Project Notes:

Project Title: Multilingual Dementia Detection through Deep Learning
Name: Gustavo Rodriguez

Contents:

Knowledge Gaps:

This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved
Definition of Alzheimer's Disease	Abstract of book about Alzheimer's Disease	Bangen, K. J., Graves, L. V., Edmonds, E. C., Thomas, K. R., & Bondi, M. W. (2023). Alzheimer's disease. In G. G. Brown, T. Z. King, K. Y. Haaland, & B. Crosson (Eds.), *APA handbook of neuropsychology, Vol. 1. Neurobehavioral disorders and conditions: Accepted science and open questions* (pp. 477–497). American Psychological Association. https://doi.org/10.1037/0000307-023	08/18/2023
Definition of Dementia	Abstract of book about care for dementia patients	Amanullah, S., Shivakumar, S. K., Thomas, C., Bhattacharyya, S., & Shah, S. (2023). Optimising patient care in dementia. In A. Shrivastava, A. De Sousa, & N. Shah (Eds.), *Handbook on optimizing patient care in psychiatry* (pp. 233–246). Routledge.	8/20/2023
How to create a machine learning/deep learning model for audio and how to create features if needed.		https://towardsdatascience.com/how-can-machine-learning-be-used-in-audio-analysis-847ebbefeb6 https://vitalflux.com/what-are-features-in-machine-learning/#What_are_the_features_in_machine_learning https://towardsdatascience.com/audio-deep-learning-made-simple-part-1-state-of-the-art-techniques-da1d3dff2504	

Literature Search Parameters:

These searches were performed between (08/18/2023) and XX/XX/2023.
List of keywords and databases used during this project.

Database/search engine	**Keywords**	**Summary of search**
APA PsycNet	Alzheimer's Disease	Found an abstract of a book with a concrete definition of Alzheimer's Disease
APA PsycNet	Dementia	Found an abstract of a book with a definition of Dementia
APA Thesaurus	Phonetics, Morphology, Lexicon, Syntax, Semantics, Pragmatics	Found definitions of words to define vocabulary in articles
Scopus	alzheimer's AND eyes AND protein AND amyloid AND beta	Found article analyzing various methods of artificial intelligence being used in relation to how parts of the eye can be used to detect Alzheimer's Disease
Scopus	alzheimer's AND conversation	Found an article analyzing parts of speech and how they affect how a person with Alzheimer's speaks

Tags:

Tag Name	
#Alzheimer's	#Detection
#Speech	#Typing

Article #1 Notes: Cognitive Writing Process Characteristics in Alzheimer's Disease

Article notes should be on separate sheets

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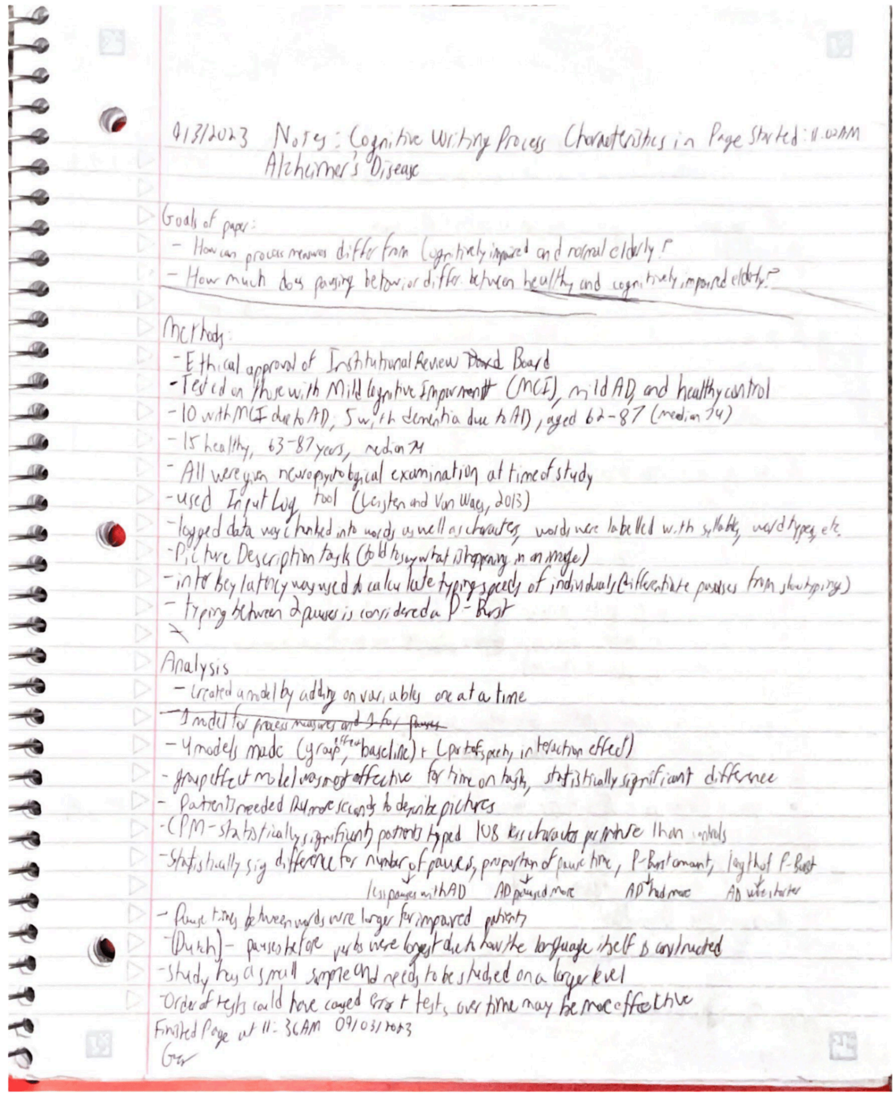
Source Title	Cognitive Writing Process Characteristics in Alzheimer's Disease
Source citation (APA Format)	Meulemans, C., Leijten, M., Van Waes, L., Engelborghs, S., & De Maeyer, S. (2022). Cognitive Writing Process Characteristics in Alzheimer's Disease. *Frontiers in Psychology*, *13*, 872280. https://doi.org/10.3389/fpsyg.2022.872280
Original URL	https://doi.org/10.3389/fpsyg.2022.872280
Source type	Journal Article
Keywords	writing processes, word categories, keystroke logging, Alzheimer's disease, dementia, mild cognitive impairment
#Tags	#Alzheimer's, #Typing, #Detection
Summary of key points + notes (include methodology)	Central Question: How can the qualities of a patient's typing be used to screen for Alzheimer's? Summary: Text generated both through speech and typing or writing by Alzheimer's patients possess weaker complexity in word structure, more indefinite phrases, amongst other qualities that weaken text. Typing can further be used in addition to text as another avenue to detect Alzheimer's, since qualities such as pausing and bursts of typing can hint at lower working memory, a main symptom of Alzheimer's. Healthy patients typically pause more times for shorter periods, whereas patients with Alzheimer's pause less frequently but for longer periods of time.



9/3/2023 Notes: Cognitive Writing Process Characteristics in Alzheimer's Disease Page Started: 11:02AM

Goals of paper:
- How can process measures differ from cognitively impaired and normal elderly?
- How much does pausing behavior differ between healthy and cognitively impaired elderly?

Methods:
- Ethical approval of Institutional Review ~~Board~~ Board
- Tested on those with Mild Cognitive Impairment (MCI), mild AD and healthy control
- 10 with MCI due to AD, 5 with dementia due to AD), aged 62-87 (median 74)
- 15 healthy, 63-87 years, median 74
- All were given neuropsychological examination at time of study
- used InputLog tool (Leijten and Van Waes, 2013)
- logged data was chunked into words as well as characters, words were labelled with syllables, word types, etc.
- Picture Description task (told to say what is happening in an image)
- inter key latency was used to calculate typing speeds of individuals (differentiate pauses from slow typing)
- typing between 2 pauses is considered a P-Burst

Analysis
- Created a model by adding on variables one at a time
- ~~1 model for process measures and 1 for pauses~~
- 4 models made (group effect, baseline) + (part of speech, interaction effect)
- group effect model was most affective for time on task, statistically significant difference
- Patients needed 141 more seconds to describe pictures
- CPM - statistically significant, patients typed 108 less characters per minute than controls
- Statistically sig difference for number of pauses, proportion of pause time, P-Burst amount, length of P-Burst
  (less pauses with AD; AD paused more; AD had more; AD were shorter)
- Pause timings between words were larger for impaired patients
- (Dutch) - pauses before verbs were longest due to how the language itself is constructed
- Study has a small sample and needs to be studied on a larger level
- Order of tests could have caused error, tests over time may be more effective

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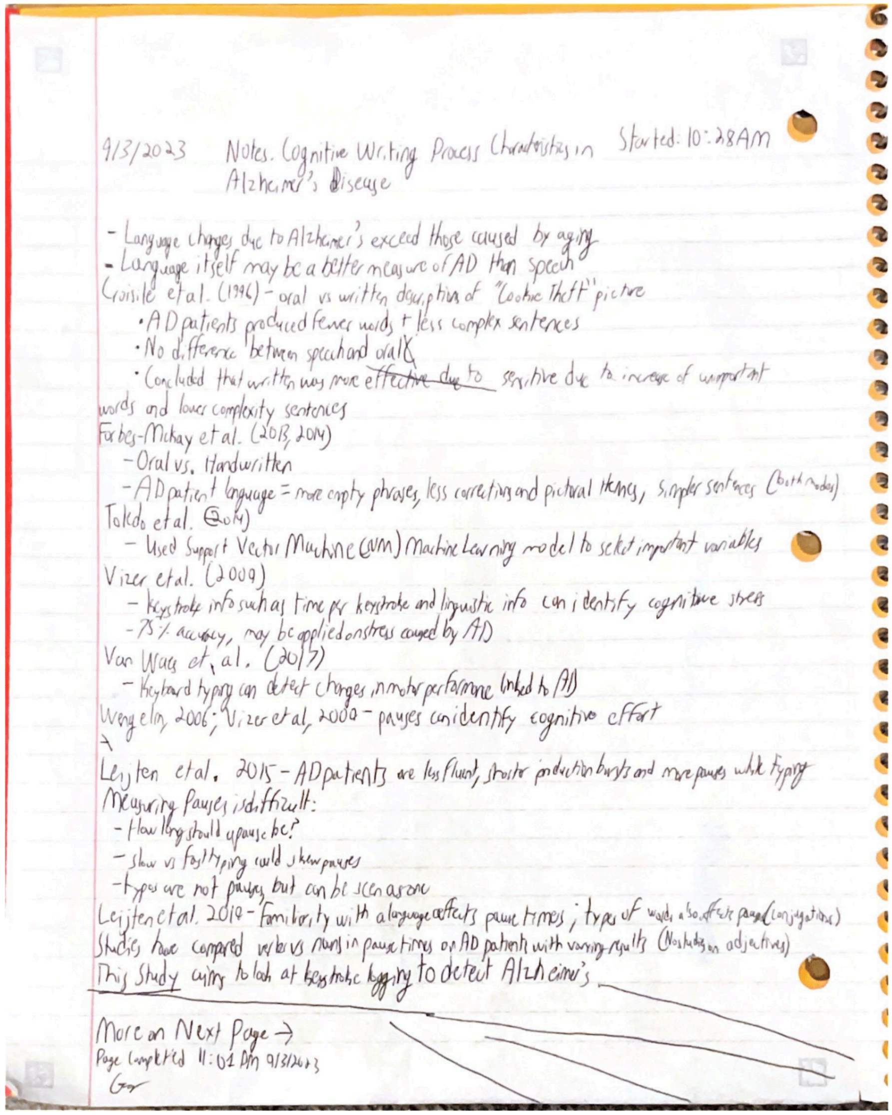
	 9/3/2023 Notes. Cognitive Writing Process Characteristics in Alzheimer's Disease Started: 10:28AM - Language changes due to Alzheimer's exceed those caused by aging - Language itself may be a better measure of AD than speech Croisile et al. (1996) - oral vs written description of "Cookie Theft" picture • AD patients produced fewer words + less complex sentences • No difference between speech and oral • Concluded that written was more ~~effective due~~ to sensitive due to increase of unimportant words and lower complexity sentences Forbes-McKay et al. (2013, 2014) - Oral vs. Handwritten - AD patient language = more empty phrases, less correcting and pictoral items, simpler sentences (both modes) Toledo et al. (2014) - Used Support Vector Machine (SVM) Machine Learning model to select important variables Vizer et al. (2009) - keystroke info such as time per keystroke and linguistic info can identify cognitive stress - 75% accuracy, may be applied on stress caused by AD Van Waes et. al. (2017) - Keyboard typing can detect changes in motor performance linked to AD Wengelin 2006; Vizer et al, 2009 - pauses can identify cognitive effort Leijten et al. 2015 - AD patients are less fluent, shorter production bursts and more pauses while typing Measuring Pauses is difficult: - How long should a pause be? - slow vs fast typing could skew pauses - typos are not pauses but can be seen as one Leijten et al. 2019 - Familiarity with a language affects pause times; types of words also affect pauses (conjugations) Studies have compared verbs vs nouns in pause times on AD patients with varying results (No studies on adjectives) This Study aims to look at keystroke logging to detect Alzheimer's More on Next Page → Page Completed 11:01 AM 9/3/2023 Ger -Added at 12:23 AM on 9/22/23
Research Question/Problem/ Need	How can a patient's language output be analyzed to detect signs of Alzheimer's?

