Detecting cognitive decline using speech only: 
The ADReSS Challenge

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Abstract
Building on the success of the ADReSS Challenge at INTERSPEECH 2020, which attracted the participation of 34 teams from across the world, the ADReSS Challenge targets three difficult automatic prediction problems of societal and medical relevance, namely: detection of Alzheimer’s Dementia, inference of cognitive testing scores, and prediction of cognitive decline. This paper presents these prediction tasks in detail, describes the datasets used, and reports the results of the baseline classification and regression models we developed for each task. A combination of acoustic and linguistic features extracted directly from audio recordings, without human intervention, yielded a baseline accuracy of 78.87% for the AD classification task, a root mean squared (RMSE) error of 5.28 for prediction of cognitive scores, and 68.75% accuracy for the cognitive decline prediction task.

Keywords: Cognitive Decline Detection, Affective Computing, Alzheimer’s dementia, computational paralinguistics

1. Introduction
Dementia is a category of neurodegenerative diseases which entail long-term and usually gradual decrease of cognitive functioning. The main risk factor for dementia is age and, hence, it is increasingly prevalent in our ageing society. Due to the severity of the disease, institutions and researchers worldwide are investing considerably on dementia prevention, early detection and disease progression monitoring [1]. There is a need for cost-effective and scalable methods for detection of early signs of Alzheimer’s Dementia (AD) as well as prediction of disease progression.

Methods for screening and tracking the progression of dementia traditionally involve cognitive tests such as the Mini-Mental Status Examination (MMSE) [2] and the Montreal Cognitive Assessment (MoCA) [3]. MMSE and MoCA are widely used because, unlike imaging methods, they are cheap, quick to administer and easy to score. Despite its shortcomings in specificity in early stages of dementia, the MMSE is still widely used [4]. The promise of speech technology in comparison to cognitive tests is twofold. First, speech can be collected passively, naturally and continuously throughout the day, gathering increasing data points while burdening neither the participant nor the researcher. Furthermore, the combination of speech technology and machine learning creates opportunities for automatic screening and diagnosis support systems for dementia. The ADReSS Challenge aims to generate systematic evidence for these promises towards their clinical implementation.

As with its predecessor, the overall objective of the ADReSS Challenge is to host a shared task for the systematic comparison of approaches to the detection of cognitive impairment and decline based on spontaneous speech. As has been pointed out elsewhere [5, 6], the lack of common, standardised datasets and tasks has hindered the benchmarking of the various approaches proposed to date, resulting in a lack of translation of these speech based methods into clinical practice.

The ADReSS Challenge provides a forum for researchers working on approaches to cognitive decline detection based on speech data to test their existing methods or develop novel approaches on a new shared standardised dataset. The approaches that performed best on last year’s dataset [5] employed features extracted from manual transcripts which were provided along with the audio data [7, 8]. The best performing method [8] made interesting use of pause and disfluency annotation provided with the transcripts. While this provided interesting insights into the predictive power of these paralinguistic features for detection of cognitive decline, extracting such features, and indeed accurate transcripts from spontaneous speech remains an open research issue. This year’s ADReSS Challenge provides a forum for researchers working on approaches to cognitive decline detection based on spontaneous speech only: Alzheimer’s Dementia Recognition through Spontaneous Speech tasks provide more challenging and improved spontaneous speech datasets, requiring the creation of models straight from speech, without manual transcription, though automatic transcription is encouraged.

The ADReSS datasets are carefully matched so as to avoid common biases often overlooked in evaluations of AD detection methods, including repeated occurrences of speech from the same participant (common in longitudinal datasets). Variations in audio quality, and imbalances of gender and age distribution. The challenge defines three tasks:

1. an AD classification task, where participants were required to produce a model to predict the label (AD or non-AD) for a short speech session. Participants could use the speech signal directly (acoustic features), or attempt to convert the speech into text automatically (ASR) and extract linguistic features from this automatically generated transcript;
2. an MMSE score regression task, where participants were asked to create models to infer the patients’ MMSE score based solely on speech data; and
3. a cognitive decline (disease progression) inference task, where they created models for prediction of changes in cognitive status over time, for a given speaker, based on speech data collected at baseline (i.e. the beginning of a cohort study).

