Speech-Based Alzheimer's Disease Classification System with Noise-Resilient Features Optimization

Virender Kadyan[1], Puneet Bawa[2], Mohd Mujtaba Akhtar[3], Muskaan Singh[4]

Speech and Language Research Centre,University of Petroleum and Energy Studies, Dehradun,India [1]
Chitkara University Institute of Engineering and Technology,Chitkara University, Punjab, India[2]
Speech and Language Research Centre,University of Petroleum and Energy Studies, Dehradun,India[3]
Cognitive Analytics Research Lab Intelligent Systems Research Centre,School of Computing, Ulster University, UK [4]

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Introduction

- Classify Alzheimer's disease by analyzing speech, which is a novel approach to early detection in the face of the global rise of AD.
- Feature selection for model accuracy emphasizes the importance of selecting the right features from speech data to enhance the accuracy of the machine learning model.
- Impact of background noise on classification addresses the challenge of background noise in speech recordings and its effect on classification accuracy.
- Comprehensive analysis provides an extensive analysis, covering dataset specifics, methodologies, and the overall architecture of the machine learning model.

Methodology

Noise Augmentation

This process uses a signal-to-noise ratio (SNR) of 15 to 20 dB to balance vocal clarity with realistic background noise.

$$Sig_{Noisy} = Sig_{Clean} + \frac{Power_{Noisy}}{\sqrt{SNR}} \times Noise \qquad (1)$$

System Architecture

1. Feature Extraction: Computes 13 Mel-Frequency Cepstral Coefficients (MFCC) from a Mel filterbank using a hamming window to capture spectral characteristics of speech.

$$M(f) = 1125 * ln(1 + \frac{f}{700}) \qquad (2)$$

2. Prosodic and Statistical Analysis: Prosodic features and seven statistical variables (e.g., IQR, standard deviation, Q25, Q75, min-fun, skewness, centroid) are analyzed for speech pattern insights.

Input:

- DementiaBank Pitt dataset : AD_{data}
- Background Noise: N_{back}
- SNR levels (SNR) : SNR_{best}

Output:

- Best performing model : M_{best}
- Optimal feature set : F_{best}
- Model performance : PM

Corpora Details

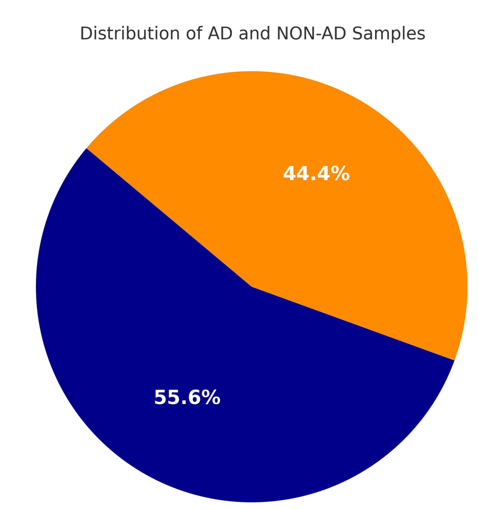

Figure 1. Dataset partition in AD and NON-AD

1. Source: DementiaBank Pitt dataset.
2. Composition:166 voice recordings—87 from individuals with AD diagnosis, 79 from healthy controls.
3. Diversity: Inclusive of both male and female speakers.
4. Application: Recordings were utilized in the training and testing set.
5. Content:Each recording is based on a visual depiction task from the Boston Diagnostic Aphasia Examination.