Important Figures

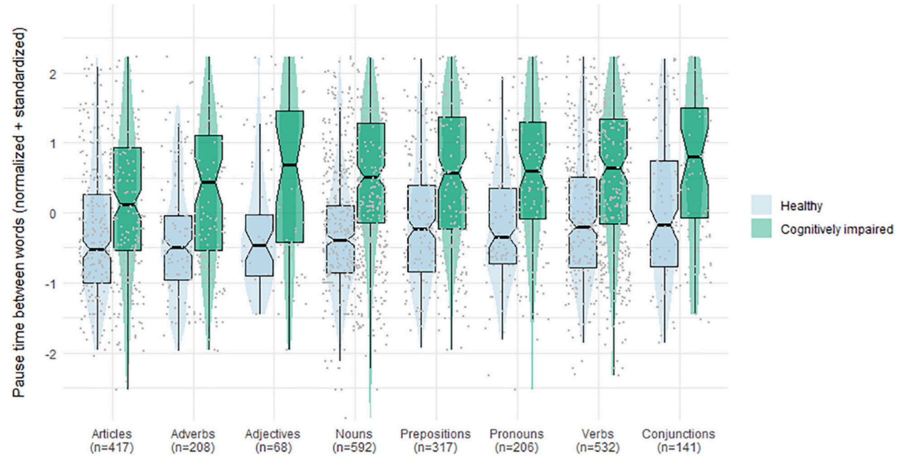


FIGURE 3 | Number of pauses and distribution of pause length per word category for healthy controls and cognitively impaired patients.

<u>Figure 3: Number of pauses and distribution of pause length per word category for healthy controls and cognitively impaired patients</u>

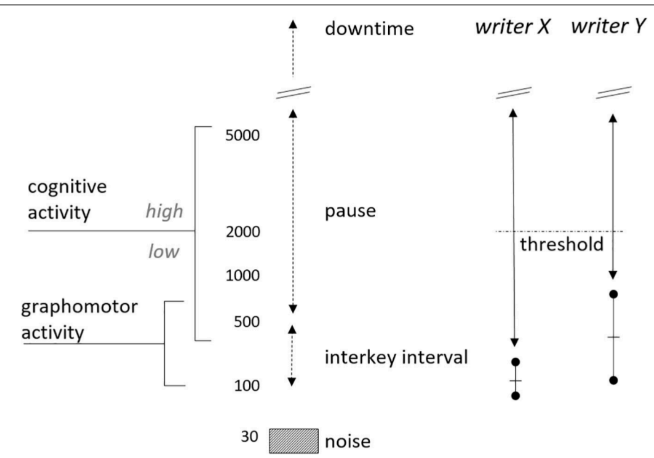


FIGURE 1 | Schematic representation of latency in relation to graphomotor activity, and low- and high-level cognitive activities. From Van Waes et al. (2021). Reprinted with permission.

<u>Figure 1: Schematic Representation of Latency in Relation to Graphomotor Activity, and Low and High-Level cognitive Activities.</u>

VOCAB: (w/definition)

Working Memory: Short-Term Memory, critical for language comprehension, stores both intermediate and final processing of language.
Alzheimer's Disease: A neurodegenerative brain disease that reduces one's ability to complete daily tasks due to cognitive decline.
Picture Description Task: A task used during studies involving patients communicating what they see happening in a picture
Graphomotor Latency: The time spent in between the pressing of keys in sequence, not representative of cognitive activity.

Cited references to follow up on

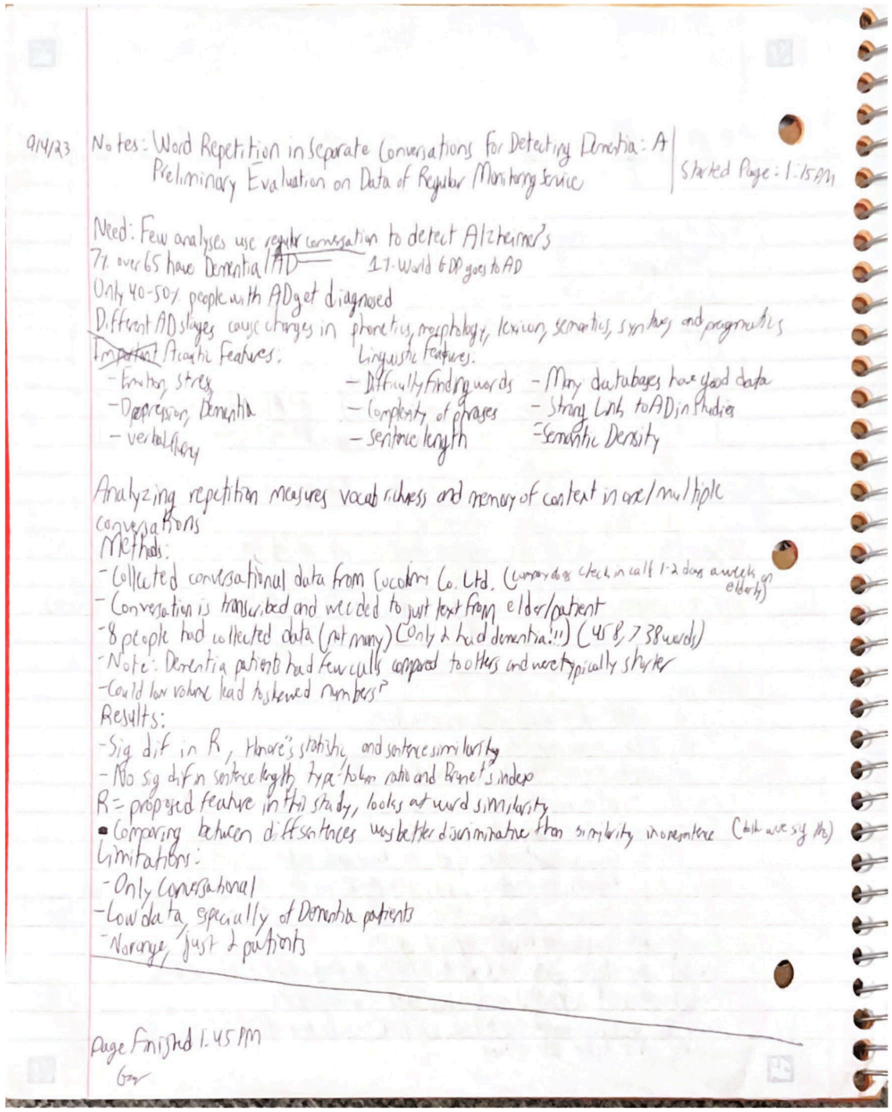
Just, M. A., & Carpenter, P. A. (n.d.). *A Capacity Theory of Comprehension:*

	Individual Differences in Working Memory.
Follow up Questions	1. How effective are the measurements of the typing speed of a person used to dictate what is or is not a pause? Could long term monitoring be used to avoid errors based on assumed typing speed? 2. How effective is typing as opposed to speaking as a detection method? 3. Is the analysis of the pauses assessed in typing transferable to the analysis of speech, which may have more researched models?

Article #2 Notes: Word Repetition in Separate Conversations for Detecting Dementia: A Preliminary Evaluation on Data of Regular Monitoring Service

Article notes should be on separate sheets

Source Title	Word Repetition in Separate Conversations for Detecting Dementia: A Preliminary Evaluation on Data of Regular Monitoring Service
Source citation (APA Format)	Shinkawa, K., & Yamada, Y. (2018). Word Repetition in Separate Conversations for Detecting Dementia:A Preliminary Evaluation on Data of Regular Monitoring Service. *AMIA Summits on Translational Science Proceedings*, *2018*, 206–215.
Original URL	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5961820/
Source type	Journal Article
Keywords	Alzheimer's disease, dementia, mild cognitive impairment
#Tags	#Alzheimer's, #Repetition, #Multi-Day
Summary of key points + notes (include methodology)	One particularly lacking aspect of Alzheimer's detection has been the use of conversations across several days. This study utilizes a service involving periodic calls by an elder monitoring company, transcribes the text, and analyzes the repetitiveness of the speech of the patient across spans of 13 to 226 calls, differing per patient. Although this study had AUC ROC values between 0.87 and 0.96, showing a strong ability to classify dementia, the sample size of 6 controls and 2 patients with dementia is extremely limited and higher quantities of data still need to be studied, although at the time of writing (5/18/2018), no other studies had investigated repetition as a variable.



