------------|
| Cepstral Coefficients    | Mean of MFCCs                             | [42, 43]   |
|                          | Kurtosis of MFCCs                         | [42, 43, 44]|
|                          | Skewness of MFCCs                         | [42, 43, 44]|
| Pauses and fillers       | Total duration of pauses                  | [42, 45, 46]|
|                          | Mean duration of pauses                   | [42, 45, 46]|
|                          | Median duration of pauses                 | [42, 46]   |
|                          | SD of the duration of pauses              | [42]       |
|                          | Long and short pause counts               | [42, 45]   |
|                          | Pause to word ratio                       | [42, 43, 45, 46, 47]|
|                          | Percentage of voiceless segments          | [48]       |
|                          | Fillers (um, uh)                         | [42, 49]   |
| Pitch and Formants       | Mean of F0, F1, F2, F3                    | [42]       |
|                          | Variance of F0, F1, F2, F3               | [42]       |
|                          | Mean, SD, Max and Min of F0              | [48]       |
| Aperiodicity             | Jitter                                    | [42, 48]   |
|                          | Shimmer                                   | [42, 48]   |
|                          | Recurrence rate                           | [42]       |
|                          | Recurrence period density entropy         | [42]       |
|                          | Determinism                               | [42]       |
|                          | Length of diagonal structures             | [42]       |
|                          | Laminarity                                | [42]       |
| Temporal aspects of the speech | Total duration                          | [42, 48]   |
|                          | Phonation time                            | [48]       |
|                          | Speech rate, syllable/s                  | [48]       |
|                          | Articulation rate, syllable/s            | [48]       |
| Others                   | Zero-crossing rate                        | [42]       |
|                          | Autocorrelation                           | [42]       |
|                          | Linear prediction coefficients            | [42]       |
|                          | Transitivity                              | [42]       |

Lexical Features: Since dementia can influence the lexical richness of patients’ language, different studies have proposed different types of lexical features as markers of language impairment in patients with AD/MCI. For example, in [40], utterances, word count, character length, total sentences, unique words, repetitions, revisions, morphemes, incomplete words, filler words, trailing off indicator, and word replacement extracted as lexical features. However, in our study, we have extracted multiple features such as Brunet’s index (BI) (see Equation (1)) and Honor’s Statistic (HS) with Equation (2) [53] to measure the lexical richness. In Equations (1) and (2), \( w \) and \( u \) are the total number of word tokens and the total number of unique word types, respectively. There are five readability scores namely the Flesch-Kincaid \( (F_K) \) (see Equation (3)), the Flesch Reading-Ease (FRES) Test (see Equation (4) [54]), to test the readability of the transcripts. Here, \( s \) and \( SYL \) indicate the total number of sentences and the total number of syllables, respectively.

\[
BI = w^{(u^{0.165})} 
\]

\[
HS = \frac{100 \log w}{1 - \frac{w}{u}} 
\]

\[
F_K = 0.39 \left( \frac{w}{s} \right) + 11.8 \left( \frac{SYL}{w} \right) - 15.59 
\]

\[
FRES = 206.835 - 1.015 \left( \frac{w}{s} \right) - 84.6 \left( \frac{SYL}{w} \right) 
\]

Syntactic Features: We have also extracted syntactic features such as POS ratios: 1) third pronouns (3rd-pron-pers) to proper nouns (prop); 2.3a) first pronouns (1st-pron-pers) to pronouns (1st-pron-pers) \[\text{[56]}\]; 3) nouns to verbs; and 4) subordinate to coordinate \[\text{[56]}\] to calculate syntactical error in speech, which is indicative of frontotemporal dementia. People with dementia may use first person singular pronouns than physicians perhaps as a way of focusing attention on their perspective [55].
dementia [57], and propositional and content density equations 5 and 6 to quantify the syntax complexity. Here, \( NN, VB, JJ, RB, IN, \) and \( CC \) are the number of nouns, verbs, adjectives, adverbs, prepositions, and conjunctions respectively.

\[
density_p = \frac{VB + JJ + RB + IN + CC}{N} \quad (5)
\]

\[
density_c = \frac{NN + VB + JJ + RB}{N} \quad (6)
\]

**Semantic-based Features:** Patients with dementia cannot easily retrieve semantic knowledge, reflecting a semantic decline in their language [46]. To develop a tool that can detect semantic decline and also incoherent speech, tangentiality [58], we suggest training ML algorithms using extracted semantic-based features, which are referred as incoherent and tangential metrics in this paper. The incoherence metrics are extracted by calculating the similarity (Equation 7) between sentence embeddings: \( v_{s_i} \). Various sentence embeddings such as Simple Average (SA) [see Equation 8], or Smooth Inverse Frequency (SIF) embeddings [59] (see Equation 9) and term frequency-inverse document frequency (tf-IDF) (see Equation 10). We have also calculated a tangential metric employing Latent Dirichlet Allocation [60, 61, 62] (see Equation 12). Using the tangential metric, we can measure tangentiality [58] in speech of patients with dementia. We measured tangential speech using Equation 12. Here, \( N_{topic} \) is the optimal number of topics for a corpus made of interview of subjects [63].

\[
\text{Similarity}_{SA}(v_{s_i}, v_{s_j}) = \frac{v_{s_i} \cdot v_{s_j}}{\|v_{s_i}\| \|v_{s_j}\|} \quad (7)
\]

\[
\text{Similarity}_{SIF}(v_{s_i}, v_{s_j}) = 1 - \frac{v_{s_i} \cdot v_{s_j}}{\|v_{s_i}\| \|v_{s_j}\|} \quad (8)
\]

\[
\text{Incoherence}_{SA} = \min_i \max_j \frac{\text{Similarity}_{SA}(v_{s_i}, v_{s_j})}{\text{abs}(i - j) + 1} \quad (9)
\]

\[
\text{Incoherence}_{SIF} = \min_i \sum_j \frac{\text{Similarity}_{SIF}(v_{s_i}, v_{s_j})}{\text{abs}(i - j) + 1} \quad (10)
\]

\[
\text{Incoherence}_{TFIDF} = \min_i \sum_j \frac{\text{Similarity}_{TFIDF}(v_{s_i}, v_{s_j})}{\text{abs}(i - j) + 1} \quad (11)
\]

\[
\text{Tangentiality} = 1 - \frac{N_{topic}}{\sum_{j} N_{topic}} \quad (12)
\]

