LANGUAGE CHARACTERISTICS SUPPORTING EARLY ALZHEIMER'S DIAGNOSIS THROUGH MACHINE LEARNING – A LITERATURE REVIEW

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ABSTRACT

Alzheimer's dementia (AD) is the most common incurable neurodegenerative disease worldwide. Apart from memory loss, AD leads to speech disorders. Timely diagnosis is crucial to halt the progression of the disease. However, current diagnostic procedures are costly, invasive, and distressing. Early-stage AD manifests itself in speech disorders, which implies examining those. Machine Learning (ML) represents a promising instrument in this context.

Nevertheless, no genuine consensus on the language characteristics to be analyzed exists. To counteract this deficit and provide topic-related researchers with a better basis for decision-making, we present, based on a literature review, favourable speech characteristics for the appliance toward AD detection via ML. Research trends to apply spontaneous speech, gained from image descriptions, as analysis basis, and points out that the combined use of acoustic, linguistic, and demographic features positively influences recognition accuracy. In total, we have identified 97 overarching acoustic, linguistic and demographic features.

KEYWORDS

Alzheimer's dementia, Diagnostic support, Speech, Impairment, Machine learning.

1. INTRODUCTION

Throughout the globe, AD is presently considered the most common underlying cause of neurodegenerative dementia. Approximately 70-76% of dementia cases occur in developed countries, whereby the population lifespan is continually expanding [1]. As a consequence, the number of people affected by dementia-related diseases such as AD is also increasing. If one also considers the falling birth rates, a future rapid growth in the number of people affected becomes even more apparent [2].

Moreover, while the underlying cause is unknown, it is clear that AD begins maliciously during adulthood and is likely to have multiple factors, resulting in cognitive and behavioural impairments. The damages caused are progressive and irreversible. The absence of a cure leads to deterioration and death of the nervous system regardless of the cause [1].

The first manifestations include memory loss, which is compounded by difficulties in language use, the ability to perform everyday activities or, in more advanced stages, even problems in performing essential bodily functions such as walking or swallowing. Ultimately, the patient loses his or her autonomy entirely and requires a caregiver or relative [3]. AD is already one of the costliest chronic diseases in society. For relatives, it is not only the financial challenge but

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also the care itself that is a burden, significantly when character and behaviour changes [4, 5]. As AD develops slowly over the years, early identification is crucial to initiate timely treatment and slow its progression [6].

Yet current early detection methods, such as Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI), are expensive and invasive [4]. Especially in AD diagnosis, a slow and cumbersome procedure which is a deterrent for many, new non-invasive technologies are sought to avoid depriving older adults of their independence and thus discouraging them from attempting diagnosis [7].

Recent research suggests that the analysis of speech and language offers a precise, easy-to-use and non-invasive method for the early detection of AD biomarkers. This presumption bases on the fact that speech production is a complex task involving several cognitive areas in addition to the language itself, including memory, attention and planning. Subtle language changes can, therefore, be observed years or even decades before the initial diagnosis. It is therefore apparent that language, in particular, is worth examining for an early diagnosis, mostly as language disorders spread rapidly and are nevertheless underestimated [6, 7].

Due to the technological progress in the field of Artificial Intelligence (AI) over the last decade and the resulting increasing acceptance among the scientific community, research in the field of pathological speech recognition, particularly in AD, has focused on ML techniques [8]. The application of ML methods creates systems that provide convenient and immediate assistance in recognition of speech pathologies, thus contributing to faster, better and more economical care [7].

However, the identification and classification of voice pathologies are one of the biggest challenges in speech-based examinations. Information system-supported language analyses are, therefore, such a demanding task, as separate models have to be designed and trained for different languages and the dialects they contain [9].

Voice-based diagnostic applications offer significant advantages, mainly due to their high accuracy and the rapid availability of results, especially due to the very high information content of speech [7, 10]. Thanks to the numerous techniques of ML-based language analysis, this information content becomes accessible.

To provide the best diagnosis support for AD through language, it is of utmost importance to precisely understand which language characteristics indicate AD at an early stage. At present, the research community does not yet have a real consensus on this issue. Therefore, the following research question emerges:

Which speech characteristics (features) are particularly noticeable in AD's early stages and should therefore be considered a supportive diagnosis within an ML approach?

