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A Comprehensive Review of Advancement in Speech-Based Approach for Alzheimer Disease Detection in India

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Abstract
Alzheimer's Disease (AD), accounting for 60%-70% of dementia cases, is poised to afflict India as the second-largest country by mid-century, as indicated by a recent World Health Organization (WHO) study. The socio-economic landscape in India presents unique challenges, with a population that may not be adequately educated on allocating resources for healthcare beyond the age of 60, especially for conditions like Alzheimer's, which currently lacks a definitive cure. Addressing this impending health crisis necessitates innovative, early diagnosis and cost-effective solutions. This comprehensive review paper explores the potential of utilizing speech data analysis for the early detection of Alzheimer's Disease (AD), offering a pragmatic approach to mitigate the severity of cases. By harnessing speech data, the aim is to diagnose the condition in its early stages, minimizing costs and enabling timely interventions to impede its progression. Early diagnosis is paramount, as it opens doors to effective treatments and preventative measures. The paper systematically reviews various processes involved in developing a mathematical model for the early detection of Alzheimer's Disease (AD). It delves into key aspects such as data collection methodologies, pre-processing techniques, feature extraction methods, and diverse classifiers. The intention is to provide a thorough understanding of the intricacies involved in creating an accurate and reliable model for early Alzheimer's detection. In light of Alzheimer's Disease (AD) representing a substantial majority of dementia cases, this review paper serves as a valuable resource for researchers, healthcare professionals, and policymakers. It fosters a deeper comprehension of potential avenues for leveraging speech data specifically in the context of Alzheimer's. As we confront the impending surge in Alzheimer's cases in India, this comprehensive review work contributes to the foundation of knowledge needed to develop scalable and accessible solutions, making a substantial impact on public health.

Keywords: *Alzheimer's Disease (AD); Speech Data Analysis; Diverse Classifiers; Scalable Solutions Impending Surge.*

1. Introduction
In an era characterized by advancing age demographics, the occasional lapses in memory or cognitive function accompanying the natural aging process raise concerns about more serious cognitive disorders. Dementia, an umbrella term for various conditions impacting memory, cognitive abilities, and daily functioning, presents a significant challenge due to its progressive nature. While dementia predominantly affects older individuals, its occurrence is not universal with aging, influenced by factors such as age, high blood pressure, diabetes, lifestyle choices, and social factors. Within the spectrum of dementia, Alzheimer's Disease (AD) takes center stage as the most prevalent form, contributing to a substantial proportion of cases. Complemented by other forms like vascular dementia, dementia with Lewy bodies, and frontotemporal dementia, the cognitive disorders landscape becomes intricate. The initial signs of Alzheimer's often manifest as subtle

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memory lapses and cognitive changes, evolving into more profound challenges in daily tasks as the disease progresses. Regrettably, there is currently no cure for Alzheimer's Disease (AD). The urgency for early detection and diagnosis is underscored, enabling individuals to access timely care and support [23]. This review paper ventures into the burgeoning field of acoustic feature-based Alzheimer's Disease (AD) detection using machine learning. The review paper explores the potential of leveraging acoustic features and cutting-edge machine learning techniques for detecting Alzheimer's Disease (AD). Through an exploration of existing literature, methodologies, challenges, and future directions, this review endeavors to offer a comprehensive overview of the evolving landscape at the intersection of acoustic features, machine learning, and Alzheimer's Disease (AD) detection.

2. Literature Survey

The literature reviews meticulously analysed scholarly works spanning the years 2020 to 2023, the review delved deeply into the vast array of feature extraction methodologies utilized during this period. The review extensively examined the spectrum of classifiers applied in the analysed studies, recognizing the pivotal role they play in Mathematical modal and data analysis. The review meticulously evaluated the efficacy of various evaluation metrics, including accuracy, precision, recall rate, and F1 scores. The methodology adopted in this review paper was carefully crafted from the extensive literature survey conducted. The review aimed to uphold the highest standards of accuracy, transparency, and reliability, thereby enhancing the credibility and robustness of its findings and conclusions. By deriving its methodology from the extensive literature survey, the review paper successfully integrated insights and perspectives from a diverse range of studies, thereby enriching its analysis and providing a comprehensive overview of the research landscape within the specified timeframe.