9/14/23 Notes: Word Repetition in Separate Conversations for Detecting Dementia: A Preliminary Evaluation on Data of Regular Monitoring Service | Started Page: 1:15 PM

Need: Few analyses use regular conversation to detect Alzheimer's
7% over 65 have Dementia/AD — 1% World GDP goes to AD
Only 40-50% people with AD get diagnosed
Different AD stages cause changes in phonetics, morphology, lexicon, semantics, syntax and pragmatics

~~Important~~ Acoustic Features:
- Emotion, stress
- Depression, Dementia
- verbal fluency

Linguistic Features:
- Difficulty finding words
- Complexity of phrases
- sentence length

- Many databases have good data
- Strong Link to AD in studies
- Semantic Density

Analyzing repetition measures vocab richness and memory of content in one/multiple conversations

Methods:
- Collected conversational data from Cocolomi Co. Ltd. (company does check in call 1-2 days a week on elderly)
- Conversation is transcribed and weeded to just text from elder/patient
- 8 people had collected data (not many) (Only 2 had dementia!!) (458,738 words)
- Note: Dementia patients had few calls compared to others and were typically shorter
- Could low volume lead to skewed numbers?

Results:
- Sig dif in R, Honore's statistic, and sentence similarity
- No sig dif in sentence length, type-token ratio and Brunet's index
R = proposed feature in this study, looks at word similarity
- Comparing between diff sentences was better discriminative than similarity in one sentence (both were sig tho)

Limitations:
- Only Conversational
- Low data, specially of Dementia patients
- No range, just 2 patients

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Research Question/Problem/ Need	How can Alzheimer's be detected using the language output of a patient?

Important Figures

Table 1: Participant data list.

Status	Gender	Age	Data duration: Start	Data duration: End	No. of calls	Ave. call time Mean (SD) [min.]	Ave. word length
Control	F	75-77	2015 Mar	2017 Apr	75	11.21 (8.85)	395.13 (124.18)
	F	80-83	2014 Jul	2017 Apr	109	16.63 (4.47)	734.34 (195.10)
	F	87-89	2016 Jan	2017 May	104	11.15 (4.46)	418.86 (235.12)
	M	66-70	2014 Jul	2017 Apr	133	10.62 (2.32)	482.89 (118.95)
	M	78-81	2014 Dec	2016 Mar	72	12.06 (2.83)	554.69 (119.03)
	M	82-85	2014 Nov	2017 Apr	226	17.75 (6.29)	572.12 (235.49)
Dementia	F	85-86	2014 Jul	2015 Nov	40	9.29 (2.15)	462.28 (204.12)
	F	88-88	2014 Jul	2014 Nov	13	7.77 (1.72)	277.94 (151.47)

Table 1: Participant Data List

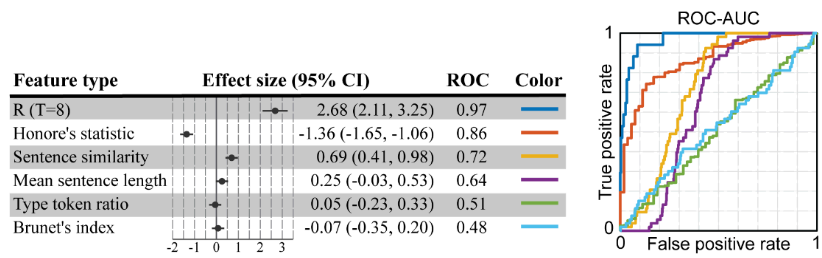

Figure 3: Comparison of our proposed feature R with the existing five features used in previous studies. Error bars are 95% confidence intervals.

Figure 3: Comparison of our Proposed Feature R with the Existing Five Features Used in Previous Studies. Error Bars are 95% Confidence Intervals

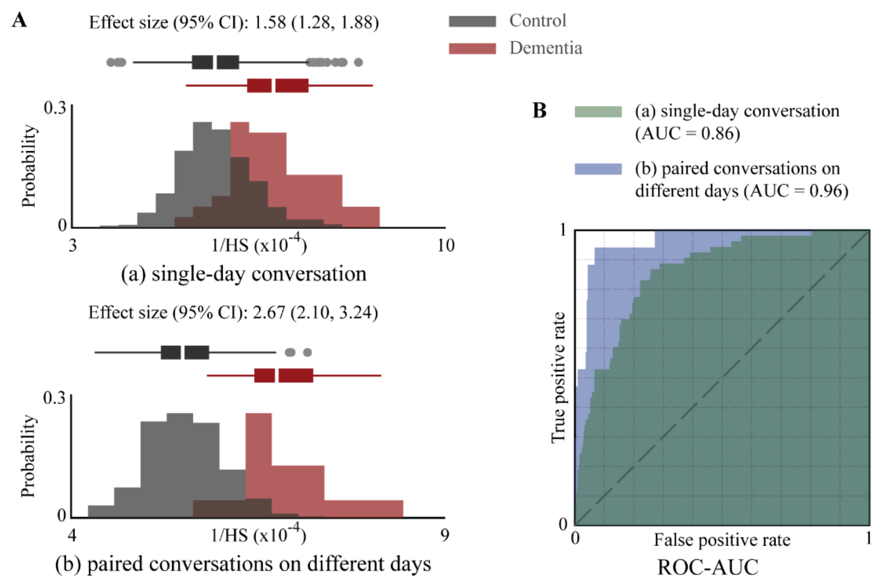

Figure 4: Comparison between our proposed feature R, extracted from single and paired conversations. (A) Histogram and boxplot for each feature. (B) ROC-AUC scores.

Figure 4: Comparison Between our Proposed Feature R, Extracted from Single and Paired Conversations

VOCAB: (w/definition)	R:The algorithm tested in the study that compares word repetition across multiple days in the study Honoré's statistic: A statistic from a single conversation used to calculate vocabulary richness Brunet's index: An index from a single conversation used to calculate vocabulary richness Type-token ratio: A ratio from a single conversation used to calculate vocabulary richness Dementia: A syndrome known for the breakdown of memory, thinking, and behavior, as well as decreased ability to perform everyday tasks in patients. Phonetics: The study of how sounds are created, transmitted, and perceived. Morphology: The study of the bare minimum linguistic units (morphemes). Lexicon: The words that one regularly uses and recognizes Semantics: The science dealing with relations between words, expressions, phrases, and the things they refer to. Syntax: The science of sentence formation Pragmatics: Study of how language is supposed to be used in certain contexts, including human interaction
Cited references to follow up on	Croisile, B., Ska, B., Brabant, M. J., Duchene, A., Lepage, Y., Aimard, G., & Trillet, M. (1996). Comparative study of oral and written picture description in patients with Alzheimer's disease. Brain and language, 53(1), 1–19. https://doi.org/10.1006/brln.1996.0033
Follow up Questions	Questions: 1. How might large scale monitoring be achieved in an effective, non-invasive, and cost-effective manner? 2. Could there have been induced repetitiveness due to the nature of the calls from the operator? How could this be mitigated if it occurred? 3. Would this algorithm hold up to a much larger sample size that could have multiple stages of dementia or Alzheimer's amongst patients? 4. Could this experiment be expanded upon to get a more reliable, controlled dataset?

Article #3 Notes: Deep learning-based speech analysis for Alzheimer's disease detection: a literature review

Article notes should be on separate sheets

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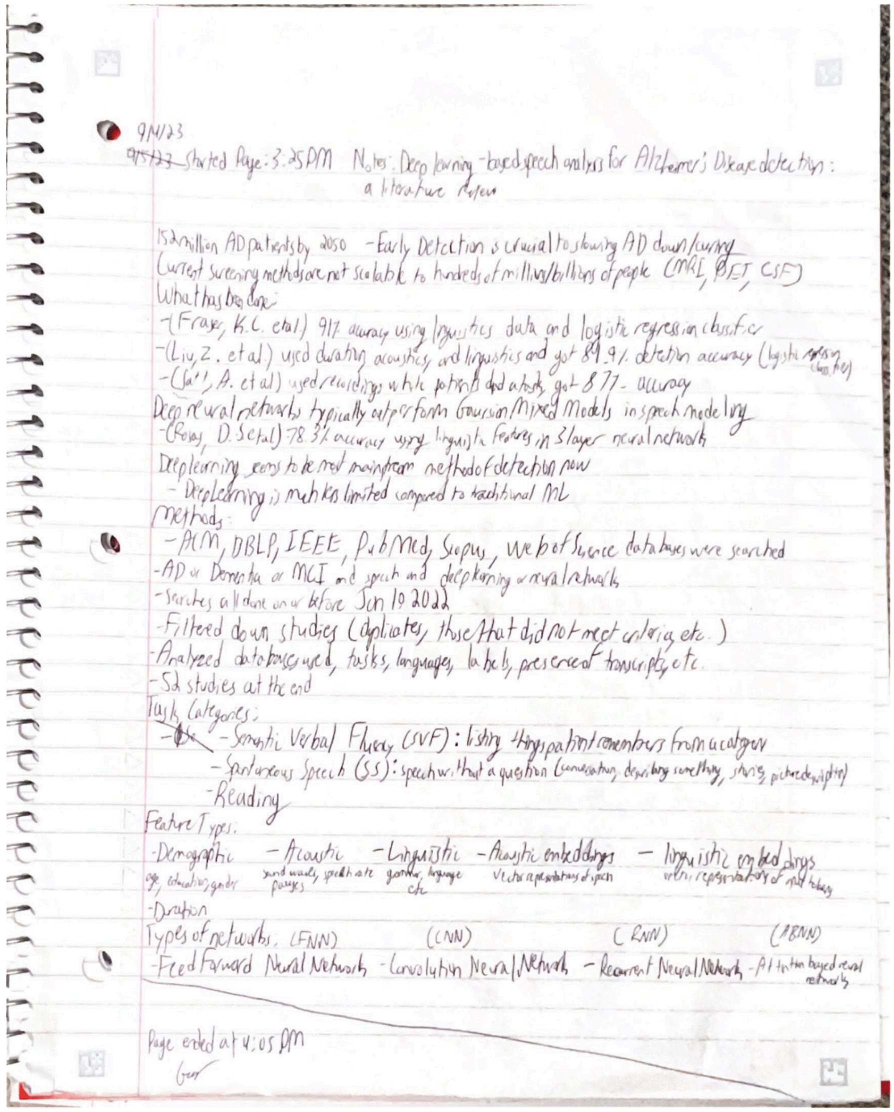
Source Title	Deep learning-based speech analysis for Alzheimer's disease detection: a literature review
Source citation (APA Format)	Yang, Q., Li, X., Ding, X., Xu, F., & Ling, Z. (2022). Deep learning-based speech analysis for alzheimer's disease detection: A literature review. *Alzheimer's Research & Therapy*, *14*(1). https://doi.org/10.1186/s13195-022-01131-3
Original URL	https://alzres.biomedcentral.com/articles/10.1186/s13195-022-01131-3#author-information
Source type	Journal Article
Keywords	Deep Learning, Alzheimer's Disease
#Tags	#DeepLearning, #MultiStudy, #Detection, #Alzheimer's
Summary of key points + notes (include methodology)	Language disorders typically appear early on during Alzheimer's Disease, and various aspects of speech have been analyzed using machine learning algorithms trained on databases of speech including Alzheimer's patients. Deep learning specifically has become a popular method of creating models that can detect Alzheimer's, and across 52 studies, data observed included patients responding to a question, speech without a prompt, and reading. Across the various studies and neural networks, spontaneous speech was found to be the most effective to detect Alzheimer's, although the data in the study only includes English and not all studies that exist could have been found, creating some margin of error within the article.