To answer this question, we first investigate the linguistic anomalies in AD by exploring the current research on language changes in AD utilizing linguistic studies. Subsequently, we examine existing approaches to detect AD by speech concerning the employed speech characteristics.

2. LANGUAGE AND AD

Most AD patients initially seem unaffected in their everyday communication, as those affected succeed in compensating their deficits at the beginning of the disease. Recent research shows that speech production is impaired even in the preclinical stages of AD [7].

While Alzheimer [11] already identified significant speech use deficits when examining the first AD patient documented, there are hardly any well-established test batteries that target speech reduction symptoms in dementia. Consequently, AD diagnosis through speech remains inadequate to its full potential even today [12].

Language-associated skills examined in AD diagnostics are therefore limited to subtests on word fluency and confrontational naming. In this regard, AD patients perform significantly worse than healthy volunteers. Particularly noticeable are difficulties in naming low-frequency terms. If we look at AD patients' everyday communication, the deficits are not limited to word fluency and word-finding difficulties in the early stages. Lacks encountered can, therefore, appear on all linguistic levels [12].

2.1. Current State of Research

Bayles [13] was able to prove the decline in semantic competencies in middle stage AD. Proof provides the result of the applied naming task. Thus, patients increasingly named similar expressions rather than the term they sought. Some answers also indicated a complete disagreement with the desired terminology. The results also supported hypotheses about the retention of morphosyntactic abilities in early AD stages. Evidence was provided by presenting incorrect sentences that needed correction from a linguistic point of view. The subjects mainly corrected syntactical errors. Since semantic mistakes were the most noticeable, Bayles [13] was able to confirm semantic impairments repeatedly.

In contrast, syntactically utterances remained mostly unaffected. The same study also revealed an increasing information deficit among expressions [13]. Later research again supported this finding [14]. Perri [15] was able to identify a significant semantic impoverishment through a feature listing task even in the early stages of the disease. Phonetic competencies, however, did not reveal any considerable deficits. Therefore, it is reasonable to conclude that the phonological level remains intact over a more extended period in the disease's course. Several studies could also confirm word-finding problems in the preliminary stages of AD.

With the aid of picture descriptions and story retellings, it was possible to reach such a result. Researchers have also demonstrated the increasing occurrence of reformulations, repetitions, and longer pauses in speech [16, 17].

In a further study, the declining naming performance in the early stages of AD was examinable using the Boston Naming Test (BNT). The affected test persons were thus able to name just three-fifths of the terms required correctly. Within the present research and other research, a different subject investigated was the processing of ambiguities. Findings demonstrated that AD subjects performed significantly worse than the control group. As a result, the presumption that sufferers cannot adequately reconstruct context even in the early stages of the disease is validatable [18, 19].

Concerning deficits in usage and reprocessing of pictographic language in AD in the sense of contextual comparison, there were also significant differences between healthy and diseased respondents [19]. The vocabulary reduction in the early stages was verifiable by comparing the total number of words in a narrative with word forms. Researchers have also demonstrated increasing difficulty using low-frequency words based on a listing test [20]. About early-stage

AD, the reduction of grammatical complexity has also been validated. Beyond these findings, insights into pronoun usage in AD patients was obtainable. Results indicate increased use of pronouns in spontaneous speech and decreasing sensitivity to pronouns' grammatically correct use. Spontaneous speech refers to unprepared spoken language that occurs without prompting or during unstructured interviews [21].

Further observations show that speech reception in AD patients can be better understood when production uses the nominal form, preferably based on pronouns. In the control group, however, the exact opposite was true [22]. Complementary evidence suggests increased use of unassignable pronouns in AD patients [20, 23]. The researchers also examined the processing of metaphors and proverbs in AD patients. Regarding metaphors, patients mainly had problems with the acquisition of the transmitted meaning. About idioms, AD sufferers were often unable to understand the literal sense [24].

Finally, evidence of a significantly increased use of early learned formulaic expressions and phrases were demonstratable in the AD language [25]. In a study by Boyé [26], 12 linguistic abnormalities were discernible in a picture description task than healthy test individuals. Thus, AD patients talk less in the same speaking time. They display a higher number of speech turns. The patients change the discourse more often and produce shorter stories.