3. Methodology

The methodological framework employed in this study adheres to a structured sequence encompassing data collection, pre-processing, feature extraction, and classification, as depicted in Figure 1. Subsequent to these core stages, validation emerges as a mandatory

3.1 Data Collection

The collection of data explores two comprehensive methods for gathering speech data in Alzheimer's Disease (AD) (AD) research. The primary approach involves utilizing audio datasets from dementia banks like Dementia Bank's Pitt Corpus T. Becker,el al., [1], ADReSS Challenge dataset S. Luz, et al., [2], ADReSS-M Luz, S., et al., [3], Aphasia Bank, CCC, and RHDBank. These repositories allow researchers efficient access to diverse datasets, enabling the examination of various speech patterns associated with Alzheimer's across different cohorts. Of the total dataset, 70% can be used for training purposes, while the remaining 30% can be utilized for testing purposes. In a secondary approach, collaboration with healthcare professionals facilitates the acquisition of speech data from individuals diagnosed with AD and healthy controls. This ensures meticulous application of inclusion and exclusion criteria. The inclusion criteria encompass individuals aged 55 and above, including both males and females, categorized into two groups: patients clinically diagnosed with early-stage AD and age-matched healthy controls. Additionally, individuals with no clinical hearing impairment or history of significant neurological disorders are included. Furthermore, individuals diagnosed with Alzheimer's Disease (AD) or cognitive impairment by a Neurologist are considered. Exclusion criteria entail the presence of illnesses that may induce dementia, such as severe anemia, thyroid disorders, syphilis, HIV infection, etc., along with other neurological conditions leading to cognitive impairment, such as Lewy body dementia, Parkinson's disease, hydrocephalus, or vascular cognitive issues. Co-occurrence with severe heart, liver, kidney, or other medical conditions, or complications like serious hypertension or diabetes are also grounds for

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exclusion. previous severe stroke, extensive multiple cerebral infarctions, critical cerebral infarctions, or severe white matter lesions in medical history, as well as a history of prior psychiatric or psychological disorders, are additional exclusion criteria. The use of microphones and audio recorders ensures high-quality recordings. The length of recorded voice ranges from 20s to 120s. Structured questionnaires and images are employed to extract pertinent information such as medical history and demographics, thereby adding depth to the dataset.