3.2.2 Acoustic Features

We have extracted the acoustic features using the COre Variable Feature Extraction Feature Extractor (COVFEFE) tool [56]. We have considered 37 acoustic features and their Mean, Standard Deviation (std), Skewness (skew) (lack of symmetry of a data distribution) and Kurtosis (kurt) (measure of peakedness around the mean of a data distribution) which resulted in a total of 148 features. We have also included the deltas of these 148 features. Therefore, our feature selection methods have considered 296 features in total. For example, we have considered mean, std, skew and kurt of an MFCC feature (described later) and its deltas. Thus from a single acoustic feature, we have extracted 8 additional features. We have followed the same procedure to extract all 296 features. We have divided our features in 3 groups: 1) Spectral Features, 2) Phonation and Voice Quality Features, and 3) Speech Features. Table 3 shows the list of features that we have considered in the research. In this section, we only describe the features that are identified as meaningful by our feature selection methods.

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8SA provides sentence embedding by averaging generated word embeddings from text files.

9SIF provides sentence embedding by calculating the weighted average of word embeddings and removing their first principal component.
Table 3: List of Acoustic Features that are Considered in this Research

| Type                      | Name                  | Functional          | # of Features |
|---------------------------|-----------------------|---------------------|---------------|
| Spectral Features         | MFCCs 0 - 14          | mean, kurt, skew, std | 60            |
|                           | ∆ MFCCs 0 - 14        | mean, kurt, skew, std | 60            |
|                           | log Mel freq 0 - 7    | mean, kurt, skew, std | 32            |
|                           | ∆ log Mel freq 0 - 14 | mean, kurt, skew, std | 32            |
|                           | LSP freq 0 - 7        | mean, kurt, skew, std | 32            |
|                           | ∆ LSP freq 0 - 7      | mean, kurt, skew, std | 32            |
| Phonation and Voice       | F0                    | mean, kurt, skew, std | 4             |
| Quality Features          | ∆ F0                  | mean, kurt, skew, std | 4             |
|                           | Jitter local          | mean, kurt, skew, std | 4             |
|                           | ∆ Jitter local        | mean, kurt, skew, std | 4             |
|                           | Jitter DDP            | mean, kurt, skew, std | 4             |
|                           | ∆ Jitter DDP          | mean, kurt, skew, std | 4             |
|                           | Shimmer               | mean, kurt, skew, std | 4             |
|                           | ∆ Shimmer             | mean, kurt, skew, std | 4             |
|                           | Loudness              | mean, kurt, skew, std | 4             |
|                           | ∆ Loudness            | mean, kurt, skew, std | 4             |
| Speech Features           | Voicing prob.         | mean, kurt, skew, std | 4             |
|                           | ∆ Voicing prob.       | mean, kurt, skew, std | 4             |

**Spectral Features:** We have considered the features derived from the Mel Frequency Cepstrum (MFC) and the Line Spectral Pairs (LSPs) to develop our ML classifiers. MFC uses the Mel scale to represent short-term power spectrum of a sound. Mel Frequency Cepstral Coefficients (MFCCs) represent energy variations between frequency bands of a speech signal and are effectively used for speech recognition and speaker verification. MFCCs aim at accurately representing the phonemes articulated by speech organs (tongue, lips, jaws, etc.). Delta MFCCs are the trajectories of the MFCCs over time. The logarithm of Mel filter banks are calculated as an intermediate step of computing MFCCs and we have considered the Log Mel Frequency Bands and the Delta Log Mel Frequency Bands as spectral features. Previous research identified the MFCCs as one of the most relevant acoustic features to distinguish patients with different types of dementia [42, 43, 44]. Our analysis also confirm this claim (see Tables 5 and 8).

LSPs are strongly related to underlying speech features and are thus useful in speech coding [64]. They are correlated to unvoiced speech, pause and silence which are reportedly effective in identifying linguistic impairments [65]. The delta of LSPs represents the change of LSPs over time. Our feature selection methods confirm the importance of LSPs and their deltas (see Tables 5 and 8).

**Phonation and Voice Quality Features:** This feature group includes Fundamental Frequency (F0), Shimmer, Jitter, Loudness, and the deltas of these features. The F0 feature is defined as the rate of oscillation of the vocal folds [66]. F0 is nearly periodic in speech of the healthy people but less periodic in patients [67]. Jitter describes frequency instability and shimmer is a measure of amplitude fluctuations. Loudness affects the amplitude of vibrations and it is correlated to the emotional states of the speaker [68]. Previous studies reported that phonation and voice quality features are correlated with MCI and AD [69, 70], and our findings also support these claims (see Tables 5 and 8).

**Speech Features:** We have considered the Voicing Probability and the delta of voicing probability as relevant acoustic features. A voicing probability shows the percentage of unvoiced and voiced energy in a speech signal. A delta voicing probability indicates the rate of change over time. Our feature selection methods identified that mean, std and kurt of both features are discriminative features to identify older adults living with dementia (see Table 8).