Furthermore, the speech output is slower. Yes, and no phrases are commonly found. Empty pauses occur increasingly [26].

Also noticeable is the increased use of pronouns, especially in the first person singular. Lexical diversity is becoming progressively restricted. Besides, more and more high-frequency words are used [26]. In an article by Szatloczki [6], it is also visible that all levels of language, from the phonetic, lexical, syntactic, semantic, and discourse levels, are increasingly deficient as the disease progresses. Especially temporal characteristics such as speech rate, number of pauses, and length have proven to be sensitive detectors for the early detection of the disease.

Furthermore, Yancheva [27] found that the impairment of working memory associated with AD affects syntactic constructions in the language. As a result, shorter utterances, less complex sentences, a higher number of pronouns, and overall lexical impoverishment are apparent. From these studies, it becomes evident that AD is characterizable by various spoken language changes. Despite the current state of knowledge regarding moderate and advanced stages of the disease, little is distinct about the early and preclinical settings.

Early diagnosis is, therefore, difficult. Very few authors deal with the first linguistic changes occurring in AD [12]. Researchers have increasingly used ML techniques over the last ten years to address this challenge broadly and as effectively as possible [8].

3. RESEARCH METHOD

A literature review based on Webster [28] aimed to understand the complex problem of pathological speech production in AD and its detection through a computerized approach. We searched the scientific databases PubMed Central, ACM Digital Library, Web of Science and Elsevier, and the academic search engine Google Scholar for relevant content. We paid attention to the fact that the results are peer-reviewed journals and peer-reviewed conferences to guarantee the best possible quality of the sources to be used. Also, we only included publications published from 2010 onward to ensure topicality. Since recognizing linguistic deterioration with ML techniques emerged only in the last ten years, there would not have been any added value using older publications.

The search string consisted of different logical combinations of the terms *'Alzheimer*', 'mild cognitive impairment', 'mci', 'speech', 'language', 'voice', 'detec*', 'recogni*', 'identify*', 'diagno*', 'predic*, 'early', 'impairment'* and *'machine learning'*. Since the different databases use different search string input syntaxes and have different emphases, we adapted the strings to the respective database demands. Similarly, within these databases, we adapted different keywords concerning the search in title or abstract. The exploration resulted in a total of 52 hits. Out of 52 originally identified sources, we rejected 30 due to a lack of relevance according to multiple criteria. We regarded articles as relevant if the abstract fulfilled three out of the four criteria. These criteria include:

Purpose of performing AD/Mild Cognitive Impairment (MCI) recognition based on speech through ML techniques Contribution to an improved selection of speech characteristics The approach involves ML techniques The approach provides invaluable background knowledge.

In the examination of the applied approaches, sources had to fulfil the first criterion in each case. Otherwise, we directly classified them as irrelevant. Additionally, we assigned the references to thematic blocks according to a variety of relevance criteria, ensuring a systematic approach:

High thematic relevance to language in AD Presentation of a speech-based system in AD detection Production and implementation of a speech-based system in AD detection Beneficial background information regarding speech in AD.

For us to include a source, they had to meet at least one of these points. In the further course of the research, additional relevant sources regarding language changes in AD were identified through backward searching using Google Scholar. Furthermore, the conducted forward search led to up-to-date contributions to the topic. Thus we obtained another 57 content-relevant sources.

4. APPLIED APPROACHES

In the literature review we identified 22 promising approaches to AD detection through speech, including ML techniques. We have paid particular attention to the extracted speech characteristics, the applied speech production task, the classification algorithms employed, the size of the data set used, and the resulting recognition accuracy that these approaches achieve.

Based on the literature research results, we can justify which language features in combination with which language generation methodology ought preferably includable in a model for AD language decay detection using ML methods. We outline these prominent language features in chapter 5. The reviewed approaches, grouped by the different combination of acoustic, linguistic and demographic feature types, are presented in Table 1.

Toward classification purposes at all, it is necessary to convert the entries into an analyzable format. Besides, suitable metrics for speech analysis need identification and extraction. A precise classification is achievable through either of the two techniques. One approach analyzes speech at the acoustic level by directly interpreting occurring speech characteristics based on the audio file. Regarding pathological speech recognition, especially concerning AD speech, it is interesting to look at acoustic features like pitch, energy, and pauses, as deficits mainly occur in this area. The other approach is to analyze speech on a linguistic level, which requires the transcription of the audio file into text format. By analyzing these transcripts, it is possible to discover features on the syntactic and lexical level and the semantics, in other words, understanding what someone has said.