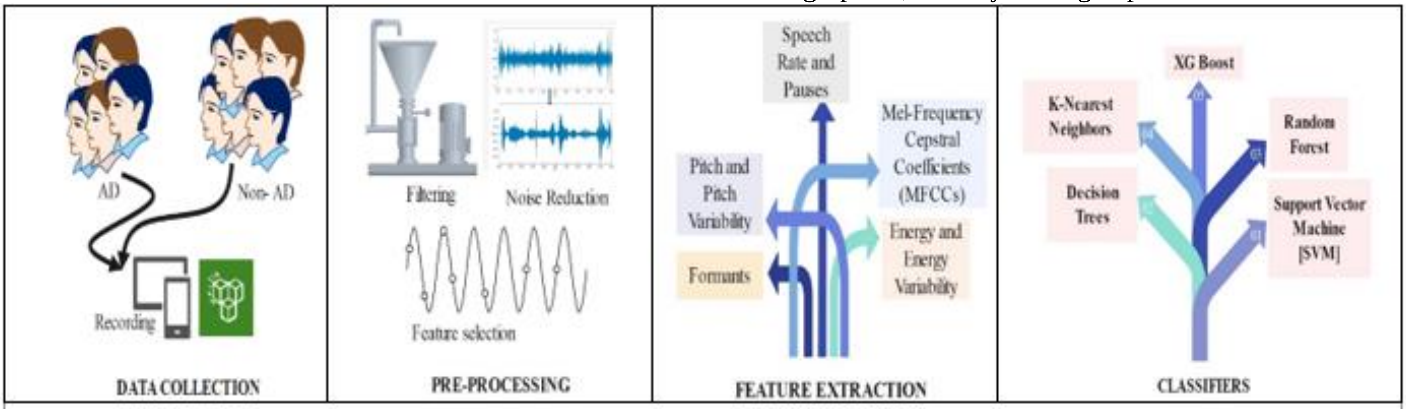

Figure 1 System Framework for AD Detection Method

3.2 Pre-Processing

The preprocessing of raw speech data constitutes a crucial initial phase in Alzheimer’s Disease (AD) (AD) research, particularly in the analysis of Spontaneous Speech recordings. This process involves a meticulously planned series of steps aimed at enhancing the quality of the data and preparing it for subsequent analysis, which is imperative for accurately detecting and labeling the stage of Alzheimer’s Disease (AD) using classifiers. One pivotal aspect of this preprocessing phase is the removal of interviewer intrusions, ensuring that only the speech segments of the participants are retained and processed. Additionally, the preprocessing method incorporates various techniques such as noise reduction, normalization, and dimensionality reduction. Noise reduction helps eliminate background noise and disturbances, thereby enhancing the clarity and intelligibility of the speech recordings. Normalization ensures that the speech data is standardized, Dimensionality reduction techniques are implemented to streamline the dataset by reducing its complexity, which can significantly improve the efficiency of subsequent analysis. The audio files are initially converted into the ‘.wav’ format, which is a widely used and standardized format for digital audio files. This conversion ensures compatibility and consistency in the data format, facilitating seamless integration with various analysis tools and algorithms.

3.3 Feature Extraction

Feature extraction plays a pivotal role in distilling meaningful information from the pre-processed data. Various techniques such as Mel-Frequency Cepstral Coefficients (MFCCs), Formants, Pitch and Pitch Variability, Energy and Energy Variability, Speech Rate and Pauses, Spectral Centroid and Spread, Voice Quality Measures, Articulation Rate, Speech Intensity, Formant Dynamics are employed to derive comprehensive features that encapsulate distinctive patterns indicative of Alzheimer's stages [20]. The methods exist for extracting features from speech data, leveraging Python, deep learning techniques, and toolkits such as the openSMILE v3.0.1 toolkit. This toolkit, an open-source software suite, specializes in the automatic extraction of features from speech signals. Within this toolkit, several built-in feature sets are available, including emobase, ComParE, eGeMAPS, MRCG functionals, and Minimal.

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Table 1 Presents A Summary of the Dataset Utilizing Solely Acoustic Features as Documented in the Literature

YEAR	NO OF PAPERS	DATA SET	FEATURE EXTRACTED
2023	[5], [7], [8], [9], [10], [11]	ADReSS-M, ADReSS, ADReSSo	IS10, Duration, Pause, Confidence score, Meta, ComParE, Acoustic, Disfluency
2022	[4], [12], [13], [16], [17]	ADReSS, Pitt Corpus, spontaneous speech	Mel Spectrogram, SoftMax (SM), VAD duration features, pleasure arousal dominance (PAD), Harmonicity to Noise ratio
2021	[8], [18], [19],[20], [21], [22], [23], [24], [25]	ADReSS, CCC, ADReSSo,	MFCC, Interactional features, COVAREP, Conventional acoustic features and wav2vec2.0 pre-trained acoustic embeddings, X-vectors & dominance embeddings, ADR, Bag-of-n-gram, Linguistic
2020	[2], [26]	DementiaBank (TalkBank), ADReSS	MMSE, Disfluency, ComParE, Interventions