### 3.3 ML Classifiers

The ML classifier are employed to analyze linguistic and acoustic features, which have been extracted from individuals’ language. For this paper, we have trained different classifiers such as DT, Extra Tree (ET), kNN, SVM using a set of extracted linguistic and acoustic features and evaluated their performances. We have selected a classifier with higher performance to be the basis of the LA tool.
4 Results

We have employed different ML algorithms and trained them on various language features extracted from subjects’ speeches during the PD and SR tasks and these speeches have been collected using phone-based and web-based interfaces. We have compared the performances of the ML classifiers to verify the language task’s impact and recording media on accuracy and reliability of our suggested approach. Note that, we have trained the classifiers separately with linguistic and acoustic features, and therefore, in the following parts, we compare the performance of the classifiers developed with these two groups of features.

4.1 Language Tasks

This subsection investigates the impact of the two language tasks (see Table ??) the PD and SR tasks on the performance of classifiers at the subject level. These two tasks assess different cognitive characteristics of patients with dementia, and thus it is worth investigating and comparing the effectiveness of these two language tasks.

Table 4: Statistics about our textual datasets

| DATA                        | Ave Sentence | Std Sentence | Ave Word  | Std Word  |
|-----------------------------|--------------|--------------|-----------|-----------|
| The PD Task                 | 9.0          | 4.4          | 153.5     | 97.92     |
| The SR Task                 | 6.79         | 4.00         | 57.07     | 26.91     |
| Recording Media (Phone)     | 5.5          | 4.66         | 74.07     | 44.90     |
| Recording Media (Web)       | 2.27         | 1.25         | 65.59     | 31.11     |

4.1.1 The PD Task

We study the efficacy of linguistic (see Figure 3) and acoustic features (see Table 5), which have been extracted from the speech of the subjects without dementia (N=3) and subjects with dementia (N=5) during completing the PD task on the performance of our proposed approach.

Classifiers with Linguistic Features

We trained various ML algorithms using lexical, semantic and syntactic features, which have been extracted from the textual datasets obtained from speech datasets. Figure 4.(b) shows that if we train the ET algorithm with a set of lexical features, we can achieve more accurate classification results than other ML algorithms. Training ML algorithms with the set of lexical, semantic and syntactic features decreases the accuracy of classifiers (see Figure 4.(a)). By training the ML classifiers using 8 Syntactic features, we observed the ET algorithm could classify the classes with an accuracy of 63.0% (+/-7%). By training various ML classifiers using 4 semantic features, we observed ET provide more accurate results than others and could classify the classes with an accuracy of 63.0% (+/-7%) (see Figure 5.(b)).

Training ML algorithms with 3 principle components (see Figure 7) extracted from 17 features, we observed that the SVM algorithm with the linear kernel could classify with 63.0% (+/-7%) accuracy. Furthermore, among lexical features, two Flesch-Kincaid (CV=23.17%, p_value=0.25) and Flesch-Reading-Ease (CV=15.15%, p_value=0.35) can provide better discrimination between these two groups of subjects, while the number of the third pronouns (the effect size equals to 1.319) and the first pronouns (the effect size equals to 2.198) among subjects without dementia has higher value than subjects with dementia. Thus, these two syntactic features can be considered as markers to detect subjects with MCI. Another interesting result is that measuring tangentiality (see Figure 6) (with the effect size of 0.020) in speech can provide a better understanding to determine subjects with dementia from healthy subjects.

Classifiers with Acoustic Features

Table 7 presents the classification results obtained by applying ML tools on the extracted features from the audio files. The ML classifiers are trained using the spectral (e.g., MFCC, LSP), speech (e.g., voicing probability), phonation (e.g., F0) and voice quality (e.g., jitter, shimmer) features as described in Section 3.2.2. We rank all these features using Analysis of Variance (ANOVA), RF and Minimal Redundancy Maximal Relevance (mRMR) methods and use the top 8 features identified by each of these methods to train the ML classifiers. Table 8 shows the top common acoustic features ranked by the above mentioned feature selection methods. We found that scikit-learn’s default configurations work fine for the considered ML classifiers. Therefore, we use the default configurations for all classifiers. The F1 micro scores in Table 7 are obtained using the 3-fold cross-validation method. Our results show that the tree-based classifiers, e.g., RF, ET, and DT outperform the others.

10 coefficient of variation
AI-powered Language Assessment Tools for Dementia

Figure 3: Correlation heat-map between 17 linguistic features.

Figure 4: ROC curves of RF and ETs trained by different sets of linguistic features

(a) ROC curves of RF trained by 17 linguistic features
(b) ROC curves of ETs by lexical features
AI-powered Language Assessment Tools for Dementia

(a) ROC curves of ETs trained by syntactic features  
(b) ROC curves of ET trained by semantic features

Figure 5: ROC curves of ETs trained by syntactic and semantic features

Figure 6: A comparison between the tangentiality measure for subjects with and without dementia.

Table 5: Common acoustic features obtained by applying ANOVA, RF and mRMR feature selection methods on the recorded audio files of the PD and SR tasks

| PD Task               | SR Task               |
|-----------------------|-----------------------|
| MFCC 13 (mean)        | MFCC 12,13 (skew)     |
| MFCC 12,13 (kurt)     | Δ MFCC 3,4,6,13 (mean) |
| MFCC 10,13 (skew)     | Δ MFCC 4 (skew)       |
| Δ MFCC 2,11 (mean)    | Δ LSP freq 7 (mean)   |
| Δ MFCC 2,3,6,7 (kurt) | Δ LSP freq 3.6 (kurt) |
| Δ MFCC 6,11,13 (skew) | Loudness (kurt, skew) |
| Δ LSP freq 3.5 (mean) | Δ Loudness (kurt, skew) |
| Δ LSP freq 2.6 (kurt) | F0 (kurt)             |
| Δ LSP freq 1 (skew)   | Δ F0 (mean)           |
Figure 7: It shows that subjects with dementia and healthy controls cannot be linearly separated using 2 principle components.

4.1.2 The SR Task

This section presents the results obtained by training different ML classifier using linguistic and acoustic features extracted from language data produced subjects without dementia \((N=10)\) and subjects with dementia \((N=4)\) during the SR task.