Table 1.Overview of Feature Types across all examined applied approaches.

References	Feature Types
Roark [29], Khodabakhsh [30], Fraser [31], Gosztolya [32], Orimaye [33]	Acoustic, Demographic, Linguistic
López-de-Ipiña [34], Satt [35], Meilán [36], König [37], Al-Hameed [38], Christensen [39], Kato [40], Martínez-Sánchez [41], Tóth [42], Themistocleous [43], López [44], Chien [5],	Acoustic, Demographic
Zhu [45],	Acoustic, Linguistic
Tóth [46], Warnita [47]	Acoustic
Baldas [48], Zhou [49]	Linguistic

Our investigation reveals that 18 of the 22 approaches aim at an analysis based on spontaneous speech. Of these 18 approaches, 11 employ a picture description task to obtain the desired speech format. Sixteen of the methods use traditional Machine Learning Algorithms (MLAs), 6 of which use deep learning algorithms for classification. The combination of language and demographic characteristics also varies significantly within these approaches, see Table 1. The mediocre sample size amounts to 128 subjects across all attempts, which results in an average classification accuracy of 81.6%.

The diversity of our investigation illustrates the depth and complexity of the domain. This complexity manifests itself in the wide range of classifiers and the variety of the analyzed language features. However, traditional MLAs like the Support Vector Machine (SVM) remain the most popular classifier for pathological speech investigation. The lack of sufficiently large data sets, which many authors have already criticized, also becomes apparent. Therefore, training and testing in the approaches base almost exclusively on meticulously annotated data sets, such as the DementiaBank. This circumstance also shows the difficulty of creating customized data sets. One reason may also be due to the personality and data protection rights that must be respected.

Therefore, the respective approaches' achieved accuracy is not particularly meaningful and only provides a basis for comparison in this context. However, a striking similarity is recognizable in language generation tasks. Here, spontaneous speech's tendency is recognizable because linguistic deficits are most evident in freely spoken language [32]. Within this setting, mostly picture description tasks are employed.

Also, the increased analysis of acoustic features is noticeable. However, the authors refer to a possible higher classification accuracy if acoustic and acoustic characteristics are apparent in the investigation. Demographic attributes such as age and gender are also often included in the analysis. The consideration of such elements is target-oriented as they are considered significant risk factors [50].

4.1. Acoustic Features

According to research, the most memorable speech characteristics in the early stages of AD relate to prosody, temporal and auditory deficits, see Table 2. These include alterations concerning the speech rhythm, meaning a diminished or fluctuating speech output frequency, more frequent word-finding pauses, and a reduced speech tempo [36, 39].

Table 2. Promising acoustic language characteristics.

Acoustic Feature Subtype	**Subfeatures**	**References**
Temporal Dynamic Features	Speech time Silence segments duration/ratios Voice segments duration/ratios Total phonation time Total locution time Phonation Rate Speech Rate Articulation Rate Transformed Phonation Rate The entire duration of pauses Mean duration of pauses Number of pauses Pause rate Fundamental frequency (F_0) Mean F_0, Hz Minimum F_0, Hz Maximum F_0, Hz Fluctuations in F_0 Jitter Shimmer Harmonics-to-Noise Ratio	Roark [29], Satt [35], López-de-Ipiña [34], Meilán [36], König [37], Tóth [46], Khodabakhsh [30], Al-Hameed [38], Fraser [31], Christensen [39], Kato [40],Martínez-Sánchez [41], Tóth [42], Warnita [47], Themistocleous [43], Zhu [45], Gosztolya [32], Orimaye [33]
Spectral Features	MFCC 1 to 13	López-de-Ipiña [34], Al-Hameed [38], Fraser [31],

	First and second level derivates of the cepstral coefficient Mean Kurtosis Skewness	Christensen [39], Kato [40], Warnita [47], Zhu [45], Chien [5], López [44]

4.1.1. Temporal Dynamic Features

Multiple studies and current approaches towards AD detection via speech utilize time-dynamic features. The reason for doing so arises from the high degree of differentiation that such features display in AD sufferers, especially in the early stages of the disease, compared to healthy individuals [6, 50, 51].