This method has been extensively utilized in recent research studies, including those conducted by Tamm et al., 2023 [9], Liu, J. 2023 [10], and Sarawgi et al., 2020. These studies highlight the effectiveness and versatility of the openSMILE toolkit in extracting pertinent features from speech data, contributing to advancements in various fields, particularly in the analysis of speech-related phenomena. VoxCeleb 1 and 2 datasets were utilized for extracting i-vectors and x-vectors from the challenge data. The i-vector and x-vector systems were constructed using Kaldi, a toolkit renowned for its applications in speech recognition (Povey et al., 2011) [6]. This method has been employed in notable research papers, including Pérez-Toro et al., 2021 [22], and Wang et al., 2021 [25]. These studies underscore the utilization of Kaldi toolkit in extracting essential vectors, showcasing its efficacy and relevance in advancing research in various domains, particularly in the realm of speech analysis and recognition. VGGish is a deep, pretrained TensorFlow model utilized as a feature extractor. It functions as an audio embedding generated through the training of a modified VGGNet model, specifically designed to predict video tags from the YouTube-8M dataset Chlasta, K., & Wołk, K. (2021) [4]. This approach underscores the versatility and adaptability of VGGish in extracting meaningful features from audio data, contributing to advancements in various applications, particularly in the realms of audio processing and analysis. Wav2vec2.0 comprises a multi-layer convolutional feature encoder responsible for encoding raw waves into latent representations, accompanied by a quantization module for masking, and a Transformer for deriving textualized representations. These representations are optimized through the minimization of a connectionist temporal classification (CTC) loss. This method has been employed in scholarly works such as those by Balagopalan et al., 2021 [21], and Zhu et al., 2021 [24]. These studies underscore the utilization of Wav2vec2.0 in achieving efficient and effective encoding of waveforms, contributing to advancements in various fields, particularly in the domain of speech processing and analysis. The Mel-Frequency Cepstral Coefficients (MFCC) technique is extensively elucidated in the review paper authored by Liu et al. in 2021. [18] Additionally, a detailed explanation of MFCC can also be found in the work of De Lara, J. R. C. in 2005. These papers delve into the theoretical foundations,

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computational processes, and practical applications of MFCC in speech processing and analysis. Presents A Summary of the Dataset Utilizing Solely Acoustic Features as Documented in The Literature Shown in Table 1.

3.4 Classifiers

After extracting features from the speech data, the subsequent step involves training mathematical models. This process entails partitioning the dataset, typically with 70% allocated for training and the remaining 30% for testing purposes. Various mathematical models are employed for Alzheimer's Disease (AD) detection, encompassing machine learning and deep learning methodologies. In a comprehensive review paper, the classifiers are categorized into two main types:

- Machine learning
- Deep learning

Table 2 The Methods with Comparison of Accuracy, Precision Recall and F1 Score

Paper Reviewed	Classifier	A	P	R	F1
Chen et al., 2023 [7]	SVM	69.6%	69.2%	75.0%	72.0%
Shah et al., 2023 [8]	LR	69.6%	-	-	-
Tamm et al., 2023 [9]	attention pooling+MLP	82.6%	88.9 %	-	80.0%
Liu, J. [10]	SVM, DT	80%	-	-	-
Jin et al., 2023 [11]	Swin transformer, RF	86.7%	-	-	-
Davuluri et al. [12]	VGG-16	95.83%	-	-	-
Flavio Bertini et al. [13]	Auto encoder and MLP with data augmentation	93.30%	90.7%	86.5%	88.5%
Wang et al., 2022a [14]	SVM	91.7%	88.5%	95.8%	92.0%
Wang et al., 2022b [15]	SVM	93.8%	92.0%	95.8%	93.8%
AI-Atroshi, C., [16]	GMM-DBN	90.28%	-	-	90.19%
Perez et al. [17]	eXtreme Gradient Boosting, ForestNet	79%	-	-	-
Wang et al., 2022b [15]	SVM	93.8%	92.0%	95.8%	93.8%
AI-Atroshi, C., [16]	GMM-DBN	90.28%	-	-	90.19%
Perez et al. [17]	eXtreme Gradient Boosting, ForestNet	79%	-	-	-
Wang et al., 2022b [15]	SVM	93.8%	92.0%	95.8%	93.8%
AI-Atroshi, C., [16]	GMM-DBN	90.28%	-	-	90.19%
Perez et al. [17]	eXtreme Gradient Boosting, ForestNet	79%	-	-	-
Wang et al., 2022b [15]	SVM	93.8%	92.0%	95.8%	93.8%
AI-Atroshi, C., [16]	GMM-DBN	90.28%	-	-	90.19%
Perez et al. [17]	eXtreme Gradient Boosting, ForestNet	79%	-	-	-
Wang et al., 2022b [15]	SVM	93.8%	92.0%	95.8%	93.8%
AI-Atroshi, C., [16]	GMM-DBN	90.28%	-	-	90.19%