These tasks depart from neuropsychological and clinical evaluation approaches that have employed speech and language [9] by focusing on prediction and recognition using spontaneous speech. Spontaneous speech analysis has the potential to enable novel applications for speech technology in longitudinal, unobtrusive monitoring of cognitive health [10], in line with the theme of this year’s INTERSPEECH, “Speech Everywhere”.

NOTE: This preprint reports new research that has not been certified by peer review and should not be used to guide clinical practice.
This paper describes the ADReSS dataset and presents baselines for all ADReSS tasks, including feature extraction procedures and models for AD detection, MMSE score regression and prediction of cognitive decline.

2. Related work

There has been increasing research on speech technology for dementia detection over the last decade. The majority of this research has focused on AD classification, but some of it targets MCI detection as well [6]. These objectives are most closely related with our first task, namely, the AD classification task. Such related research includes the best performing models presented in the ADReSS challenge in 2020. These achieved an 85.45% [7] and 89.6% [8] accuracy in AD classification using acoustic features and text-based features extracted from manual transcripts. Classification based on acoustic features only was also attempted in [7], and obtained 76.85% accuracy with the IS10-Paralinguistics feature set (a low dimensional version of ComParE [11]) and Bag-of-Acoustic-Words (BoAW).

Few works rely exclusively on acoustic features or text features extracted through ASR. One of these achieved a 78.7% accuracy on a subset of the Cookie Theft task of the Pitt dataset, using different comprehensive paralinguistic feature sets and standard machine learning algorithms [12]. Another, using the complete Pitt dataset, obtained 68% accuracy using only vocalisation features (i.e. speech-silence patterns) [10]. A classification accuracy of 62.3% was reported in a study that used fully automated ASR features with a different dataset [13].

As regards the second task, regression over MMSE scores, there is less literature available and most of it has been presented in recent workshops [6]. Several of these works used the above mentioned Pitt dataset to extract different linguistic and acoustic features and predict MMSE scores. A recent study captured different levels of cognitive impairment with a multiview embedding and obtained a mean absolute error (MAE) of 3.42 [14]. Another study reported a MAE of 3.1, having relied solely on acoustic features to build their regression model (a set of 811 features) [15]. Error scores as low as 2.2 (MAE) have been obtained, but relying on non-spontaneous speech data elicited in semantic verbal fluency (SVF) tasks [16].

Studies addressing the progression task are far less common. Notable in this category is [17], which incorporated a comprehensive set of features (i.e. lexicosyntactic, semantic and acoustic) into Bayesian network with, reporting a MAE of 3.83 on prediction of MMSE scores throughout different study visits. Two other studies account for disease progression in classification experiments. One of them extracted speech-based from the ISLE dataset achieving 80.4% accuracy to detect intra-subject cognitive changes, that is, to distinguish healthy participants who remained healthy from those who developed some kind of cognitive impairment [18]. The second study uses SVF scores to build a machine learning classifier able to predict changes from MCI to AD over a 4-year follow-up, with 84.1% accuracy [19].

3. The ADReSS Datasets

We provided two distinct datasets for the ADReSS Challenge:

1. a set of recordings of speech recordings of Alzheimer's patients performing a category (semantic) fluency task [20] at their baseline visit, for prediction of cognitive decline over a two year period, and

2. a set of recordings of picture descriptions produced by cognitively normal subjects and patients with an AD diagnosis, who were asked to describe the Cookie Theft picture from the Boston Diagnostic Aphasia Examination [21, 22].

The recorded data also included speech from different experimenters who gave instructions to the patients and occasionally interacted with them in short dialogues. No transcripts were provided with either dataset, but segmentation of the recordings into vocalisation sequences with speaker identifiers [23] were made available for optional use. The ADReSS challenge’s participants were asked to specify whether they made use of these segmentation profiles in their predictive modelling. Recordings were acoustically enhanced with stationary noise removal and audio volume normalisation was applied across all speech segments to control for variation caused by recording conditions such as microphone placement.