In the studies, significant differences in AD patients' speech and silence behaviour compared to healthy individuals are observable [37]. However, the threshold above which a silence segment qualifies as a pause varies considerably between approaches. These deviations have several reasons. For example, pause lengths correlate with the speaker's social characteristics such as location, ethnicity, age, and gender. Campione [52] also found differences in pause length in different European languages.

To arrive at a common understanding about the pauses' size, we decided to follow the guidelines based on research carried out by Singh [53], as other researchers such as Roark [29] also refer to this work. Accordingly, we recommend classifying a segment of silence with two or more seconds as a pause. Subsequently, additional features are extractable from the audio signal: the speech time in milliseconds, the total phonation time, the total locution time, and the phonation rate. The total phonation time represents the speech time without including pauses, whereas the total locution time represents the speech time, including breaks. The phonation rate is obtainable by dividing the total phonation time by the total locution time [54]. Several studies observed a longer phonation time in AD patients than healthy individuals [6, 41, 51].

Moreover, research has shown that the tempo of speech declines with increasing AD [55-57]. This decline is because AD patients tend to find that speaking requires much mental effort and attention most of the time [38]. Therefore, it is essential to include the speech rate in the features. The calculation involves dividing the total number of phonemes uttered by the total localization time. The same applies to the articulation rate, which results from dividing the total number of spoken phonemes by the total phoneme time [42].

In further research, the transformed phonation rate is a powerful indicator of AD detection via speech, which results from the sine of the phonation rate's square root [51]. Studies have also observed an increased incidence of speech pauses in AD patients compared to healthy people and those in mild to moderate stages of AD [42, 51]. For this reason, it is important to include several significant features regarding pauses in the feature selection, involving the separate measurement of the total duration of pauses and the average duration of breaks, on the one hand. On the other hand, the number of intermissions is of relevance [44].

Moreover, the pause rate appears to be a significant factor in detecting AD [42]. It results by dividing the number of phonemes uttered by the number of pauses occurring in the narrative [54]. Since various authors employ $FF0$ in current approaches, and a higher mean value has already been found in AD patients when compared to healthy people, it is of interest to include this feature, including the minimum, maximum, and the mean value [10, 40, 43, 50].

Jitter and shimmer are acoustic characteristics of speech signals and are quantifiers in terms of the cycle-to-cycle variations of the fundamental frequency amplitude. Research indicates that the voice-quality features jitter and shimmer are well suited to detect speech disorders. Among other things, in pathological speech disorders, the extent of these micro variations increases, especially in diseases affecting the vocal cords' symmetry [58, 59].

Regarding signal processing, jitter is a shape of modulation noise. More precisely, jitter is a modulation of the periodicity of a speech signal. A high jitter level results in a rough voice, typically perceived in pathological voice recordings [60]. Jitter and shimmer parameters are also increasingly employed in AD language research [10, 27, 31, 36]. In this way, a significant fluctuation rate in AD patients' language could already be detected, even in the disease's early stages [61]. Since approaches incorporating these features can already achieve high accuracy in distinguishing AD patients from healthy individuals, it is recommendable to include them.

Meilán [36] used the Harmonics-To-Noise Ratio (HNR), including the jitter and shimmer parameters, showing good discrimination between AD patients and healthy individuals. HNR quantifies the rate of noise due to turbulent airflow. In speech pathologies, this is due to incomplete vocal fold closure [60].

4.1.2. Spectral Features

Although their introduction dates back 40 years is based on research carried out by Davis and Mermelstein [62], Mel Frequency Cepstral Coefficients (MFCCs) are still considered to be state of the art today and, therefore, indispensable for speech recognition research [31, 63]. The triumphal procession of MFCCs has its origins on the first hand in compactly representing the speech amplitude spectrum. On the other hand, under the movement of their robustness and accuracy even under unfavourable recording conditions [64, 65]. MFCCs have also shown promising results in recent studies in pathological speech recognition [66]. Fraile [67] has mathematically proven that MFCCs provide several relevant parameters in the context of pathological speech recognition, especially for those corresponding to the lowest quefrencies. In further research, Fraile [67] proved that the automatic detection of laryngeal pathology by MFCCs is significantly improved. Recently, MFFCs are also increasingly applied in research on AD detection via speech recognition. In this research area, the application of acoustic features such as MFFCs also delivers promising results [10, 27, 38, 44, 47, 68].