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Machine learning classifiers encompass a range of algorithms including Support Vector Machines (SVM), Random Forest, Decision Trees, k-Nearest Neighbors (k-NN), Logistic Regression, Gaussian Naive Bayes, and Ensemble methods like AdaBoost and Gradient Boosting Machines (GBM). These classifiers utilize statistical techniques to learn patterns from the training data and make predictions based on learned relationships. Support Vector Machines (SVM): SVM is a machine learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best separates two classes in a dataset, with the maximum margin between the classes. SVM classifiers have been widely employed in various algorithms due to their ability to achieve high classification accuracy. For example, Nasreen et al. [19] achieved an accuracy of 90% using SVM, while Randa Ben Ammar et al. [26] achieved an accuracy of 91% with the same classifier. On the other hand, deep learning classifiers leverage neural network architectures with multiple layers to automatically learn hierarchical representations of the input data. Common deep learning models for Alzheimer's Disease (AD) detection include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformer-based models, and Siamese networks. In addition, evaluation metrics such as accuracy, precision, recall, and F1 score are often used to assess the performance of classifiers. These metrics quantify different aspects of a classifier's performance, such as its ability to correctly classify instances of Alzheimer's Disease (AD), its ability to avoid misclassifications, and its overall effectiveness in capturing both true positive and true negative instances. By comparing the performance metrics obtained from recent papers, researchers can identify the most effective method for achieving high accuracy in Alzheimer's Disease (AD) detection. This comprehensive approach aids in selecting the most suitable classifier for the specific task at hand, considering factors such as the nature of the data, computational resources, and the desired level of performance. The Methods with Comparison of Accuracy, Precision Recall and F1 Score Shown in Table 2.

4. Frequently Applied Evaluation Metrics

In the realm of mathematical modeling, classification tasks commonly rely on a set of evaluation metrics to assess performance. These metrics include accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). Accuracy (Acc): Accuracy stands as a fundamental measure in classification, representing the ratio of correctly predicted samples to the total number of samples.

$$Acc = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \times 100 \qquad \ldots(i)$$

where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative rates, respectively. Precision (P_r): Precision gauges the proportion of true positive samples among those predicted as positive.

$$Precision = \frac{T_P}{T_P + F_P} \times 100 \qquad \ldots(ii)$$

Recall (Re): Recall, or sensitivity, reflects the percentage of true positive samples accurately identified among all actual positives.

$$Re = \frac{T_P}{T_P + F_N} \times 100 \qquad \ldots(iii)$$

F1-score: The F1-score combines precision and recall into a single metric, providing a harmonic mean of the two. It is especially useful in scenarios with class imbalance.

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100 \quad F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100 \qquad \ldots(iv)$$

These evaluation metrics collectively offer insights into classification model performance, illuminating the balance between true positive and false positive rates. By employing these measures, researchers can effectively evaluate model accuracy and make informed decisions regarding model selection and refinement.

Conclusion

In conclusion, Alzheimer's Disease (AD) poses a significant challenge globally, particularly in countries like India where the aging population is on the rise. The impending surge of Alzheimer's cases

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necessitates innovative approaches for early detection and intervention, especially considering the socioeconomic landscape and resource constraints in such regions.This comprehensive review paper has explored the potential of utilizing speech data analysis as a tool for the early detection of Alzheimer’s Disease (AD). By leveraging speech data, researchers aim to diagnose the condition in its early stages, enabling timely interventions to mitigate its progression. The paper systematically reviewed various processes involved in developing mathematical models for early Alzheimer's detection, encompassing data collection methodologies, pre-processing techniques, feature extraction methods, and diverse classifiers. By delving into the intricacies of these processes, the paper provides valuable insights for researchers, healthcare professionals, and policymakers grappling with the challenges posed by Alzheimer’s Disease (AD). As India braces for the impending surge in Alzheimer's cases, this review work serves as a foundation for the development of scalable and accessible solutions to address the growing public health crisis. The study also highlights the importance of evaluating classification models using standard metrics such as accuracy, precision, recall, and F1-score. By comparing the performance of various classifiers, researchers can identify the most effective methods for Alzheimer’s Disease (AD) detection, thus guiding future research and clinical practice.

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