The dataset used for AD and MMSE prediction was matched for age and gender so as to minimise risk of bias in the prediction tasks. We matched the data using a propensity score approach [24, 25] implemented in the R package MatchIt [26]. The final dataset matched according to propensity scores defined in terms of the probability of an instance of being treated as AD given covariates age and gender. All standardised mean differences for the age and gender covariates were < 0.001 and all standardised mean differences for age and two-way interactions between covariates were well below 1, indicating adequate balance for the covariates. The propensity score was estimated using a probit regression of the treatment on the covariates. The age/gender matching is summarised in Figure 1, which shows the respective (empirical) quantile-quantile plots for the original and balanced datasets. A quantile-quantile plot showing instances near the diagonal indicates good balance.

The resulting dataset encompasses 237 audio files. These were split into training and test sets, with 70% of instances allocated to the former and 30% allocated to the latter. These partitions were generated so as to preserve gender and age matching.

The dataset for the disease prognostics task (prediction of cognitive decline) was created from a longitudinal cohort study involving AD patients. The time period for assessment of disease progression spanned the baseline and the year-2 data collection visits of the patients to the clinic. The task involves classifying patients into ‘decline’ or ‘no-decline’ categories, given speech collected at baseline as part of a verbal fluency test. Decline was defined as a difference in MMSE score between baseline and year-2 greater than or equal 5 points (i.e. \( \text{mmse(baseline)} - \text{mmse(year2)} \geq 5 \)). This dataset has a total of 105 audio recordings split into training and test sets as with the diagnosis dataset (70% and 30% of recordings, respectively).

4. Data representation

4.1. Acoustic features

We applied a sliding window with a length of 100 ms on the audio files of the dataset with no overlap and extracted eGeMAPS features over such frames. The eGeMAPS feature set [27] resulted from an attempt to reduce the somewhat unwieldy feature sets above to a basic set of acoustic features based on their potential to detect physiological changes in voice production, as well as theoretical significance and proven usefulness in previ-
5. Diagnosis baseline

5.1. Task 1: AD Classification

The AD classification experiments were performed using five different methods, namely decision trees (DT), nearest neighbour (KNN), linear discriminant analysis (LDA), Tree Bagger (TB), and support vector machines (SVM). The results for accuracy in the AD vs Control (CN) classification task are summarised in Table 1. As indicated in boldface, DT achieved 78.92% and 72.89% accuracy using acoustic and linguistic features, respectively. On the test set, however, the results were reversed, with linguistic features producing an overall best accuracy of 77.46%, with the SVM classifier. Late fusion of the acoustic and linguistic models improves the accuracy on the test set further to 78.87% (Figure 2).

Table 1: Task 1: AD classification accuracy on leave-one-subject out CV and test data.

|       | LDA | DT   | SVM | TB   | KNN | mean (sd) |
|-------|-----|------|-----|------|-----|-----------|
| CV Acoustic | 62.65 | **78.92** | 69.28 | 65.06 | 65.06 | 68.19 (6.4) |
| CV Linguistic | 72.29 | 72.89 | 72.89 | 75.90 | 65.06 | 71.81 (4.0) |
| Test Acoustic | 50.70 | 60.56 | **64.79** | 63.38 | 53.52 | 58.59 (6.2) |
| Test Linguistic | 76.06 | 74.65 | **77.46** | 73.24 | 59.15 | 72.11 (7.4) |

5.2. Task 2: MMSE prediction

For this regression task we used five types of regression models: linear regression (LR), DT, support vector regression (SVR), Random Forest regression ensembles (RF), and Gaussian process regression (GP). The regression methods are implemented in MATLAB using the statistics and machine learning toolbox.