Classifiers with Linguistic Features

This section examines the efficiency of using different linguistic features to train ML classifiers. Using 5 lexical features to train classifiers, the SVM (with the Radial Basis Function (RBF) kernel and \(C=0.01\)) and RF \((n\_estimators=2\) and \(max\_depth=2\)), can classify subjects with dementia and healthy subjects accurately with 71% accuracy. We can get the same results using 8 syntactic features to train the SVM (with the RBF kernel and \(C=0.01\)) and RF\((n\_estimators=2\) and \(max\_depth=2\)). If we train the classifiers (3-fold Cross-Validation) with 17 lexical, semantic, and syntactic features, the SVM (with the RBF kernel and \(C=0.01\)) can classify subjects with dementia and healthy adults accurately with 72% accuracy (see Figure 9(a)). It is interesting that measuring tangentiality (see Figure 12) in speech can provide a better understanding to determine subjects with dementia from healthy subjects. Training ML algorithms with 3 principle components (see Figures 13 and 14) extracted from 17 features, we observed that the SVM algorithm with the RBF kernel could classify with 71% accuracy.

Classifiers with Acoustic Features

In this section, we present the classification results obtained by applying ML algorithms on the features extracted from the audio files. We use audio data collected from subjects without dementia \((N=10)\) and subjects with dementia \((N=4)\). We follow the same approach that we use in Section 4.1.1 to rank the acoustic features and use the top 15 features to develop the classifiers. Table 5 shows the top common acoustic features ranked by ANOVA, RF and mRMR feature selection methods. We use scikit-learn’s default configurations for
AI-powered Language Assessment Tools for Dementia

Figure 8: It presents the values of cumulative explained variance for different number of principle components.

(a) ROC curves of SVM trained by 17 features
(b) ROC curves of SVM trained by lexical features

Figure 9: ROC curves of SVM trained by all and lexical features
Table 6: F1 (micro) scores obtained by applying ML algorithms on linguistic features

| Features  | Algorithms | PD Task | SR Task | Web | Phone |
|-----------|------------|---------|---------|-----|-------|
|            |            | (+/- 0.07) | (+/- 0.00) | (+/- 0.17) | (+/- 0.17) | (+/- 0.00) | (+/- 0.17) | (+/- 0.17) | (+/- 0.00) |
| Lexical   | DT         | 0.63     | 0.71     | 0.42     | 0.92     |
|           | ET         | **0.73** | 0.57     | 0.83     | 0.92     |
|           | kNN        | 0.52     | 0.42     | 0.45     | 0.45     |
|           | LDA        | 0.63     | 0.63     | 0.75     | 0.92     |
|           | R_SVM      | 0.63     | **0.71** | 0.83     | 0.83     |
|           | L_SVM      | 0.63     | **0.71** | 0.83     | 1.00     |
|           | LR         | 0.63     | 0.63     | 0.83     | 1.00     |
|           | RF         | 0.47     | **0.71** | 0.83     | 0.92     |
| Syntactic | DT         | 0.73     | 0.57     | 0.83     | 0.83     |
|           | ET         | 0.80     | 0.64     | 0.83     | 0.83     |
|           | kNN        | 0.69     | 0.53     | 0.45     | 0.45     |
|           | LDA        | 0.37     | 0.50     | 0.75     | 0.75     |
|           | R_SVM      | 0.63     | **0.71** | 0.83     | 0.83     |
|           | L_SVM      | 0.63     | **0.71** | 0.83     | 0.67     |
|           | LR         | 0.80     | 0.71     | 0.83     | 0.75     |
|           | RF         | 0.47     | 0.57     | 0.75     | 0.92     |
| Semantic  | DT         | 0.53     | 0.64     | 0.83     | 0.83     |
|           | ET         | 0.57     | 0.71     | 0.83     | 0.83     |
|           | kNN        | 0.69     | 0.53     | 0.45     | 0.45     |
|           | LDA        | 0.63     | **0.71** | 0.83     | 0.58     |
|           | R_SVM      | 0.63     | **0.71** | 0.83     | 0.83     |
|           | L_SVM      | 0.63     | **0.71** | 0.83     | 0.83     |
|           | LR         | 0.63     | 0.50     | 0.83     | 0.83     |
|           | RF         | **0.73** | 0.57     | 0.83     | 0.83     |
| All       | DT         | 0.73     | 0.64     | 0.75     | 1.00     |
|           | ET         | 0.63     | **0.79** | 0.83     | 0.75     |
|           | kNN        | 0.52     | 0.39     | 0.45     | 0.45     |
|           | LDA        | 0.63     | 0.64     | 0.75     | 0.75     |
|           | R_SVM      | 0.63     | 0.71     | 0.83     | 0.83     |
|           | L_SVM      | 0.63     | 0.64     | 0.75     | 1.00     |
|           | LR         | 0.70     | 0.64     | 0.83     | 0.75     |
|           | RF         | 0.63     | 0.71     | 0.83     | 1.00     |

All classifiers of this sub-section. The F1 micro scores in Table 7 are obtained using the 3-fold cross-validation method. Our results show that the ET classifiers outperform others.