Another reason why MFCCs are one of the most popular features to extract is that they originate on the Mel scale's frequency range, based on the frequency range of human hearing [10]. Furthermore, as MFCC features are considered frequency domain features and allow a more precise representation as time-domain features, their widespread application becomes apparent [65].

Recent studies have also calculated their mean values, kurtosis, skewness, and the 13-39 common values and included these as features for their analyses to extract further information [27, 31, 38]. Al-Hameed [38] again emphasizes the usefulness of MFCCs in the context of pathological speech analysis, as they contribute effectively to the distinction between AD patients and healthy individuals.

4.2. Linguistic Features

Linguistic features focus on the lexical and semantic level of the spoken word. Table 3 shows the most promising linguistic features that are already in use in various approaches regarding the detection and differentiation of AD language. On the one hand, selecting these were chosen based on an implemented ML approach's accuracy. On the other hand, the overlap of those features used in different approaches and the agreement of speech decay features in clinical studies.

Table 3. Promising linguistic language characteristics

Linguistic Feature Subtype	**Subfeatures**	**References**
Syntactic Complexity Features	Total Utterance length Average Word length Average Sentence length Average Utterance length The average amount of subordinate clauses Number of Not in the dictionary words and Paraphasias Rate of unanalyzed words	Roark [29], Fraser [31], Khodabakhsh [30], Zhou [49], Gosztolya [32], Orimaye [33]
Lexical Richness and Diversity Features	Type-Token-Ratio (TTR) Honoré’s statistic (HS) Number of different words spoken once (V1) Brunet’s Index (BI) Moving-Type-Token Ratio (MATTR) Age of Acquisition Number of words spoken (N) Number of different words spoken (V)	Baldas [48], Roark [29], Khodabakhsh [30], Fraser [31], Zhu [45]
Informativity Features	Lexical density Number of interjections Number of mentioned pre-defined Keywords and Information Units related to the picture description task Repetitions	Fraser [31], Zhou [49], Zhu [45], Gosztolya [32],

Part-of-Speech: Word and Phrase Type Count and Ratio Features	Investigation of the average rate of occurrence for each part-of-speech (PoS) category: Adjectives, Adverbs, Articles, Conjunctions, Interjections, Nouns, Numerals, Prepositions, Pronouns Verbs Phrase type proportions Phrase type rate Phrase type mean length	Baldas [48], Roark [29], Khodabakhsh [30], Fraser [31], Zhou [49], Zhu [45], Gosztolya [32], Orimaye [33]

4.2.1. Syntactic Complexity Features

As described in 3.1, language deficits already occur in the early stages, reflected in sentence production length. Therefore, it is interesting to analyze the average word, sentence, and utterance length of a narrative as sentence structures of AD patients tend to be shorter.

There are also fewer subordinate clauses in AD patient records. This phenomenon is analyzable by counting and averaging the conjunctions that introduce a subordinate clause. Besides, it is observable that deficits in production and reception of pronouns, even in the early stages of AD, occur [22].

Compared to healthy people, AD patients use pronouns more frequently, where the described object or person is not unambiguous assignable. In addition to Boyé [26], König [37], Yancheva [27], Fraser [31], Noorian [69], and Zhu [45] successfully included these features in their approaches.

In AD, word-finding disorders increase. This degradation reflects itself in the increased utilization of phonological paraphasia (Forbes-McKay 2005). Therefore, it is advantageous to compare the transcribed words of a sentence or a narrative with an extensive dictionary. In this way, we can determine whether and to what extent this language deficit is already apparent in the user's speech. Along with Fraser [31], Zhou [49], Zhu [45], and López [44] use this feature in their approaches.

4.2.2. Lexical Richness Features

Many studies report a weakening of communication skills in the early stages of AD, primarily talking about the individual's regressive vocabulary [20]. Numerous approaches are utilizable to analyze the richness of a speaker's tongue. The three most frequently used ones are: Type-Token Ratio (TTR), Brunét's Index (BI), and Honoré's Statistic (HS). By providing these approaches and the associated algorithms, it is possible to analyze a transcribed voice recording's lexical richness.