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~~9/15/23~~ Started Page: 3:25 PM Notes: Deep learning-based speech analysis for Alzheimer's Disease detection: a literature review

152 million AD patients by 2050 - Early Detection is crucial to slowing AD down/curing
Current screening methods are not scalable to hundreds of millions/billions of people (MRI, PET, CSF)
What has been done:
-(Fraser, K.C. et al) 91% accuracy using linguistics data and logistic regression classifier
-(Liu, Z. et al) used duration, acoustics, and linguistics and got 84.9% detection accuracy (logistic regression classifier)
-(Sa'i, A. et al) used recordings while patients did a task, got 87% accuracy
Deep neural networks typically outperform Gaussian Mixed Models in speech modeling
-(Rosas, D.S et al) 78.3% accuracy using linguistic features in 3 layer neural network
Deep learning seems to be most mainstream method of detection now
- Deep Learning is much less limited compared to traditional ML
Methods:
- ACM, DBLP, IEEE, PubMed, Scopus, Web of Science databases were searched
-AD or Dementia or MCI and speech and deep learning or neural networks
-Searches all done on or before Jan 19 2022
-Filtered down studies (duplicates, those that did not meet criteria, etc.)
-Analyzed databases used, tasks, languages, labels, presence of transcripts, etc.
-52 studies at the end
Task Categories:
- ~~Dx~~ -Semantic Verbal Fluency (SVF): listing things patient remembers from a category
-Spontaneous Speech (SS): speech without a question (conversation, describing something, stories, picture description)
-Reading
Feature Types:
-Demographic (age, education, gender) -Acoustic (sound waves, speech rate, pauses) -Linguistic (grammar, language etc) -Acoustic embeddings (Vector representations of speech) - linguistic embeddings (vector representations of text tokens)
-Duration
Types of networks:
-Feed Forward Neural Network (FNN) -Convolution Neural Network (CNN) - Recurrent Neural Network (RNN) -Attention based neural networks (ABNN)

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	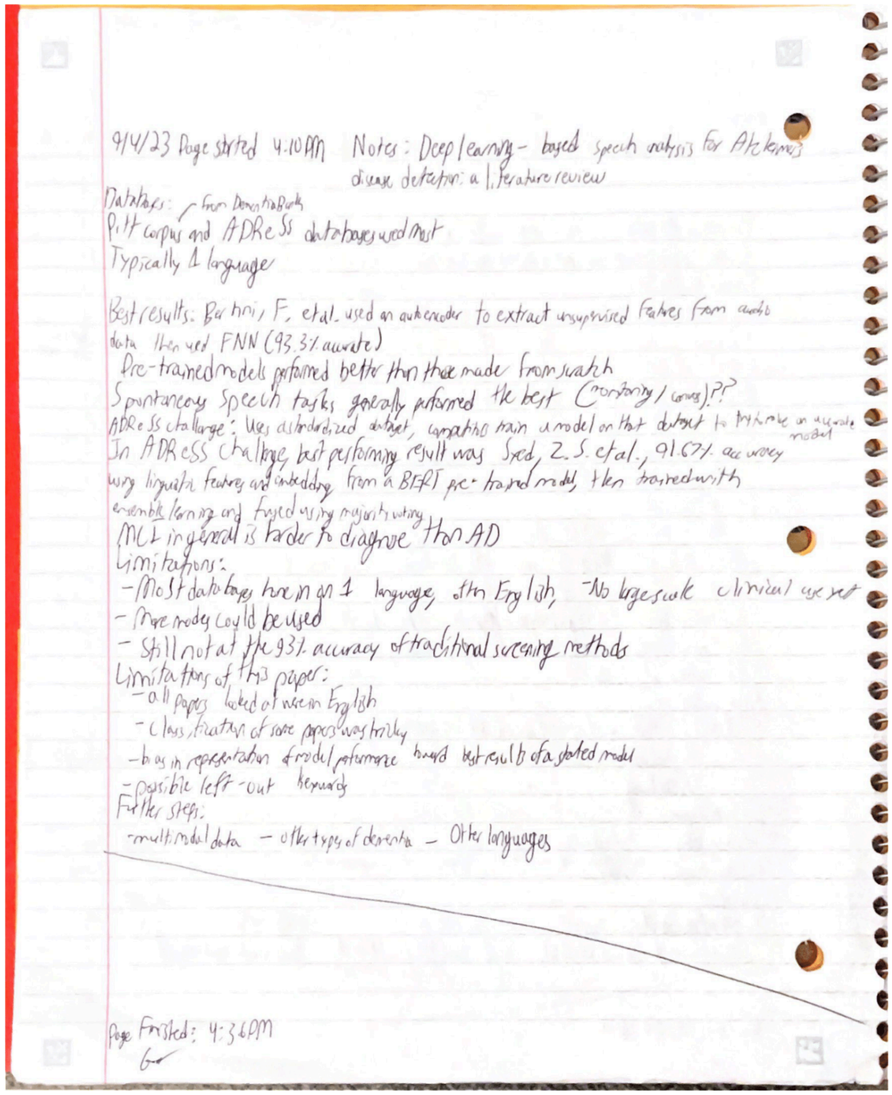 9/4/23 Page started 4:10 PM Notes: Deep learning-based speech analysis for Alzheimer's disease detection: a literature review Databases: from DementiaBank Pitt corpus and ADReSS databases used most Typically 1 language Best results: Bertini, F. et al. used an autoencoder to extract unsupervised features from audio data then used FNN (93.3% accurate) Pre-trained models performed better than those made from scratch Spontaneous Speech tasks generally performed the best (monitoring / cameras)?? ADReSS challenge: Uses a standardized dataset, competitors train a model on that dataset to try to make an accurate model In ADReSS challenge, best performing result was Syed, Z. S. et al., 91.67% accuracy using linguistic features and embedding from a BERT pre-trained model, then trained with ensemble learning and fused using majority voting MCI in general is harder to diagnose than AD Limitations: - Most databases are in only 1 language, often English, - No large scale clinical use yet - More models could be used - Still not at the 93% accuracy of traditional screening methods Limitations of this paper: - all papers looked at were in English - Classification of some papers was tricky - bias in representation of model performance toward best results of a stated model - possible left-out keywords Further steps: - multimodal data - other types of dementia - Other languages Page Finished: 4:36 PM -Added at 12:17 AM on 9/22/23
Research Question/Problem/ Need	How have speech and language processing been used to detect Alzheimer's Disease, and what are the most effective methods?

Important Figures

Table 1 Dementia-related speech-based databases information

Task name			Database name	Abbreviation	Language	Label distribution	Speech included	Transcription included
VF	SVF	Animal naming	PGA-OREKA [20]	VF1	Spain	HC (62)/MCI (38)	Yes	No
			- [21]	VF2	French, Dutch, and German	HC (66)/MCI (66)	Yes	-
		Vegetable naming	Mandarin_Lu (DementiaBank) + NTU dataset [22]	VF3	Chinese	AD (30)/HC (30)	Yes	No
		Location naming	Mandarin_Lu (DementiaBank) + NTU dataset [22]	VF4	Chinese	AD (30)/HC (30)	Yes	No
SS	Conversation/interview		PROMPT database [23]	cvs1	Japanese	Dementia (49)/MCI(42)/ HC(72)	Yes	-
			- [24]	cvs2	Italian	eD (16)/MCI (32)/HC (48)	Yes	Yes
			The Carolina Corpus Conversation database [14]	cvs3	English	AD (30)/HC (16)	Yes	Yes
			IVA dataset [25]	cvs4	English	ND (21)/MCI (24)/HC (25)	Yes	-
			The Hungarian MCI-mAD Database [26, 27]	cvs5	Hungarian	MCI (48)/HC (36) AD (25)/MCI (25)/HC (25)	Yes	No
			AZTIAHO AZTIAHORE [28]	cvs6	multilingual	AD (20)/HC (50) AD (20)/MCI (20)	Yes	No
			- [29]	cvs7	Italian	MCI (19)/HC (20)	Yes	Yes
			- [16]	cvs8	Hungarian	MCI (32)/HC (19)	Yes	No
			Framingham Heart Study Dataset [30]	cvs9	English	Dementia (223)/MCI (309)/ HC (291)	Yes	No
	Recall		NTUHV dataset [31]	recall1	Chinese Taiwan	AD (40)/HC (40) MCI (30)/HC (30)	-	-
			The Wallet Story from ABCD [32]	recall2	Brazilian Portuguese	MCI (23)/HC (12)	-	-
			The Lucia Story Datasets from BALE [32]	recall3	-	AD (9)/HC (80)	-	-
			The Hungarian MCI-mAD Database [26, 27]	recall4	Hungarian	MCI (48)/HC (36) AD (25)/MCI (25)/HC (25)	Yes	No
			- [33]	recall5	Chinese Taiwan	HC (30)/AD (30)	Yes	No
	PD	Cookie theft	pitt Corpus [34]	SS-PD-CT1	English	HC (244)/MCI (309)	Yes	Yes
			ADReSS [19]	SS-PD-CT2	English	AD (78)/non-AD (78)	Yes	Yes
			ADReSSo [35]	SS-PD-CT3	English	AD (87)/HC (79)	Yes	Yes
			Wisconsin Longitudinal Study (WLS) [36]	SS-PD-CT4	English	AD (115)/HC (839)		
			- [37]	SS-PD-CT5	English	AD (26)/HC (46)	Yes	Yes
			NTUHV dataset [31]	SS-PD-CT6	Chinese Taiwan	40 AD/40 HC//30HC/30 MCI	-	-
		-	- [29]	SS-PD1	Italian	MCI (19)/HC (20)	Yes	-
		-	- [24]	SS-PD2	Italian	eD (16)/MCI (32)/HC (48)	Yes	Yes
		MINI-PGA	MINI-PGA [12]	SS-PD3	Spain	AD (6)/HC (12)	Yes	No
		The Dog Story	The Dog Story from BALE [32]	SS-PD4	Brazilian Portuguese	AD (12)/MCI (12)/HC (82)	No	Yes
		The Cinderella Dataset	The Cinderella Dataset [32]	SS-PD5	Brazilian Portuguese	AD (20)/amnestic MCI(20)/ HC (20)	Yes	Yes
Reading	Transcripts Reading		Gothenburg MCI study [38]	Reading	Swedish	AD (25)/HC (30)	Yes	No

The full names of abbreviations can be found in "Abbreviations"

<u>Table 1: Dementia-related speech-based databases information</u>

VOCAB: (w/definition)

Semantic Verbal Fluency (SVF)- A type of database data in which patients are tested on their semantic memory, language skills, and executive functions by being asked to recall lists of a certain type of item.
Spontaneous Speech (SS)-Speech in the form of a conversation, interview, etc.
Picture Description (PD)-A form of database data in which patients are recorded describing what they see in an image.
Traditional Linguistic Features (TLF)-Lexical features of speech such as word rate, frequency, repetition, word meaning, idea density, and grammatical construction

	Traditional Acoustic Features (TAF)- Features involving the properties of sound waves, speech rate, and pauses produced from patient speech. Demographic Features (DeF)-Data including the age, education, and gender of a patient in a speech database Duration Features (DF)-Data such as the duration spent speaking. Linguistic Embeddings (LE)-Vector representations relating to input tokens (words inputted) Acoustic Embeddings (AE)- Feature vector representations of speech Deep Neural Network (DNN)- A type of pre-trained model that can analyze speech, used in many studies to attempt to diagnose Alzheimer's Gaussian Mixture Model (GMM)-A type of pre-trained model that is used to analyze speech and diagnose Alzheimer's, found to be generally less effective than DNNs. Logistic Regression (LR) Natural Language Processing (NLP)-The use of machine learning to process Language Convolutional Neural Network (CNN)
Cited references to follow up on	https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6296526 Hinton G, Deng L, Yu D, Dahl GE, Mohamed A-r, Jaitly N, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal Process Mag. 2012;29:82–97 IEEE.
Follow up Questions	How might the collection of data in more languages be carried out? What steps can be made to reach a clinical level of accuracy? Is this reliable?