4.1.3 Comparison between the PD and the SR Tasks

As mentioned earlier, we have also evaluated the impact of language tasks on the accuracy of our approach in detecting AD and MCI. We have used audio recordings and transcribed textual datasets to extract linguistic and acoustic features from PD and SR tasks. Our datasets are imbalanced and therefore micro F1 scores are more appropriate to report the performance of the ML classifiers. To assess the efficiency of PD and SR tasks, we have calculated a range of F1 scores using different feature sets and classifiers as shown in Tables 6 and 7. We have used lexical, syntactic, semantic and combination of all these 3 feature groups as linguistic features. For acoustic features, we have used ANOVA, RF and mRMR feature selection methods. We have also used the common features in these 3 feature selection methods as another set of acoustic features. Finally, we have apply DT, ET, Linear SVM, RBF SVM, Linear Discriminant Analysis (LDA), Logistic Regression (LR), kNN and RF algorithms to compute the F1 scores. Figure 15(a) shows the distributions of F1 scores for PD and SR tasks. A one-way ANOVA test performed on the F1 scores of the PD and SR tasks shows that the means are significantly different (F(1,126) = 8.27, p = 0.005). A Tukey’s post-hoc test shows that the mean F1 scores of the PD task are higher than the SR task (p = 0.005), i.e., the ML classifiers developed by using PD stimuli perform better than the SR stimuli.

4.2 Recording Media

We were also interested in figuring out the direct effect of using web-interface or phone-interface on the quality of recorded language data that indirectly affect on the accuracy of AI-powered LA Tools.
Table 7: F1 (micro) scores obtained by applying ML algorithms on acoustic features

| Features | Algorithms | PD Task  | SR Task  | Web Task  | Phone Task |
|----------|------------|----------|----------|-----------|------------|
| ANOVA    | DT         | 0.83 (+/- 0.24) | 0.50 (+/- 0.24) | **0.89 (+/- 0.16)** | 0.81 (+/- 0.02) |
|          | ET         | 0.98 (+/- 0.03) | **0.86 (+/- 0.09)** | 0.83 (+/- 0.24) | 0.93 (+/- 0.09) |
|          | kNN        | 0.83 (+/- 0.24) | 0.78 (+/- 0.02) | **0.89 (+/- 0.16)** | 0.93 (+/- 0.09) |
|          | LDA        | 0.89 (+/- 0.16) | 0.70 (+/- 0.14) | **0.89 (+/- 0.16)** | **1.00 (+/- 0.00)** |
|          | R_SVM      | 0.72 (+/- 0.21) | 0.78 (+/- 0.02) | **0.89 (+/- 0.16)** | 0.76 (+/- 0.06) |
|          | L_SVM      | 0.83 (+/- 0.24) | 0.70 (+/- 0.14) | 0.72 (+/- 0.21) | **1.00 (+/- 0.00)** |
|          | LR         | 0.83 (+/- 0.24) | 0.78 (+/- 0.02) | 0.72 (+/- 0.21) | 0.93 (+/- 0.09) |
|          | RF         | **0.99 (+/- 0.02)** | 0.83 (+/- 0.06) | 0.83 (+/- 0.24) | 0.93 (+/- 0.09) |
|          | RF         | **0.99 (+/- 0.02)** | 0.70 (+/- 0.17) | **1.00 (+/- 0.00)** | 0.87 (+/- 0.09) |
|          | ET         | 0.99 (+/- 0.02) | 0.80 (+/- 0.04) | **1.00 (+/- 0.00)** | 0.99 (+/- 0.02) |
|          | kNN        | 0.89 (+/- 0.16) | 0.78 (+/- 0.02) | 0.89 (+/- 0.16) | 0.93 (+/- 0.09) |
|          | LDA        | **1.00 (+/- 0.00)** | 0.57 (+/- 0.17) | 0.89 (+/- 0.16) | 0.93 (+/- 0.09) |
|          | R_SVM      | 0.61 (+/- 0.08) | 0.78 (+/- 0.02) | 0.61 (+/- 0.08) | 0.76 (+/- 0.06) |
|          | L_SVM      | 0.89 (+/- 0.16) | 0.78 (+/- 0.02) | 0.72 (+/- 0.21) | **1.00 (+/- 0.00)** |
|          | LR         | 0.89 (+/- 0.16) | **0.87 (+/- 0.09)** | 0.72 (+/- 0.21) | 0.93 (+/- 0.09) |
|          | RF         | **1.00 (+/- 0.00)** | 0.78 (+/- 0.02) | 0.90 (+/- 0.14) | **1.00 (+/- 0.00)** |
| mRMR     | DT         | **1.00 (+/- 0.00)** | 0.70 (+/- 0.14) | 0.83 (+/- 0.24) | 0.87 (+/- 0.09) |
|          | ET         | **1.00 (+/- 0.00)** | 0.81 (+/- 0.05) | 0.97 (+/- 0.05) | **1.00 (+/- 0.00)** |
|          | kNN        | 0.50 (+/- 0.14) | 0.78 (+/- 0.02) | **1.00 (+/- 0.00)** | 0.81 (+/- 0.16) |
|          | LDA        | **1.00 (+/- 0.00)** | 0.77 (+/- 0.21) | **1.00 (+/- 0.00)** | **1.00 (+/- 0.00)** |
|          | R_SVM      | 0.61 (+/- 0.08) | 0.78 (+/- 0.02) | 0.72 (+/- 0.21) | 0.76 (+/- 0.06) |
|          | L_SVM      | 0.78 (+/- 0.31) | 0.50 (+/- 0.08) | **1.00 (+/- 0.00)** | 0.87 (+/- 0.19) |
|          | LR         | 0.78 (+/- 0.31) | 0.78 (+/- 0.02) | **1.00 (+/- 0.00)** | 0.87 (+/- 0.19) |
|          | RF         | 0.99 (+/- 0.02) | 0.78 (+/- 0.02) | 0.88 (+/- 0.16) | **1.00 (+/- 0.00)** |
| Common   | DT         | **1.00 (+/- 0.00)** | 0.52 (+/- 0.37) | **1.00 (+/- 0.00)** | 0.80 (+/- 0.28) |
|          | ET         | **1.00 (+/- 0.00)** | **0.84 (+/- 0.11)** | 0.74 (+/- 0.21) | 0.94 (+/- 0.08) |
|          | kNN        | 0.83 (+/- 0.24) | 0.70 (+/- 0.14) | 0.89 (+/- 0.16) | **1.00 (+/- 0.00)** |
|          | LDA        | 0.78 (+/- 0.16) | 0.80 (+/- 0.16) | 0.89 (+/- 0.16) | 0.87 (+/- 0.19) |
|          | R_SVM      | 0.72 (+/- 0.21) | 0.78 (+/- 0.02) | 0.78 (+/- 0.16) | 0.76 (+/- 0.06) |
|          | L_SVM      | 0.83 (+/- 0.24) | 0.77 (+/- 0.21) | 0.72 (+/- 0.21) | **1.00 (+/- 0.00)** |
|          | LR         | 0.83 (+/- 0.24) | 0.70 (+/- 0.14) | 0.72 (+/- 0.21) | **1.00 (+/- 0.00)** |
|          | RF         | 0.98 (+/- 0.02) | 0.78 (+/- 0.02) | 0.81 (+/- 0.20) | 0.95 (+/- 0.07) |