Thereby the algorithms weigh the meaning of a unique vocabulary against the full wording [55]. In addition to Baldas [48], Yancheva [27], Fraser [31], Beltrami [54], and Zhu [45] also apply these features in their approaches.

Various studies show that AD patients forget autobiographical memories that happened later in life more quickly than those they experienced earlier. The same is true for the vocabulary of an AD patient. Therefore, it is of interest to measure the average age of acquisition of the words used in a narrative [50].

4.2.3. Informativity Features

In general, stories of AD patients are often inadequate in content and less detailed. Furthermore, important information is missing in an image description, for example [2]. On the one hand, it is, therefore, advantageous to examine the lexical density of a narrative more closely. The proportion of content words, like nouns, verbs, adjectives, and adverbs, to the total number of words, is meant by lexical density. Therefore, a narrative with a high content word counts contains more information than a story with an increased number of function words. Lexical density is also examinable in pure terms of grammar. It divides the words with linguistic properties by the number of orthographic representations [45].

On average, healthy persons show a lexical density of less than 40% [70]. Yancheva [27], Al-Hameed [38], Kokkinakis [68], Beltrami [54], and Orimaye [33] make use of these measures. Another indicator of an informational deficit is the increased use of exclamations. Boyé [26] and Zhu [45] exploit this feature.

Another way to determine the information content is to define keywords that represent dominant characteristics. Fraser [31] and Zhu [45] have already demonstrated that the information content increases with a higher number of keyword references to a topic in a narrative.

Furthermore, a lack of information manifests itself in the form of repetition [16]. To detect such recurrences, usually, the similarity of sentences is localized across the cosine distance. Fraser [31], Noorian [69], and Zhu [45] employ this method of repetition detection.

4.2.4. Part-of-Speech: Word and Phrase Type Count and Ratio Features

The use of word types in AD patients changes significantly to healthy individuals. AD patients may use more pronouns, conjunctions, prepositions, a higher rate of adjectives, and a lower rate of nouns than healthy individuals [2, 20, 22, 50, 61, 71]. Thus, it is interesting to discover all word types and ratios and put them into relation. The same applies to phrase formations. Therefore, AD patients create less prepositional phrase constructions and fewer noun phrases [27].

Consequently, it is vital to figure out the proportion usage of different phrase types, the ratio they occur, and the average length of the respective phrase types. Fraser [31] has already identified common phrase types in the AD language. As additional researchers, like Yancheva [27], Zhou [49], Kokkinakis [68], Noorian [69], Beltrami [54], and Orimaye [33], have adopted them, it is advantageous to include them since they are likely to be of great importance for the accurate recognition of impairments.

4.3. Demographic Features

It is essential to create a balanced data set to ensure a reliable basis for the analysis. Research shows that well-balanced training data lead to the most superior balance accuracy [72]. Therefore, language data should be subject to certain demographic factors in which aspects of language differ from each other to differentiate classifications. The demographic characteristics most frequently found in the literature are shown in Table 4.

Table 4. Promising demographic characteristics

Demographic Feature Subtype	**References**
Age	Roark [29], Satt [35], López-de-Ipiña [34], Meilán [36], König [37], Khodabakhsh [30], Al-Hameed [38], Fraser [31], Christensen [39], Kato [40], Martínez-Sánchez [41], Tóth [42], Themistocleous [43], Chien [5], López [44], Orimaye [33]
Gender	Satt [35], López-de-Ipiña [34], Meilán [36], König [37], Khodabakhsh [30], Fraser [31], Christensen [39], Kato [40], Martínez-Sánchez [41], Tóth [42], Themistocleous [43], Chien [5],
Education	Roark [29], Meilán [36], Khodabakhsh [30], Fraser [31], Christensen [39], Martínez-Sánchez [41], Tóth [42], Chien [5], López [44]
Neurophysiological Tests	Roark [29], König [37], Christensen [39], Martínez-Sánchez [41], Tóth [42], Chien [5], López [44]

On the one hand, people's speech data corresponding to the desired target group's age range is necessary. A reason for defining a manageable age group is that even with healthy ageing, language is undergoing specific changes, and broad age differences in data collection may lead to inaccurate conclusions [73]. We recommend a target group of older people over 65 years of age in the AD language area who are fluent in the desired target language [74]. The vast majority of the approaches examined make use of the age characteristic, see Table 4.