Article #4 Notes: Blood test for early Alzheimer's detection

Article notes should be on separate sheets

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Source Title	Blood test for early Alzheimer's detection
Source citation (APA Format)	*Blood test for early Alzheimer's detection*. (2023, January 9). National Institutes of Health (NIH). https://www.nih.gov/news-events/nih-research-matters/blood-test-early-alzheimer-s-detection
Original URL	https://www.nih.gov/news-events/nih-research-matters/blood-test-early-alzheimer-s-detection
Source type	Science News Article
Keywords	Alzheimer's Early Detection
#Tags	#Blood #Alzheimer's #Detection
Summary of key points + notes (include methodology)	Alzheimer's is marked as much as 10 years before onset by amyloid beta proteins that form in the brain of patients. Using a soluble binding assay and a synthetic alpha sheet molecule, these proteins can be detected in cerebrospinal fluid and in blood plasma. This method is fairly accurate in samples of less than 400 people and could be expanded to detect other cognitive illnesses.

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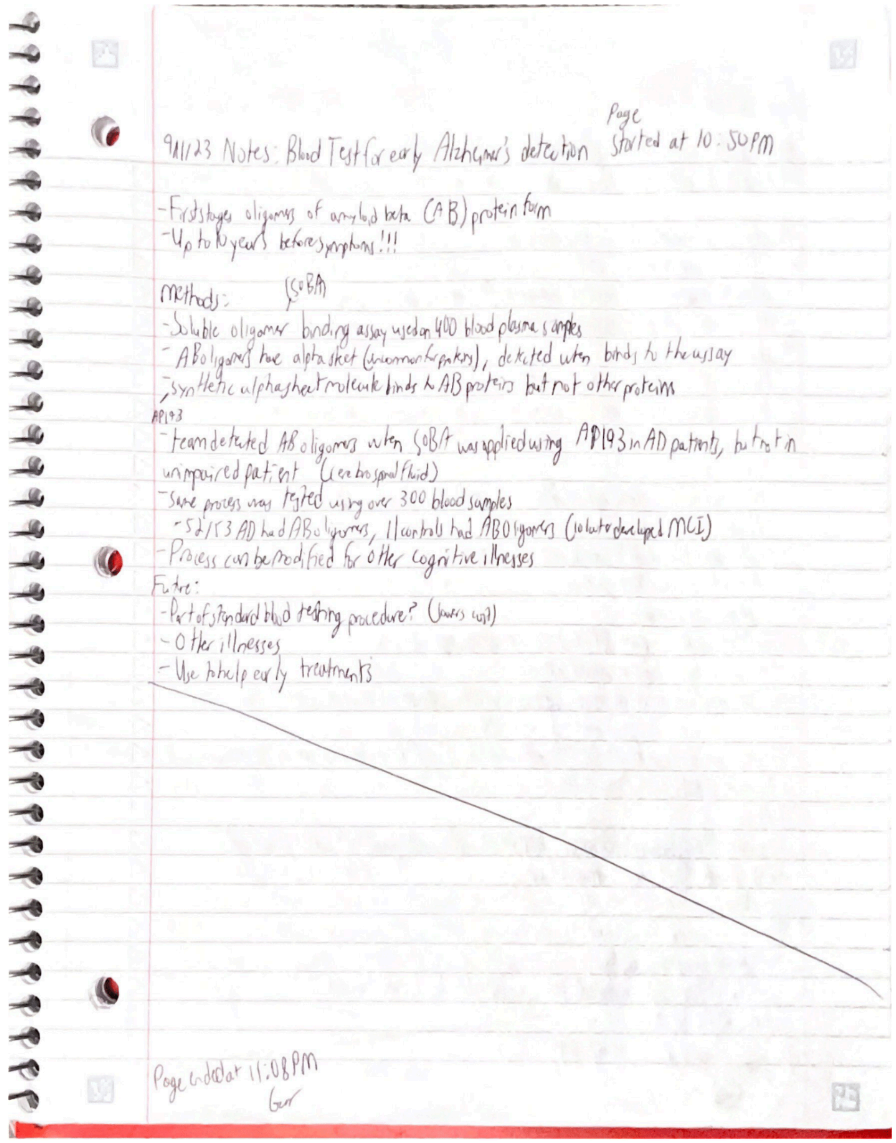

9/1/23 Notes: Blood Test for early Alzheimer's detection Page started at 10:50PM

-First stages oligomers of amyloid beta (AB) protein form
-Up to 10 years before symptoms!!!

Methods: (SOBA)
-Soluble oligomer binding assay used on 400 blood plasma samples
- AB oligomers have alpha sheet (uncommon for proteins), detected when binds to the assay
- synthetic alpha sheet molecule binds to AB proteins but not other proteins
AP193
- team detected AB oligomers when SOBA was applied using AP193 in AD patients, but not in unimpaired patient (cerebrospinal fluid)
- Same process was tested using over 300 blood samples
- 52/153 AD had AB oligomers, 11 controls had AB oligomers (10 later developed MCI)
- Process can be modified for other cognitive illnesses
Future:
- Part of standard blood testing procedure? (lowers cost)
- Other illnesses
- Use to help early treatments

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<tr>
<td>Research Question/Problem/ Need</td>
<td>How can Alzheimer’s be detected in a timely, and cost effective manner</td>
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<tr>
<td>Important Figures</td>
<td>None</td>
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VOCAB: (w/definition)	Oligomers: Toxic aggregates Amyloid Beta Protein: A harmful protein that marks the onset of Alzheimer's Soluble Oligomer Binding Assay: The method used by researchers to detect Amyloid Beta Proteins in the study discussed. Alpha Sheet:An uncommon protein structure that bonds to other alpha sheets and is present in the Amyloid Beta Protein AP193: A molecule designed by researchers that binds to alpha sheets
Cited references to follow up on	None
Follow up Questions	How much does this technology cost? Is it feasible to implement as standard procedure in a blood test at a certain age? How might the SOBA be modified to fit other diseases without diagnosing too broadly?

Article #5 Notes: Potential Ocular Biomarkers for Early Detection of Alzheimer's Disease and Their Roles in Artificial Intelligence Studies

Article notes should be on separate sheets

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Source Title	Potential Ocular Biomarkers for Early Detection of Alzheimer's Disease and Their Roles in Artificial Intelligence Studies
Source citation (APA Format)	Chaitanuwong, P., Singhanetr, P., Chainakul, M., Arjkongharn, N., Ruamviboonsuk, P., & Grzybowski, A. (2023). Potential ocular biomarkers for early detection of Alzheimer's Disease and their roles in artificial intelligence studies. *Neurology and Therapy*, *12*(5), 1517–1532. https://doi.org/10.1007/s40120-023-00526-0
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-85165216617&origin=resu

	ltslist&sort=plf-f&src=s&sid=21f5c4678f45423dcc59ca3ad5dd37d6&sot=b&sdt=b&s=TITLE-ABS-KEY%28alzheimer%27s+AND+eyes+AND+protein+AND+amyloid+AND+beta%29&sl=35&sessionSearchId=21f5c4678f45423dcc59ca3ad5dd37d6
Source type	Journal Article
Keywords	alzheimer's AND eyes AND protein AND amyloid AND beta
#Tags	#Alzheimer's #MachineLearning #Eyes
Summary of key points + notes (include methodology)	Mini Summary: With rates of Alzheimer's globally increasing, early detection is necessary to aid those with the disease, yet the current methods of detection are often costly or intrusive. By using deep learning and analyzing features within the eyes, there is the increasing potential for a reliable method of detection to be developed that would solve many of the current issues with diagnosis. This review looked at various different methods from articles and came to the conclusion that with more database data and multimodal data, retinal images analyzed by a deep learning model could be very effective in the future.

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9/17/23 Notes: Potential Ocular Biomarkers for Early Detection of Alzheimer's Disease and Their Roles in Artificial Intelligence studies

- Review of research using eye biomarkers and artificial intelligence (AI)
  - Tears, corneal nerves, retina, visual function, eye movement tracking
- multimodal imagery could be used to detect Alzheimer's before symptoms (currently not viable however)
- 46.8 mil in 2010 to estimated ~~131.8 mil in 2050~~ 131.5 mil in 2050

Need:
- No medicine can currently cure Alzheimer's
- by detecting Alzheimer's pre-symptoms, disease can be slowed or otherwise dealt with to reduce its burden

\+ Current Field:
- Positron Emission Tomography (PET) scans detect amyloid in brain using tracer
  - High Cost - Less Invasive
- Cerebrospinal Fluid (CSF) analysis
  - detect amyloid beta protein
  - cheaper, more invasive
- Electroencephalogram (EEG) + brain imaging
  - less invasive, not as reliable results
- AI has been used to detect eye diseases without manual feature identification

Goal:
- Review prior research on eye biomarkers and AI for AD detection and make recommendations on future application of tech

Methods:
- Keywords: "Alzheimer's disease" AND "artificial intelligence" OR "Deep learning"
- 224 texts that were narrowed down

Biomarkers:
- Tears:
  - proteomic composition
  - total tau and amyloid beta peptide levels (more than in CSF)
  - miRNA levels

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Page Started: 4:42 pm 9/17/23

Notes: Potential Ocular Biomarkers for Early Detection of Alzheimer's Disease and Their Roles in Artificial Intelligence Studies

Corneal Nerves:
- reduction in sensitivity with AD
- Corneal confocal microscopy is used to examine cornea
- corneal nerve fiber density, branch density, and fiber length all affected
- higher accuracy

Pupil
- AD patients have low acetylcholine levels causing abnormalities in pupils
- larger pupils, abnormal reaction to cholinergic antagonists, less latency and strength of light reflex
- not a sign of Early AD (cognitive impairment that does not fully meet AD guidelines)

Lens:
- Amyloid beta plaque developing in human lens is mostly unknown
- not a high specificity biomarker

Retina and Choroid
- Patients with amyloid beta protein in PET scans have different retinal reflectance from controls (may be correlation) - can scan retina to predict what's in brain
- Retinal fundus imaging, optical coherence tomography (OCT), optical coherence tomography angiography (OCTA) can be used to detect changes in blood vessels in the retina. (narrowing, less density, less complexity, less density) (GC-IPL)

Fundus Fotography

- OCT and OCTA use retinal nerve fiber layer thickness (RNFL), ganglion cells - inner plexiform layer complex, foveal avascular zone (FAZ) area, vessel density and perfusion density to identify AD