Classifiers with Linguistic Features

We have trained various ML classifiers using linguistic features extracted from recorded language data (12 samples, 10 samples related to subjects without dementia and 2 samples related to subjects with dementia) that were collected using the phone-interface and the web-interface. Table 6 shows that the results obtained from the web-interface data is more accurate than the results obtained from the phone-interface data. Using 5 lexical features, the SVM (with the linear kernel) classifier and the LR can classify samples with 99.9% accuracy. However, using 8 syntactic features, we drop all ML classifiers’ performance, including the SVM (with the linear kernel); thus, the SVM can determine subjects with dementia with 83% accuracy. Similarly, if we use 4 semantic features to train classifiers, they can provide better performance than using 8 syntactic features.

Classifiers with Acoustic Features

We have developed the classifiers using the acoustic features extracted from the audio files. We used 16 phone-based recordings from 3 healthy adults and 1 dementia patient (each participant attended 4 sessions). Similarly, we have considered 8 web-based recordings from subjects with dementia (N = 3) and subjects with dementia (N = 5) (only 1 session each). We have followed the same approach to rank the acoustic features as we described before for the acoustic features. Table 8 shows the common features ranked by ANOVA, RF and mRMR methods. We use the top 15 features to train the classifiers. Table 7 shows the F1 scores obtained from the DT, ET, Linear SVM, RBF SVM, LDA, LR, kNN and RF algorithms. We have used scikit-learn’s default configurations and the 3-fold cross-validation method to calculate the F1 scores. We found that DT perform better for web-based recordings and linear the SVM showed better performance for phone-based recordings.

4.2.1 Comparison between the phone-based and the web-based interfaces

We have performed a one-way ANOVA test on the F1 scores of the phone and web-based recordings as shown in Tables 6 and 7. Our analysis shows that the means of these 2 groups are significantly different (F(1,126) = 4.26, p = 0.04).
AI-powered Language Assessment Tools for Dementia

(a) ROC curves of SVM trained by syntactic features

(b) ROC curves of SVM trained by 4 semantic features

Figure 10: ROC curves of SVM trained by syntactic and semantic features

Figure 11: The correlation between different features

Figure 15(b) shows the distributions of F1 scores of these 2 groups. A Tukey’s post-hoc test shows that the mean F1 scores of the classifiers developed by the extracted features from the phone-based recordings are higher than web-based recordings ($p = 0.04$), i.e., the ML classifiers trained with the phone-based recordings perform better than the web-based recordings.
AI-powered Language Assessment Tools for Dementia

![Figure 12: A comparison between the tangentiality measure for subjects with dementia and healthy subjects.](image)

Figure 12: A comparison between the tangentiality measure for subjects with dementia and healthy subjects.

| Web Feature | Phone Feature |
|-------------|---------------|
| MFCC 5,11,12 (mean) | MFCC 6, 9 (std) |
| ∆ MFCC 11, 13 (mean) | MFCC 3 (skew) |
| ∆ MFCC 0,3,6,9,10 (skew) | MFCC 3, 5 (kurt) |
| ∆ log Mel freq 0,5,6 (skew) | ∆ MFCC 0 (std) |
| Voicing prob. (kurt, std) | LSP freq 7 (mean) |
| ∆ Voicing prob. (kurt, mean, std) | LSP freq 2, 3, 4 (skew) |
| LSP freq 0 (kurt) | LSP freq 1 (kurt) |
| F0 (skew) | ∆ LSP freq 3 (mean) |
| Jitter local (kurt, skew) | ∆ LSP freq 5 (skew) |
| ∆ Jitter local (kurt) | log Mel freq 2 (skew) |
| ∆ Jitter DDP (kurt) | ∆ log Mel freq 1, 2, 3 (std) |
| ∆ Shimmer local (kurt) | Voicing prob. (kurt, std) |
|  | Loudness (kurt) |

| Web Feature | Phone Feature |
|-------------|---------------|
| MFCC 5,11,12 (mean) | MFCC 6, 9 (std) |
| ∆ MFCC 11, 13 (mean) | MFCC 3 (skew) |
| ∆ MFCC 0,3,6,9,10 (skew) | MFCC 3, 5 (kurt) |
| ∆ log Mel freq 0,5,6 (skew) | ∆ MFCC 0 (std) |
| Voicing prob. (kurt, std) | LSP freq 7 (mean) |
| ∆ Voicing prob. (kurt, mean, std) | LSP freq 2, 3, 4 (skew) |
| LSP freq 0 (kurt) | LSP freq 1 (kurt) |
| F0 (skew) | ∆ LSP freq 3 (mean) |
| Jitter local (kurt, skew) | ∆ LSP freq 5 (skew) |
| ∆ Jitter local (kurt) | log Mel freq 2 (skew) |
| ∆ Jitter DDP (kurt) | ∆ log Mel freq 1, 2, 3 (std) |
| ∆ Shimmer local (kurt) | Voicing prob. (kurt, std) |
|  | Loudness (kurt) |

4.3 Linguistic and Acoustic Features

Tables 6 and 7 show the results obtained by using ANOVA, RF and mRMR feature selection methods on phone and web-based recordings. We consider all F1 scores (total 256) to compare the performance between the classifiers trained with linguistic and acoustic features. Figure 15(c) shows the distributions of F1 scores of these 2 groups. A one-way ANOVA test performed on the F1 scores shows that the means are significantly different (F(1, 256) = 62.43, p ≈ 0). A Tukey’s test for post-hoc analysis shows that the mean F1 scores of the classifiers trained with the acoustic features are higher than the classifiers trained with the linguistic features (p = 0). That is, the ML classifiers trained with the acoustic features perform better than the classifiers trained with the linguistic features.