Moreover, within this age range, the distribution of genders should be as even as possible. The differentiation between genders is interesting as studies concerning the AD language have shown considerable linguistic deficits in comparing a given gender and its counterpart of the same age. Also, a more rapid decline in the language is observable in one gender compared against the other [20]. Again, this characteristic is integrated by the predominant part of the examined approaches into the analysis, see Table 4.

Extensive studies show that lower education is significantly associated with an increased risk of developing AD [75]. Therefore, the speakers' educational level should find consideration and distribute evenly across the genders. Recent research shows that this parameter generally acts gainful [41, 76]. Nine of the examined approaches include this characteristic in the analysis, see Table 4.

Especially when collecting training data, the test speakers have to undergo an appropriate AD diagnosis. Ideally, an accurate diagnostic methodology like the S3 Dementia Guideline is applied [77]. This extensive diagnostic method requires trained personnel and is therefore quite expensive. Alternatively, there should be a switch to Cognitive and Neuropsychological Examinations such as the Mini-Mental Status Test (MMST), DemTect, the Test for the Early Detection of Dementia with Depression Discrimination (TFDD) or the Montreal Cognitive Assessment Test (MoCA) [77].

Combined with other tests mentioned above procedures, the clock test may enhance diagnostic accuracy. Nevertheless, this test is not suitable as a stand-alone cognitive test. A neuropsychological short test's diagnostic quality is furthermore strongly dependent on the examination setting (Deuschl 2016). Quick cognitive tests, especially in data collection, deserve to be included in the analysis as a demographic feature. Roark [29], König [37], Christensen [39], Martínez-Sánchez [41], Tóth [42], Chien [5], and López [44] for instance, incorporate such characteristics in their proposals.

We recommend applying the 97 different overarching acoustic, linguistic and demographic characteristics identified in this literature review if intending to develop an ML model in the context of AD early detection through language. While developers must individually verify the meanings of language features in the respective application context, prior significance recognition concerning other scientific publications ensures self-sufficient recognition and classification of pathological AD language features.

While the inclusion of acoustic, lexical, and demographic features increases the system's complexity in general, the literature indicates that the additional effort involved payoffs in the subsequent classification in terms of achievable accuracy [32].

5. LIMITATIONS AND FURTHER RESEARCH

The presented work is subject to some limitations, which we explain hereafter. Surprisingly, none of the investigated approaches was the intake of medication of the test persons included as a demographic characteristic. Meyer [78] states that many drugs reduce people's cognitive ability, including in language behaviour, to a degree comparable to MCI. Thus, it also affects the classification underlines the importance of including this feature. Besides, Vogt [79] claims that certain prescribed drugs associated with dementia syndromes in the elderly aggravate chronic cognitive impairment, further reinforcing the above argument. However, this feature type's inclusion requires a more in-depth understanding, which we did not address in this research.

The features presented here are also similar to each other through the different languages used in the examined approaches. For example, classifications involving English, French, Spanish and Japanese language data exist. Due to the subject area's immense breadth, we cannot guarantee 100% coverage of all relevant publications. Nevertheless, the present study shows the most prominent language and demographic features of consideration in an ML approach to detect AD-related language changes. However, the set of language features presented must undergo large-scale testing across different languages, over an extended period, to identify differences and verify its feasibility.

6. CONCLUSION

Due to the ever-increasing number of research approaches to AD screening by speech, it is becoming increasingly important to establish a consensus on the speech features to be analyzed in this context, thereby guiding researchers in the field. Therefore, this work's goal was to systematically review related literature to extract favourable speech features for application to AD detection using ML.

Thus, this work analyzed 22 recent research articles that addressed AD detection approaches through speech, including ML techniques. These articles included various combinations of acoustic, linguistic, and demographic features that enable AD detection at early stages using ML.

Through this extensive literature review, we identified 97 different promising acoustic, linguistic, and demographic features. Together, these should prove a useful consideration if the intention is to develop an ML model in the context of early AD detection through speech. This work is significant because well-designed feature extraction will increase the quality, efficiency, and accuracy of this future supportive diagnostic procedure.

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