OCT - RNFL ~~thickness~~ thinning, decrease in GC-IPL (may be due to age and not AD)
- retinal inclusion bodys
- sig difference in choroidal thickness in one study, recent one found no diff

OCTA - FAZ Area increase in AD patients (one meta analysis found no diff however)
- macular vessel density (Less in AD patients) - the lower, the more impairment

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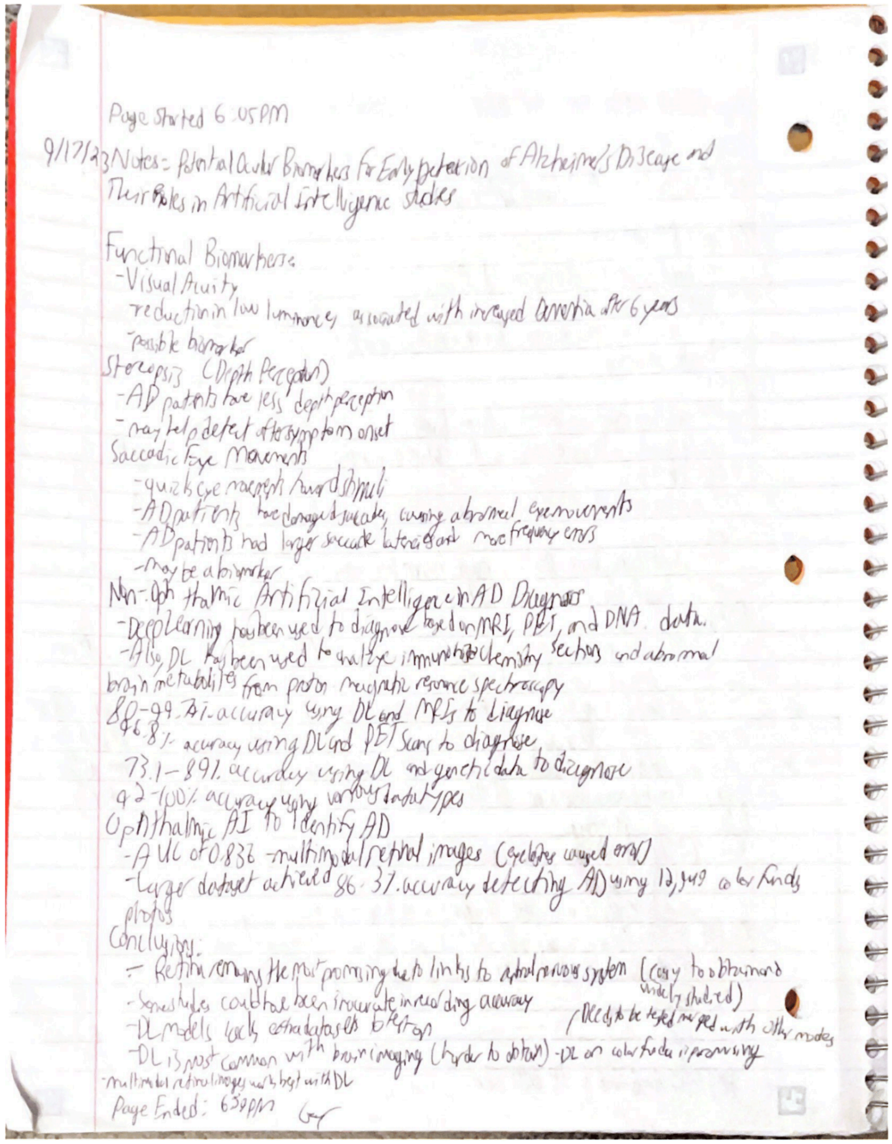

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9/17/23 Notes: Potential Ocular Biomarkers for Early Detection of Alzheimer's Disease and Their Roles in Artificial Intelligence studies

Functional Biomarkers:
- Visual Acuity
  reduction in low luminance associated with increased dementia after 6 years
  - possible biomarker

Stereopsis (Depth Perception)
- AD patients have less depth perception
- may help detect after symptom onset

Saccadic Eye Movements
- quick eye movements toward stimuli
- AD patients have damaged saccades, causing abnormal eye movements
- AD patients had larger saccade latencies and more frequency errors
- May be a biomarker

Non-Ophthalmic Artificial Intelligence in AD Diagnosis
- Deep Learning has been used to diagnose based on MRI, PET, and DNA data.
- Also, DL has been used to analyze immunohistochemistry sections and abnormal brain metabolites from proton magnetic resonance spectroscopy

80-99.7% accuracy using DL and MRIs to diagnose
96.8% accuracy using DL and PET scans to diagnose
73.1-89% accuracy using DL and genetic data to diagnose
92-100% accuracy using various data types

Ophthalmic AI to Identify AD
- AUC of 0.836 - multimodal retinal images (eyelashes caused error)
- Larger dataset achieved 86.3% accuracy detecting AD using 12,949 color fundus photos

Conclusions:
- Retina remains the most promising due to links to central nervous system (easy to obtain and widely studied)
- Some studies could have been inaccurate in recording accuracy
- DL models lack external datasets to test on / Needs to be tested merged with other modes
- DL is most common with brain imaging (harder to obtain) - DL on color fundus is promising
- multimodal retinal images work best with DL

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	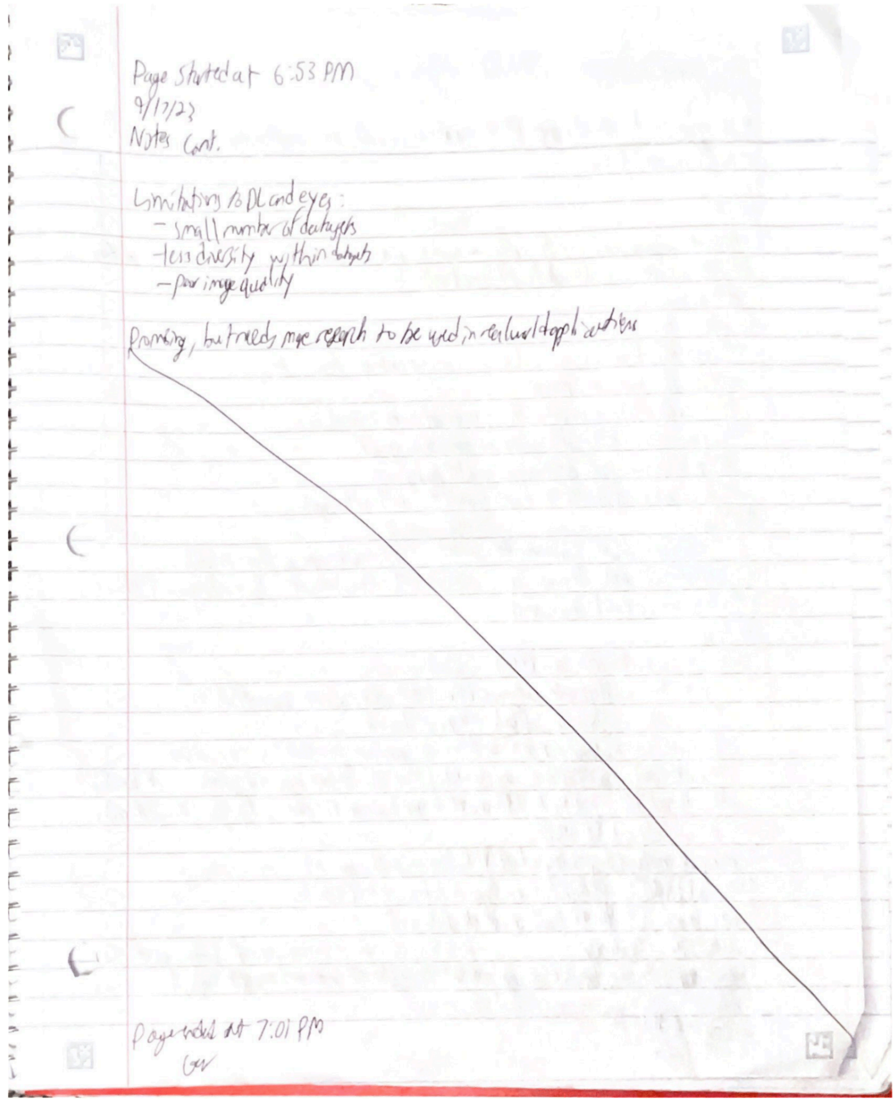 Page Started at 6:53 PM 9/17/23 Notes Cont. Limitations to DL and eyes: - small number of datasets - less diversity within datasets - poor image quality Promising, but needs more research to be used in real world applications Page ended at 7:01 PM -Added at 12:19 AM on 9/22/23
Research Question/Problem/ Need	How can Alzheimer's be detected in an unobtrusive, cost effective, accurate manner?

Important Figures

Table 1 Ocular biomarkers for detecting Alzheimer's disease and early Alzheimer's disease

Ocular biomarkers	Specific description	Detecting AD[a]	Early AD[a]
Structural biomarkers			
Tears	Proteomics components [14, 18, 19]	✔	x
	Elevated levels of t-tau and Aβ42 [20]	✔	✔
	microRNA-200b-5p, higher level of total microRNA [25]	✔	±
Corneal nerves	Reductions in corneal sensitivities [26]	✔	x
	Different morphology of corneal nerve fibers in CCM. Progressive reduction in [27–29]:	✔	±
	Corneal nerve fiber length		
	Density		
	Branch density		
Pupil	Increased pupillary size [33]	✔	x
	Decreased latency and amplitude of the pupillary light reflex [33]		
Lens	Aggregates of misfolded, insoluble proteins (not highly specific; also found in aging process) [37]	±	x
Retinal and choroid	Aβ plaques [38] lead to [39]:	✔	±
	Severe ganglion cell degeneration		
	Tinning of the retinal nerve fiber layers		
	Loss of optic nerve axonal projections		
	Retinal imaging reflectance scores from hyperspectral imaging (predict the amount of Aβ in the brain) [41]	✔	✔
	Retinal vessels from fundus imaging: (suggest changes in the cerebral vasculature associated with early stages of neurodegenerative diseases) [46, 47]:	✔	±
	Narrowing or widening of vessels		
	Low complexity		
	Decreased density of retinal vessels		
	Thinning of peripapillary RNFL [44, 48, 50, 51, 53, 54] (small range of significance [62]; no significant difference between early AD and AD [44, 50])	✔	±
	Thinning of macular RNFL (not specific to AD; may also be from aging and other causes) [60]	±	x
	Decreased GC-IPL (not specific to AD; may also be from aging and other causes) [60]	±	x
	Retina inclusion bodies (correlation with cortical amyloid deposits, detected by florbetapir PET imaging) [61]	✔	±
	Thinner choroidal thickness [48, 63]	✔	x
	Widening of the FAZ [44, 55–58] (no difference in AD and healthy controls from meta-analysis [62])	✔	x
	Lower whole macular enface superficial and deep vascular density (VD), lower parafoveal superficial VD [56]	✔	x
	Lower macular vessel density (m-VD) [65]	✔	±
Functional biomarkers			
Visual acuity	Reduction in low luminance [31, 68]	✔	x
	Moderate-to-severe vision impairment [69]	✔	±
Stereopsis	Less stereopsis [31, 37, 71]	✔	x

Table 1: Ocular biomarkers for detecting Alzheimer's disease and early Alzheimer's disease

VOCAB: (w/definition)

Amyloid Beta Protein: A plaque that is commonly associated with Alzheimer's Disease. Current methods look at its presence in the brain through MRI or PET scans. Researchers have tested its presence in tears and in the retina as alternative methods of diagnosis.
Corneal confocal microscopy (CCM): A method used to examine the cornea at a cellular level. CCM data has been used in studies to attempt Alzheimer's Diagnosis.
Optical coherence tomography(OCT)- A method that uses light waves to capture cross-section pictures of the retina.
Optical coherence tomography angiography(OCTA)-A method that uses light waves to visualize vascular networks in the retina.
Retinal nerve fiber layer(RNFL)- a nerve fiber layer whose thickness has been used

	to predict Alzheimer's in studies. Macular vessel density(m-VD): One of the key variables analyzed by many studies using OCTA. It has been found that as levels of m-VD lessen, patients are typically more cognitively impaired. Saccade:A quick eye movement in response to a stimulus. Alzheimer's patients typically display some abnormality in their saccades.
Cited references to follow up on	
Follow up Questions	How many databases currently exist for the various modes of data that were analyzed in the review?