The results are summarised in Table 2. As with classification, DT regression outperformed the other models in CV, with a radial basis function kernel with box constraint of 0.1, and a sequential minimal optimisation solver. Random Forest regression ensembles (RF), and Gaussian process regression (GP, with a squared exponential kernel). The regression methods are implemented in MATLAB using the statistics and machine learning toolbox.

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Table 2: Task 2: MMSE score prediction error scores (RMSE) for leave-one-subject out CV and test data.

|                | LR | DT | SVM | TB  | KNN | mean (sd) |
|----------------|----|----|-----|-----|-----|-----------|
| Acoustic       | 6.88 | 6.88 | 6.96 | 7.89 | 6.71 | 7.06 (0.47) |
| CV             | 6.65 | 5.92 | 6.42 | 7.02 | 6.50 | 6.50 (0.40) |
| Acoustic       | 6.23 | 6.47 | 6.09 | 8.18 | 6.81 | 6.73 (0.84) |
| Test           | 5.87 | 6.24 | 5.28 | 6.94 | 5.43 | 5.95 (0.67) |

As before, we fused the predictions of the best models for each feature type, hoping that the diversity of models might improve classification. The confusion matrix for the fusion model is shown in Figure 3. This time, however, decision fusion did not yield any improvement in accuracy. However, it is noted that the recall (sensitivity) improved from 40% to 70% for patients exhibiting cognitive decline.

Figure 3: Task 3: Decision fusion of the best results of acoustic and linguistic features on the test set.

7. Discussion

The AD classification baseline yielded a maximum accuracy of 78.87% on the test set, through the fusion of models based on linguistic and acoustic features. Despite the fact that the ASR transcripts had relatively high word error rates, linguistic features contributed considerably to the predictions. The overall baseline results for this task are in fact comparable to results obtained for similar picture description data using manual transcripts (see Section 2). DT classifiers performed well on the CV experiments, but accuracy decreased on the test set, indicating probable overfitting. Overall, however, all models proved fairly robust.

A similar picture was observed in the MMSE regression task. Linguistic features contributed appreciably to the prediction, even though the transcripts contained many errors. In this case, however, late fusion only improved the RMSE score in CV; the test set RMSE remained practically unchanged.

The prognosis task proved to be the most difficult prediction task. The CV results varied considerably among models, with a standard deviation of 11.64 for the linguistic models. The test set results were also varied, reaching a maximum F1 score of 66.67%, even when the best model predictions were fused. Although the acoustic features produced the best classification results in CV (F1 = 66.05% vs 59.06% for linguistic features), these results were not born out by test set evaluation, suggesting that the acoustic features made the classifiers more prone to overfitting. It is possible that this could be mitigated by training the acoustic feature extractor (ADR) on a larger set of off-task recordings (data augmentation) and fine tuning the resulting model on the ADReSS data.

8. Conclusions

The ADReSS Challenge is the first shared task to target cognitive status prediction using raw, non-annotated non-transcribed speech, and to address prediction of changes in cognition over time. We believe this moves the speech processing and machine learning methods one step closer to the real-world of clinical applications. A limitation of the AD classification and the MMSE regression tasks share with most approaches to the use of these methods in dementia research is that they provide little insight into disease progression. This has been identified as the main issue hindering translation of these technologies into clinical practice [6] and, hence, preclinical modelling emerges as clear avenue for future research [31]. However, these tasks remain relevant in application scenarios involving automatic cognitive status monitoring, in combination with wearable and ambient technology. The addition of the progression task should open avenues for relevance also in more traditional clinical contexts.

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10. References

[1] K. Ritchie, I. Carrière, L. Su, J. T. O’Brien, S. Lovestone, K. Wells, and C. W. Ritchie, “The midlife cognitive profiles of adults at high risk of late-onset Alzheimer’s disease: The PREVENT study,” Alzheimer’s & Dementia, vol. 13, no. 10, pp. 1089–1097, 2017.

[2] M. F. Folstein, S. E. Folstein, and P. R. McHugh, “‘Mini-mental state’; a practical method for grading the cognitive state of patients for the clinician,” Journal of psychiatric research, vol. 12, no. 3, pp. 189–198, 1975.