Proposed System Architecture

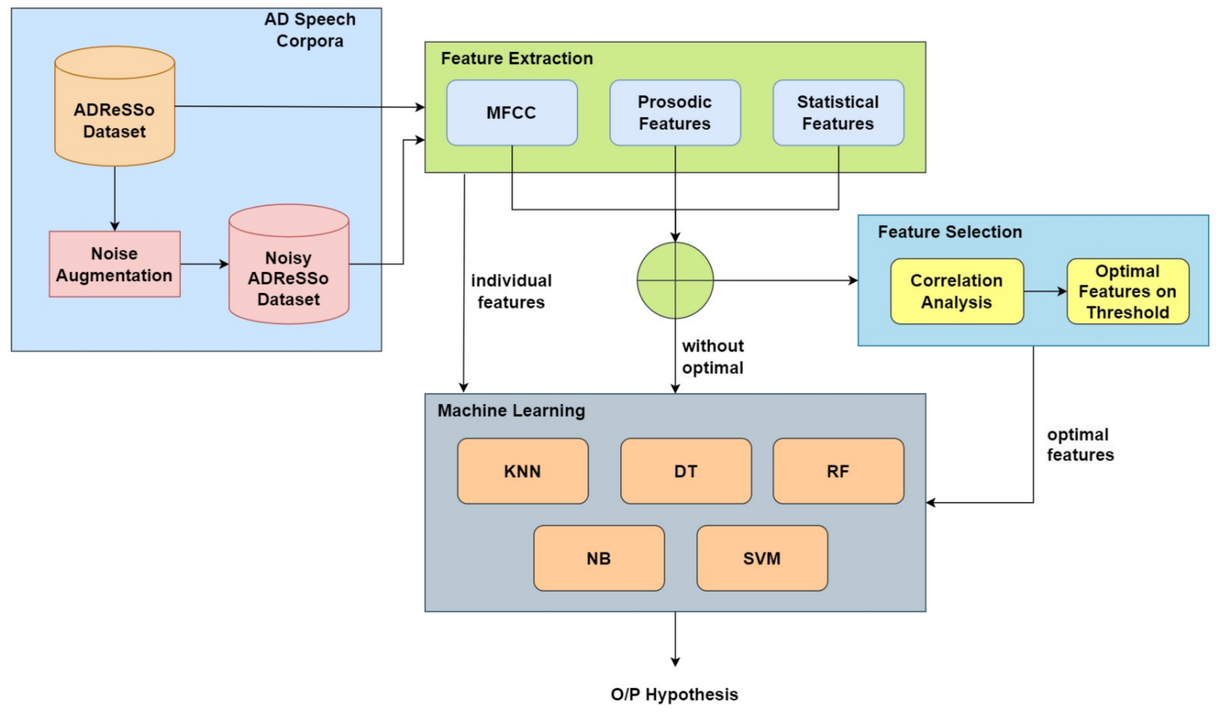

Figure 2. Block diagram depicting the proposed optimal feature selection-based noise-robust AD classification system using hybrid front-end

Results and Discussion

Our study rigorously evaluated several machine learning models (KNN, DT, RF, NB, SVM) in both clean and noisy environments, using a dataset split of 80% for training and 20% for testing.

1. Performance Evaluation in Clean Conditions
2. Optimal Feature Selection
3. Evaluation in Noisy Conditions

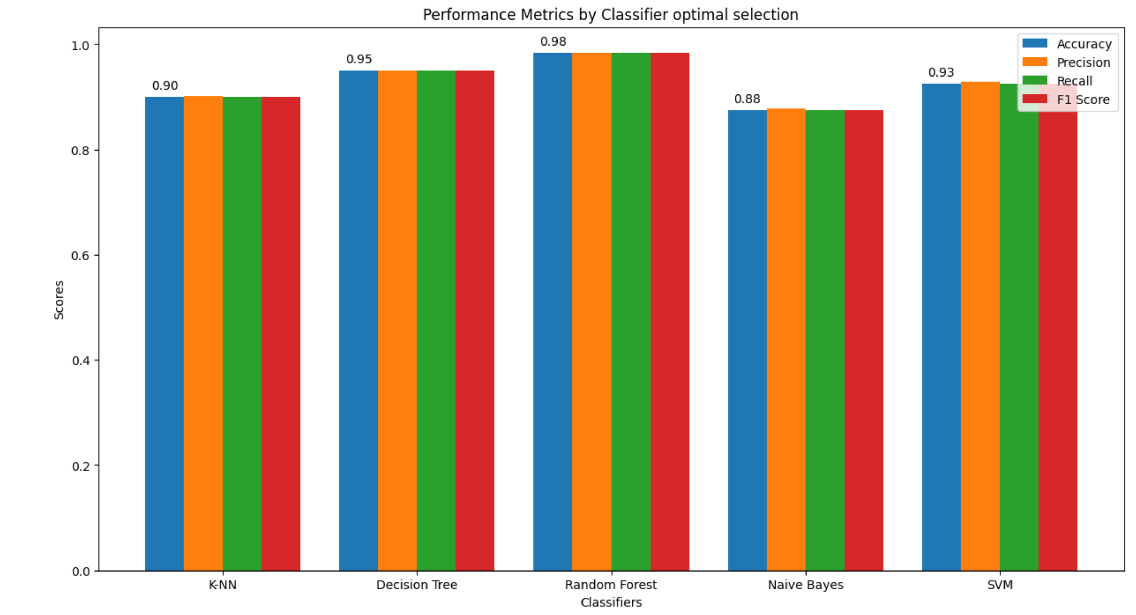

Figure 3. Performance analysis of machine learning classifiers

The experiments confirm the crucial role of feature selection in AD classification, with optimal features significantly improving model performance in diverse conditions.

Performance Evaluation on Noisy Conditions

This approach enhances the realism of the scenarios, thereby improving the robustness and applicability of our machine-learning models.

1. Enhanced Model Resilience: The RF-Optimal (RF-O) and SVM-Optimal (SVM-O) techniques, with optimal feature selection.
2. High Accuracy: An impressive accuracy rate of 98.3% was achieved, showcasing the superiority of these models in noisy conditions over traditional RF and SVM classifiers using non-optimal features.
3. Adaptability: This approach proves the models' ability to adapt and generalize across various scenarios, a critical factor in real-world applications.

Table 1. Accuracy obtained on optimal and non-optimal features using noise augmentation approaches

Classifiers	Accuracy	Precision		Recall		F1-Score	
		0	1	0	1	0	1
RF	0.97	0.97	0.97	0.97	0.97	0.97	0.97
SVM	0.93	0.93	0.95	0.92	0.95	0.93	0.93
RF-O	**0.98**	0.97	1.00	1.00	0.97	0.98	0.98
SVM-O	0.93	0.96	0.89	0.89	0.97	0.92	0.93