Article #6 Notes: Lexical-semantic properties of verbs and nouns used in conversation by people with Alzheimer's Disease

Article notes should be on separate sheets

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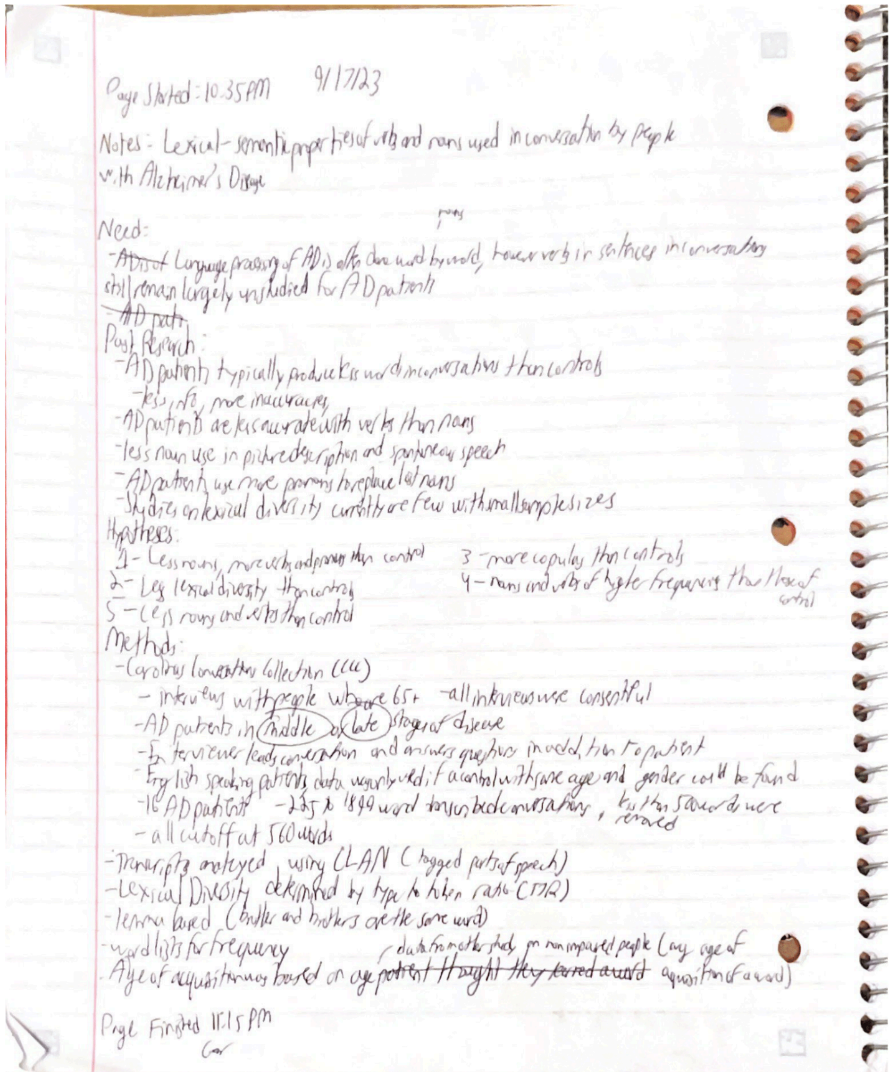
Source Title	Lexical-semantic properties of verbs and nouns used in conversation by people with Alzheimer's disease
Source citation (APA Format)	Williams, E., Theys, C., & McAuliffe, M. (2023). Lexical-semantic properties of verbs and nouns used in conversation by people with Alzheimer's disease. *PLOS ONE*, *18*(8). https://doi.org/10.1371/journal.pone.0288556
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-85166563687&origin=resultslist&sort=plf-f&src=s&sid=37c6806ecd3da0ec1a0e69711d3a8131&sot=b&sdt=b&s=TITLE-ABS-KEY%28alzheimer%27s+AND+conversation%29&sl=36&sessionSearchId=37c6806ecd3da0ec1a0e69711d3a8131
Source type	Journal Article
Keywords	Alzheimer's AND conversation
#Tags	#Alzheimer's #Speech
Summary of key points + notes (include methodology)	This study aimed to further the knowledge around Alzheimer's and speech by looking into relationships between types of words, time at which a word was learnt, complexity of speech in the context of Alzheimer's patients. The study used 12 conversations with Alzheimer's and control groups alongside database data on the times when words are typically learnt based on surveys. The conversations were reduced to be the same length in words and were then analyzed. Despite many limitations in the data, the conclusion was made that since verbs are typically more complex yet also more common than nouns in Alzheimer's patients, data in general on sentence complexity must be normalized based on parts of speech in order to properly assess a patient's condition and aid them.



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Notes: Lexical-semantic properties of verbs and nouns used in conversation by people with Alzheimer's Disease

Need:
- ~~AD is of~~ Language processing of AD is often done word by word, however verbs in sentences in conversations [pronouns] still remain largely unstudied for AD patients
- ~~AD pati~~

Past Research:
- AD patients typically produce less words in conversations than controls
  - less info, more inaccuracies
- AD patients are less accurate with verbs than nouns
- less noun use in picture description and spontaneous speech
- AD patients use more pronouns to replace lost nouns
- Studies on lexical diversity currently are few with small sample sizes

Hypotheses:
1 - Less nouns, more verbs and pronouns than control
2 - Less lexical diversity than control
3 - more copulas than controls
4 - nouns and verbs of higher frequency than those of control
5 - Less nouns and verbs than control

Methods:
- Carolinas Conversation Collection (CCC)
  - interviews with people who are 65+ - all interviews were consentful
  - AD patients in (middle) or (late) stages of disease
  - Interviewer leads conversation and answers questions in addition to patient
  - English speaking patients data was only used if a control with same age and gender could be found
  - 16 AD patients - 225 to 1899 word transcribed conversations, but transcribed were removed
  - all cut off at 560 words
- Transcripts analyzed using CLAN (tagged parts of speech)
- Lexical Diversity determined by type to token ratio (TTR)
- lemma based (brother and brothers are the same word)
- word lists for frequency
- Age of acquisition was based on age ~~patient thought they learned a word~~ (data from another study on non impaired people (avg age of acquisition of a word)

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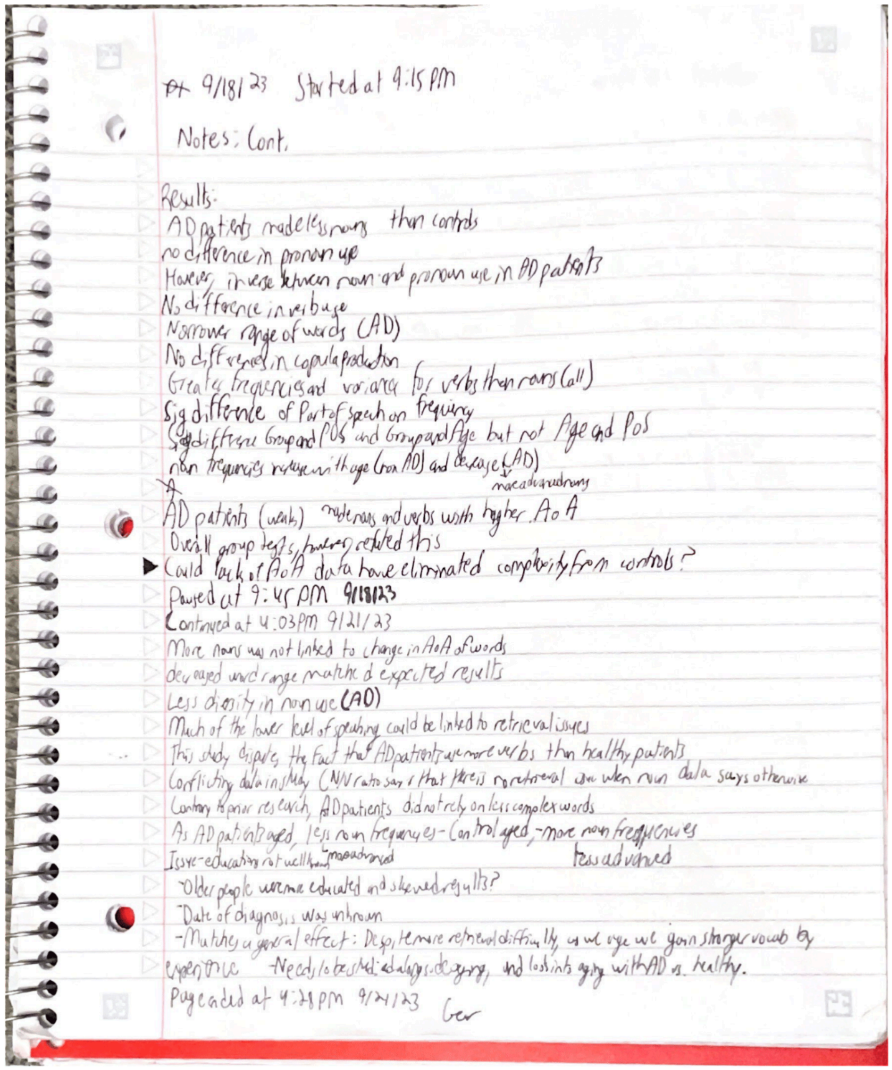

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Notes: Cont.