[3] Z. S. Nasreddine, N. A. Phillips, V. Bédard, S. Charbonneau,
V. Whitehead, I. Collin, J. L. Cummings, and H. Chertkow, “The Montreal cognitive assessment, moCA: a brief screening tool for mild cognitive impairment,” *Journal of the American Geriatrics Society*, vol. 53, no. 4, pp. 695–699, 2005.

[4] I. Arevalo-Rodriguez, N. Smailagic, M. R. i Figuls, A. Ciapponi, E. Sanchez-Perez, A. Giannakou, O. L. Pedraza, X. B. Cosp, and S. Cullum, “Mini-mental state examination (mmse) for the detection of alzheimer’s disease and other dementias in people with mild cognitive impairment (mci),” *Cochrane Database of Systematic Reviews*, no. 3, 2015.

[5] S. Luz, F. Haider, S. de la Fuente, D. Fromm, and B. MacWhinney, “Alzheimer’s dementia recognition through spontaneous speech: The ADReSS Challenge,” in *Proceedings of INTERSPEECH 2020*, Shanghai, China, 2020. [Online]. Available: https://arxiv.org/abs/2004.06833

[6] S. de la Fuente Garcia, C. Ritchie, and S. Luz, “Artificial intelligence, speech and language processing approaches to monitoring Alzheimer’s disease: a systematic review,” *Journal of Alzheimer’s Disease*, vol. 78, no. 4, pp. 1547–1574, 2020.

[7] M. S. Syed, Z. S. Syed, M. Lech, and E. Pirotoga, “Automated Screening for Alzheimer’s Dementia Through Spontaneous Speech,” in *Proc. Interspeech 2020*, 2020, pp. 2222–2226.

[8] J. Yuan, Y. Bian, X. Cai, J. Huang, Z. Ye, and K. Church, “Classifiers and Fine-Tuning Pre-Trained Language Models for Detection of Alzheimer’s Disease,” in *Proc. Interspeech 2020*, 2020, pp. 2162–2166.

[9] V. Taler and N. A. Phillips, “Language performance in alzheimer’s disease and mild cognitive impairment: A comparative review,” *Journal of Clinical and Experimental Neuropsychology*, vol. 30, no. 5, pp. 501–556, 2008.

[10] S. Luz, “Longitudinal monitoring and detection of Alzheimer’s type dementia from spontaneous speech data,” in *Computer Based Medical Systems*. IEEE Press, 2017, pp. 45–46.

[11] B. Schuller, S. Steidl, A. Batliner, F. Burkhardt, L. Devillers, C. Müller, and S. S. Narayanan, “The INTERSPEECH 2010 paralinguistic challenge,” in *Procs. of the 11th Annual Conference of the International Speech Communication Association, INTERSPEECH 2010*, pp. 2794–2797.

[12] F. Haider, S. de la Fuente, and S. Luz, “An assessment of paralinguistic acoustic features for detection of alzheimer’s dementia in spontaneous speech,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 14, no. 2, pp. 272–281, 2020.

[13] B. Mirheidari, D. Blackburn, T. Walker, A. Venneri, M. Reuber, and H. Christensen, “Detecting Signs of Dementia Using Word Vector Representations,” in *Interspeech*, 2018, pp. 1893–1897.

[14] C. Pou-Prom and F. Rudzicz, “Learning multiview embeddings for assessing dementia,” in *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, 2018, pp. 2812–2817.

[15] S. Al-Hameed, M. Benaissa, and H. Christensen, “Detecting and predicting alzheimer’s disease severity in longitudinal acoustic data,” in *Proceedings of the International Conference on Bioinformatics Research and Applications*, 2017, pp. 57–61.

[16] N. Linz, J. Tröger, J. Alexandersson, M. Wolters, A. König, and P. Robert, “Predicting dementia screening and staging scores from semantic verbal fluency performance,” in 2017 IEEE International Conference on Data Mining Workshops (ICDMW). IEEE, 2017, pp. 719–728.