5 Discussion

This paper proposed an approach to develop an AI system to recognize different dimensions of language impairments in subjects with dementia. This section discusses what is the limitation of such a development and how we can develop a valid, reliable, fair, and explainable AI-based LA tool.
AI-powered Language Assessment Tools for Dementia

5.1 Data Limitation

No doubt having a lot of data samples, ML algorithms, which are cores of our AI-powered LA tool can learn better [72] to map linguistic features to the group of subjects (i.e., with dementia or without dementia). In other words, determining the optimal sample size for developing an efficient AI-powered LA tool assures an adequate power to detect statistical significance [73]. However, for our problem, collecting language data from too many subjects is expensive and needs a lot of time. Thus, even it is necessary to estimate what is the sufficient size of samples for achieving acceptable classification results and then start to develop an AI-powered assessment tool, but our results have shown that we could achieve good performance even with using the language data of less than 10 subjects (see Figure 16).

5.2 End-to-end Learning Approach

To develop an AI-powered language assessment tool, we can use an end-to-end learning approach. Table 9 presents the obtained results employing Convolutional Neural Networks (ConvNet/CNN) on classifying the textual datasets. It shows that we can obtain approximately same results using CNN to classify our dataset. It might be a good idea to employ deep learning algorithm if we have sufficient samples.

5.3 Generalization - Selecting Meaningful Features

One of the problems we have faced with the acoustic features is that when we have applied ANOVA, RF, and mRMR feature selection methods on different datasets (i.e., obtained from various recording media or language tasks), each time we have received different sets of features (see Tables 5 and 8). Therefore, we are interested in combining all features so that we get almost consistent performance with all datasets. For this purpose, we have used Principal Component Analysis of the SR Dataset

Figure 13: It shows that subjects with dementia and healthy controls cannot be linearly separated using 2 principle components.
AI-powered Language Assessment Tools for Dementia

Figure 14: It presents the values of cumulative explained variance for different number of principle components.

Table 9: Results from CNN

| Experiment          | Model Structure                                   | Accuracy |
|---------------------|---------------------------------------------------|----------|
| PD task             | 2-channel CNN, Filter Size= 4, Kernel Size=2      | 66.7%    |
| SR task             | 2-channel CNN, Filter Size= 4, Kernel Size=2      | 71.4%    |
| Recording Media (Web) | 2-channel CNN, Filter Size= 4, Kernel Size=2      | 80.0%    |
| Recording Media (PHONE) | 2-channel CNN, Filter Size= 4, Kernel Size=2 | 40.0%    |

Component Analysis (PCA) to combine a group of features, as shown in Table 10. We have considered MFCCs (0 to 14th order coefficients), the deltas of these MFCCs, and the deltas of LSP frequency bands (0 to 7) in the PCA because these groups of features appear more frequently in our rankings (see Tables 5 and 8). We found that the first two Principal Components (PCs) can retain, on average 75% of the variance, and hence we have considered only the first 2 PCs to train the classifiers. Table 11 shows how these PCA features perform with 4 different sets of data. Our results show that we achieved almost consistent performance with the tree-based classifies ranging from 78% to 93% F1 scores with these generalized set of features.

5.4 Is an AI-powered LA tool Valid and Reliable?

We refer to reliability as the measure to trust the classification results [74]. We can assess the reliability and validity of an AI-powered LA tool measuring the Intra-class Correlation Coefficient (ICC) [75] and the Pearson Correlation Coefficient (PCC) [75] (i.e., if PCC returns a value close to 1, then the ML tool provides valid results; however, if the value is below, 0.5 indicates less correlation and validation).
5.5 Is an AI-powered LA tool fair?

AI-powered LA tools are supervised classifiers, and are therefore prone to producing unfair results. In our work, we tried not to consider sensitive attributes such as gender, race as features [76]. However, we are working on different verbal tasks that might slightly be influenced by gender differences [77]. Another issue is that this type of assessment tool compares the user’s language against similar users who are assumed to have AD or MCI [78]. Another essential attribute that might affect the fairness of AI-powered LA tools is the level of education. It has been shown that some LA tools cannot provide accurate diagnosis when there are subjects with low levels of education among the population of study [10]. AI-powered LA tools require a set of mechanisms to ensure that end-users trust in their performances and know how the system provides output. It is essential to motivate people to adopt not only the methods but also to share their data. Fairness and explainability are essential concerns, especially as AI-powered assessment tools are being deployed more broadly in detecting other types of mental health problems. Fairness, in the end, comes down to robustness aspect. When we create our AI-powered assessment tool, we want it to be fair, and this means robust when deployed in different geographic settings and populations.
Figure 16: A description of using a power analysis to estimate the minimum sample size is required for achieving a desired effect size; It shows the impact of different effect sizes (es) and various sizes of the data sample on the statistical power.

