

# MULTILINGUAL ALZHEIMER'S DEMENTIA RECOGNITION THROUGH SPONTANEOUS SPEECH: A SIGNAL PROCESSING GRAND CHALLENGE

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## ABSTRACT

This Signal Processing Grand Challenge (SPGC) targets a difficult automatic prediction problem of societal and medical relevance, namely, the detection of Alzheimer's Dementia (AD). Participants were invited to employ signal processing and machine learning methods to create predictive models based on spontaneous speech data. The Challenge has been designed to assess the extent to which predictive models built based on speech in one language (English) generalise to another language (Greek). To the best of our knowledge no work has investigated acoustic features of the speech signal in multilingual AD detection. Our baseline system used conventional machine learning algorithms with Active Data Representation of acoustic features, achieving accuracy of 73.91% on AD detection, and 4.95 root mean squared error on cognitive score prediction.

**Index Terms**— Alzheimer's dementia detection, speech processing, speech biomarkers.

## 1. INTRODUCTION

Dementia is a category of neurodegenerative diseases that entail a long-term and usually gradual decrease of cognitive functioning. As cost-effective and accurate biomarkers of neurodegeneration have been sought in the field of dementia research, speech-based “digital biomarkers” have emerged as a promising possibility. While there has been much interest in automated methods for cognitive impairment detection through speech by the signal processing and machine learning communities [1], most of the proposed approaches have not investigated which speech features can be generalised and transferred across languages for AD prediction, and to the best of our knowledge no work has investigated acoustic features of speech in multilingual AD detection. This SPGC, “ADReSS-M: Multilingual Alzheimer's Dementia Recognition through Spontaneous Speech” targets this issue by defining prediction tasks whereby participants train their models on English speech data and assess their models' performance on spoken Greek data. The models submitted to the challenge

focus on acoustic or linguistic features of the speech signal whose predictive power is preserved across languages.

This SPGC aims to provide a platform for contributions and discussions on applying signal processing and machine learning methods for multilingual AD recognition, and stimulate the discussion of machine learning architectures, novel signal processing features, feature selection and extraction methods, and other topics of interest to the growing community of researchers interested in investigating the connections between speech and dementia.

## 2. THE PREDICTION TASKS

The ADReSS-M challenge consists of the following tasks: (1) a classification task, where the model will aim to distinguish healthy control speech from AD/MCI speech, and (2) an MMSE score prediction (regression) task, where you create a model to infer the speaker's Mini Mental Status Examination (MMSE) score based on speech data. Participants could choose to do one or both tasks. They were provided with a training set and, two weeks prior to the paper submission deadline, with test sets on which to test their models. Up to five sets of results were allowed for scoring for each task per participant. All attempts had to be submitted together.

### 2.1. The data sets

This SPGC data sets were made available through Dementia-Bank<sup>1</sup>, upon request. The training dataset consists of spontaneous speech samples corresponding to audio 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 test[2]. The participants were speakers of English. The test set consists of spontaneous speech descriptions of a different picture, in Greek. The recordings were made in one of these languages. Participants were initially allowed access only to the training data (in English) and some sample Greek data (8 recordings) for development purposes.

<sup>1</sup><https://dementia.talkbank.org/>

The Greek recordings assess participants' verbal fluency and mood using a picture that the participant describes while looking at it. The assessor first shows the participant a picture representing a lion lying with a cub in the dessert while eating. The assessor then asks the participants to give a verbal description of the picture in a few sentences.

The training dataset was balanced with respect to age and gender in order to eliminate potential confounding and bias. As we employed a propensity score approach to matching we did not need to adjust for education, as it correlates with age and gender, which suffice as an admissible for adjustment (see [3, pp 348-352]). The dataset was checked for matching according to scores defined in terms of the probability of an instance being treated as AD given covariates age and gender estimated through logistic regression, and matching instances were selected. All standardized mean differences for the covariates were below 0.1 and all standardized mean differences for squares and two-way interactions between covariates were below 0.15, indicating adequate balance for those covariates.

## 2.2. Evaluation

The classification task is evaluated in terms of accuracy, specificity, sensitivity and  $F_1$  scores. For the regression task (MMSE prediction), the metrics used are the coefficient of determination and root mean squared error. The ranking of submissions is based on accuracy scores for the classification task (task 1), and on RMSE scores for the MMSE score regression task (task 2).

## 3. BASELINE MODELS

First we normalised the volume of audio files using FFMPEG's EBU R128 scanner filter. A sliding window of 1 s, with no overlap, was then applied to the audio, and eGeMAPS features were extracted over these frames. The eGeMAPS feature set [4] is a basic set of acoustic features designed to detect physiological changes in voice production. It contains the F0 semitone, loudness, spectral flux, MFCC, jitter, shimmer, F1, F2, F3, alpha ratio, Hammarberg index and slope V0 features, as well as their most common statistical functionals, totalling 88 features per frame. Given the eGeMAPS features, we applied the active data representation method (ADR) [5] to generate a frame level acoustic representation for each audio recording. The ADR method has been used previously to generate large scale time-series data representation. It employs self-organising mapping to cluster the original acoustic features and then computes second-order features over these clusters to extract new features [5]. This method is entirely automatic in that no speech segmentation or diarisation information is provided to the algorithm.

For task 1, we employed a Naïve Bayes classifier with kernel smoothing estimation. The ADR for feature extraction was optimised using a grid search ( $C = 5, 10, 15, 20, 25$ ). We achieved accuracies of 75.00% and **73.91%** on sample and test data respectively using 15+2 ADR, age and gender

features per recording. On the test set, specificity was 79.2%, precision was 75%, sensitivity was 68.2%, and  $F_1$  was 71.4%. The feature to training audio ratio was 19:237.

For the MMSE regression task (task 2), we employed a support vector machine (SVM) model with a RBF kernel with box constraint of 1, and sequential minimal optimization solver. The ADR for feature extraction was optimised using a grid search ( $C = 5, 10, 15, 20, 25$ ). This model achieved a root mean squared error (RMSE) of 3.887 ( $r = 0.348$ ) and **4.955** ( $r = 0.273$ ) on sample and test data respectively using 25+2 ADR, age and gender features per recording. The feature to training audio recordings ratio was also 29:237.

## 4. CONCLUSION

Spontaneous speech analysis has the potential to enable novel applications for speech technology in longitudinal, unobtrusive monitoring of cognitive health. By focusing on AD recognition using spontaneous speech, this SPGC investigates an alternative to neuropsychological and clinical evaluation approaches to AD detection and cognitive assessment. Furthermore, the multilingual setting provided by this SPGC allows the investigation of features that might generalise across languages, extending the applicability of the models. In keeping with the objectives of AD prediction evaluation, the ADReSS-M challenge provides a statistically matched data set so as to mitigate common biases often overlooked in evaluations of AD detection methods, including repeated occurrences of speech from the same participant, variations in audio quality, and imbalances of gender, age and educational level. We hope this might serve as a benchmark for future research on multilingual AD assessment.

## 5. REFERENCES

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