[17] M. Yancheva, K. C. Fraser, and F. Rudzicz, “Using linguistic features longitudinally to predict clinical scores for alzheimer’s disease and related dementias,” in *Proceedings of SLTAT 2015: 6th Workshop on Speech and Language Processing for Assistive Technologies*, 2015, pp. 134–139.

[18] J. Weiner and T. Schultz, “Detection of Intra-Personal Development of Cognitive Impairment From Conversational Speech,” in *Speech Communication: 12. IIT Symposium*, 2016, pp. 1–5.

[19] D. G. Clark, P. M. McLaughlin, E. Woo, K. Hwang, S. Hurtz, L. Ramirez, J. Eastman, R. M. Dukes, P. Kapur, T. P. DeRamus, and L. G. Apostolova, “Novel verbal fluency scores and structural brain imaging for prediction of cognitive outcome in mild cognitive impairment,” *Alzheimer’s and Dementia: Diagnosis, Assessment and Disease Monitoring*, vol. 2, pp. 113–122, 2016.

[20] A. L. Benton, “Differential behavioral effects in frontal lobe disease,” *Neuropsychologia*, vol. 6, no. 1, pp. 53–60, 1968.

[21] J. T. Becker, F. Boiler, O. L. Lopez, J. Saxton, and K. L. McGonigle, “The Natural History of Alzheimer’s Disease,” *Archives of Neurology*, vol. 51, no. 6, p. 585, 1994.

[22] H. Goodglass, E. Kaplan, and B. Barresi, *BDAE-3: Boston Diagnostic Aphasia Examination – Third Edition*. Lippincott Williams & Wilkins Philadelphia, PA, 2001.

[23] S. Luz, S. de la Fuente, and P. Albert, “A method for analysis of patient speech in dialogue for dementia detection,” in *Resources for processing of linguistic, paralinguistic and extra-linguistic data from people with various forms of cognitive impairment*, D. Kokkinakis, Ed. ELRA, May 2018, pp. 35–42.

[24] P. R. Rosenbaum and D. B. Rubin, “The central role of the propensity score in observational studies for causal effects,” *Biometrika*, vol. 70, no. 1, pp. 41–55, 04 1983.

[25] D. B. Rubin, “Matching to remove bias in observational studies,” *Biometrics*, vol. 29, no. 1, pp. 159–183, 1973.

[26] D. Ho, K. Imai, G. King, and E. A. Stuart, “Matchit: Nonparametric preprocessing for parametric causal inference,” *Journal of Statistical Software, Articles*, vol. 42, no. 8, pp. 1–28, 2011. [Online]. Available: https://www.jstatsoft.org/v042/i08

[27] F. Eyben, K. R. Scherer, B. W. Schuller, J. Sundberg, E. André, C. Busso, L. Y. Devillers, J. Epps, P. Laukka, S. S. Narayanan et al., “The Geneva minimalistic acoustic parameter set GeMAPS for voice research and affective computing,” *IEEE Trans. Affect. Comput.*, vol. 7, no. 2, pp. 190–202, 2016.

[28] B. MacWhinney, “Tools for analyzing talk part 2: The CLAN program,” 2017, pittsburgh, PA: Carnegie Mellon University. [Online]. Available: http://talkbank.org/manuals/CLAN.pdf

[29] M. A. Covington and J. D. McFall, “Cutting the gordian knot: The matchit: Nonparametric preprocessing for parametric causal inference,” *Journal of Statistical Software, Articles*, vol. 42, no. 8, pp. 1–28, 2011. [Online]. Available: https://www.jstatsoft.org/v042/i08

[30] MATLAB, version 9.6 (R2019a). Natick, Massachusetts: The MathWorks Inc., 2019.

[31] S. de la Fuente, C. Ritchie, and S. Luz, “Protocol for a conversation-based analysis study: Prevent-ED investigates dialogue features that may help predict dementia onset in later life,” *BMJ Open*, vol. 9, no. 3, 2019. 