| Feature Name  | Functional | Principle Component (PC) |
|---------------|------------|--------------------------|
| MFCC 0 - 14   | mean       | 1st PC from the means of 15 MFCCs |
|               |            | 2nd PC from the means of 15 MFCCs |
|               | kurt       | 1st PC from the kurt of 15 MFCCs |
|               |            | 2nd PC from the kurt of 15 MFCCs |
|               | skew       | 1st PC from the skew of 15 MFCCs |
|               |            | 2nd PC from the skew of 15 MFCCs |
| Δ MFCC 0 - 14 | mean       | 1st PC from the means of 15 Δ MFCCs |
|               |            | 2nd PC from the means of 15 Δ MFCCs |
|               | kurt       | 1st PC from the kurt of 15 Δ MFCCs |
|               |            | 2nd PC from the kurt of 15 Δ MFCCs |
|               | skew       | 1st PC from the skew of 15 Δ MFCCs |
|               |            | 2nd PC from the skew of 15 Δ MFCCs |
| Δ LSP freq 0 - 7 | mean    | 1st PC from the means of 8 Δ LSP freq |
|                 |            | 2nd PC from the means of 8 Δ LSP freq |
|                 | kurt       | 1st PC from the kurt of 8 Δ LSP freq |
|                 |            | 2nd PC from the kurt of 8 Δ LSP freq |
|                 | skew       | 1st PC from the skew of 8 Δ LSP freq |
|                 |            | 2nd PC from the skew of 8 Δ LSP freq |

5.6 Is an AI-powered LA tool Explainable?

An AI-powered LA tool should be accurate and explainable to be adopted by psychiatrists during their assessment procedures. Thus, it is essential to choose an ML algorithm to develop a reliable AI-powered LA tool that can describe its purpose, rationale, and decision-making process that can be understood by both clinicians and patients; it can foster the confidence of mental health professionals in employing it to detect subjects with dementia quickly.

5.7 What are other Application of an AI-powered LA tool?

Automated analysis of spontaneous connected speech can be useful for assessing and monitoring the progress of AD in patients. For example, integrating the AI-powered LA tools to a conversational robot that can record patients’ speech provides us, clinicians, an automated approach to follow the progress of the diseases [79]. In more detail, we can ask elderly individuals to describe the cookie theft picture to engage them to attend in a conversation. By extracting linguistic and acoustic features from the speech produced by them, we can identify if they are suffering
Table 11: Results obtained by applying ML algorithms on PCA-based acoustic features that are extracted from all datasets

| Classifier | PD (+/- 0.16) | SR (+/- 0.02) | Web (+/- 0.21) | Phone (+/- 0.16) |
|------------|---------------|---------------|----------------|------------------|
| DT         | 0.78 (+/- 0.16) | 0.78 (+/- 0.02) | 0.72 (+/- 0.21) | 0.80 (+/- 0.16)  |
| ET         | 0.61 (+/- 0.28) | 0.61 (+/- 0.28) | 0.68 (+/- 0.22) | 0.92 (+/- 0.10)  |
| kNN        | 0.61 (+/- 0.08) | 0.78 (+/- 0.02) | 0.61 (+/- 0.08) | 0.80 (+/- 0.28)  |
| LDA        | 0.50 (+/- 0.14) | 0.50 (+/- 0.14) | 0.50 (+/- 0.14) | 0.87 (+/- 0.09)  |
| R_SVM      | 0.61 (+/- 0.08) | 0.65 (+/- 0.18) | 0.72 (+/- 0.21) | 0.76 (+/- 0.17)  |
| L_SVM      | 0.50 (+/- 0.14) | 0.35 (+/- 0.33) | **0.89 (+/- 0.16)** | 0.67 (+/- 0.25)  |
| LR         | 0.72 (+/- 0.21) | 0.22 (+/- 0.16) | **0.89 (+/- 0.16)** | 0.60 (+/- 0.28)  |
| RF         | 0.54 (+/- 0.15) | 0.78 (+/- 0.02) | 0.79 (+/- 0.23) | **0.93 (+/- 0.07)** |

from the linguistic disorder associated with AD or MCI [79]. The AI-powered LA tools are the core part of any smartphone application that aims to support elderly individuals with limited access to clinical services to receive real-time, cost-effective health care services. It decreases the burden on the caregivers.

6 Conclusion

In this paper, we suggested an approach to develop an efficient AI-powered language assessment tool. Such a tool can accurately and quickly detect language impairment in the older adults. We showed that the assessment tool could be developed using traditional ML classifiers, which could be trained with various sets of linguistic and acoustic features. Our results showed that the classifiers that have been trained using the PD dataset perform better than the SR dataset. We also found that the dataset obtained using phone-based recordings could increase ML classifiers’ performance compared to the web-based dataset. Finally, we revealed that the classifiers trained only with the selected features using feature selection methods had higher performance than classifiers trained with the whole set of extracted features.

In the future, we will be working in the following directions: 1) Developing a cascade classifier that will be trained using both linguistic and acoustic features; 2) Using other types of data, such as eye-tracking; 2) Using few-shot ML algorithms and transfer learning techniques; 3) Considering pragmatic features such as fillers, GoAhead utterances, repetitions, incomplete words, and also contextual features using BERT (Bidirectional Encoder Representations from Transformers); 4) Using text data augmentation techniques such as EDA: Easy Data Augmentation techniques to augment data samples. 5) Classifying data.

7 Declarations

7.1 Consent for publication

It is not applicable to our manuscript

7.2 Ethics approval and consent to participate

The consent form has been approved by the Research Ethics Board protocol 31127 of the University of Toronto and has been signed by each subject has signed a consent form that has been.

7.3 Availability of data and material

The datasets and codes would be accessible upon sending requests to the first author.

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AI-powered Language Assessment Tools for Dementia

Author’s contributions

Dr. Parsa and Dr. Alam worked with the linguistic and acoustic features, respectively, and they contributed equally to the methodology and results in sections. Dr. Mihailidis reviewed the manuscript and provided valuable feedbacks on the manuscript.

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