Results:
AD patients made less nouns than controls
no difference in pronoun use
However, inverse between noun and pronoun use in AD patients
No difference in verb use
Narrower range of words (AD)
No differences in copula production
Greater frequencies and variance for verbs than nouns (all)
Sig difference of Part of speech on frequency
Sig difference Group and POS and Group and Age but not Age and POS
noun frequencies increase with age (non AD) and decrease (AD)
more advanced nouns
AD patients (weak) made nouns and verbs with higher AoA
Overall group tests, however, refuted this
Could lack of AoA data have eliminated complexity from controls?
Paused at 9:45 PM 9/18/23
Continued at 4:03 PM 9/21/23
More nouns was not linked to change in AoA of words
decreased word range matched expected results
Less diversity in noun use (AD)
Much of the lower level of speaking could be linked to retrieval issues
This study disputes the fact that AD patients use more verbs than healthy patients
Conflicting data in study (N/V ratio says that there is no retrieval issue when noun data says otherwise
Contrary to prior research, AD patients did not rely on less complex words
As AD patients aged, less noun frequencies - Control aged, more noun frequencies
more advanced / less advanced
Issue - education not well known
-Older people were more educated and skewed results?
-Date of diagnosis was unknown
-Matches a general effect: Despite more retrieval difficulty, as we age we gain stronger vocab by experience
-Needs to be studied: dialogues, decoding, and look into aging with AD vs. healthy.
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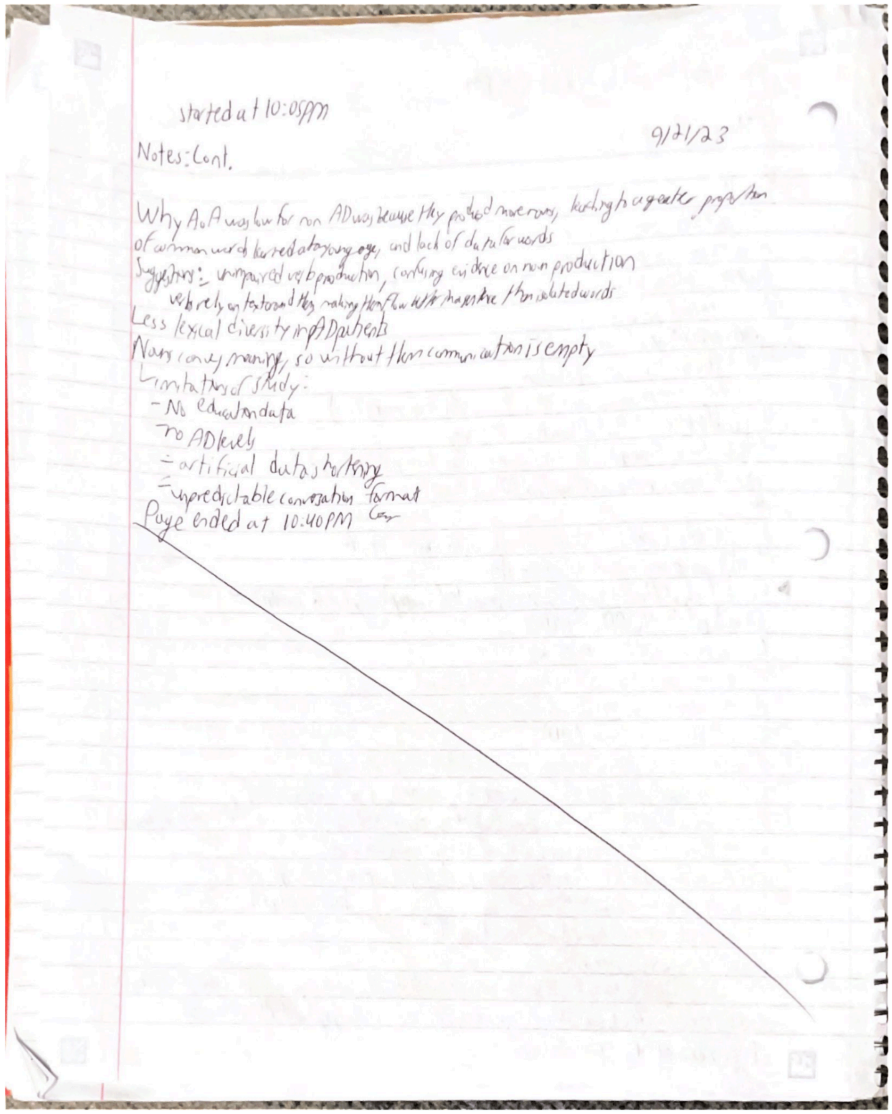
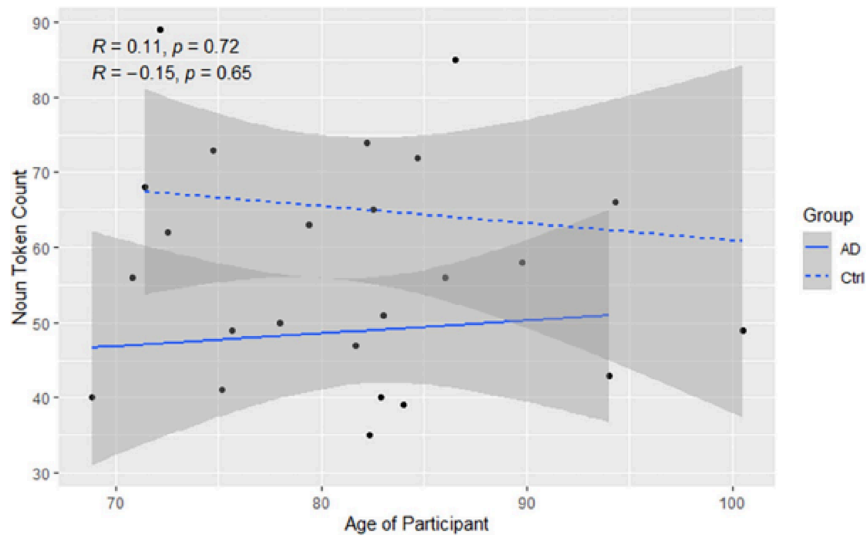
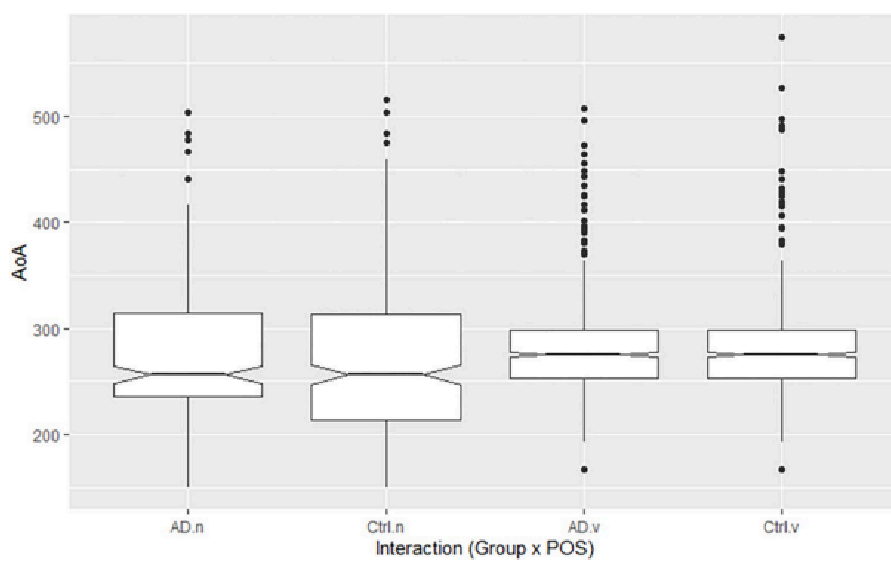
	 -Added at 12:19 AM on 9/22/23 
Research Question/Problem/ Need	How can parts of speech affect an Alzheimer's patients' speech? How might this data be used to better improve Alzheimer's aid and analysis of study data?

Important Figures	 **Fig 3. Relationship between age and noun token production, by group.** https://doi.org/10.1371/journal.pone.0288556.g003  **Fig 4. AoA by POS and group.** *Note*. AD = pwAD, Ctrl = controls, n = nouns, v = verbs. https://doi.org/10.1371/journal.pone.0288556.g004
VOCAB: (w/definition)	Spontaneous speech:Speech in the form of a conversation. pwAD:A person with Alzheimer's disease. Word Frequency:The commonality of a word. This was determined using external database data. Noun tokens:Tokens consisting of the nouns (pronouns included). Used to perform further analysis Verb tokens:Tokens consisting of the verbs (copulas and participles included)
Cited references to follow up on	

Follow up Questions	How might a larger, more objective database be obtained for age of learning a word? Is education expected to have a large, medium, or small impact on the performances of AD patients? Could an AD patient with a high level of education speak stronger than a control with a lesser education?

Article #7 Notes: Cognitive Exercise for Persons with Alzheimer's Disease and Related Dementia using a social robot

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Source Title	Cognitive exercise for persons with Alzheimer's Disease and related Dementia using a social robot
Source citation (APA Format)	Yuan, F., Boltz, M., Bilal, D., Jao, Y.-L., Crane, M., Duzan, J., Bahour, A., & Zhao, X. (2023). Cognitive exercise for persons With Alzheimer's Disease and related Dementia using a social robot. *IEEE Transactions on Robotics*, *39*(4), 3332–3346. https://doi.org/10.1109/TRO.2023.3272846
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-85161021780&origin=resultslist&sort=plf-f&src=s&sid=5aa502c1eb99745b21821aa449aa35f0&sot=b&sdt=b&s=TITLE-ABS-KEY%28alzheimer%27s+AND+conversation%29&sl=43&sessionSearchId=5aa502c1eb99745b21821aa449aa35f0
Source type	Journal Article
Keywords	Alzheimer's AND conversation
#Tags	#Alzheimer's #Care #AI
Summary of key points + notes (include methodology)	Reminiscence therapy is a beneficial service to Dementia patients, yet its price and the need for a trained professional make it out of reach for many. This study aims to test how a social robot could be used to provide reminiscence therapy that could eventually become much more cost effective. The results of the study proved that the patients generally had a positive experience with the robot, although there were some flaws that need to be worked out before a product like this could become mainstream.

Page Started: 11:57PM: Cognitive Exercise for Persons with Alzheimer's Disease and Related Dementia using a social robot

Social robot shows visual cue, has conversation based around it
Overall Positive effect
(RT) Reminiscence Therapy: intervention in dementia care involving discussion of past experiences using prompts
- provided by trained people
- some app forms of this exist
- robot would make this 3 dimensional and connect more to patient

Previous testing:
- huggable human type robot (positive effect)
- 19cm tall robot (prepared good questions based on pictures
- another humanoid robot also posed strong questions
- Few tests have been done on AD patients

Methods:
- 1.21m tall, .48m wide, 17 joints - body language, eye contact
- uses sensors and AI to interact
- tablet on chest to display prompts (images etc.)
- Files obtained from public domain to reminisce on (video, photo, audio) ([illegible] < 3 min long)
- Professional input on media chosen - nine topics were chosen to focus on
- made an app for the robot, female because it appears more human
- user chooses a topic which robot then provides queues and discussion
- robot provides background (talks about a memory) then asks a question to the patient to open conversation

Study:
- those who interacted were between 18 and 95, fluent in English, either caretakers or Dementia patients
- Verbal confirmation was required (patient must be able to explain what the study is about to ensure proper consent)
- demographic data collected
- video, conversation, and observations were recorded
- Surveys used to determine satisfaction with the robot

Results:
- 12 adults (3 caregivers, 9 patients)
- many laughed, giggled, etc. during experience (good!!!)

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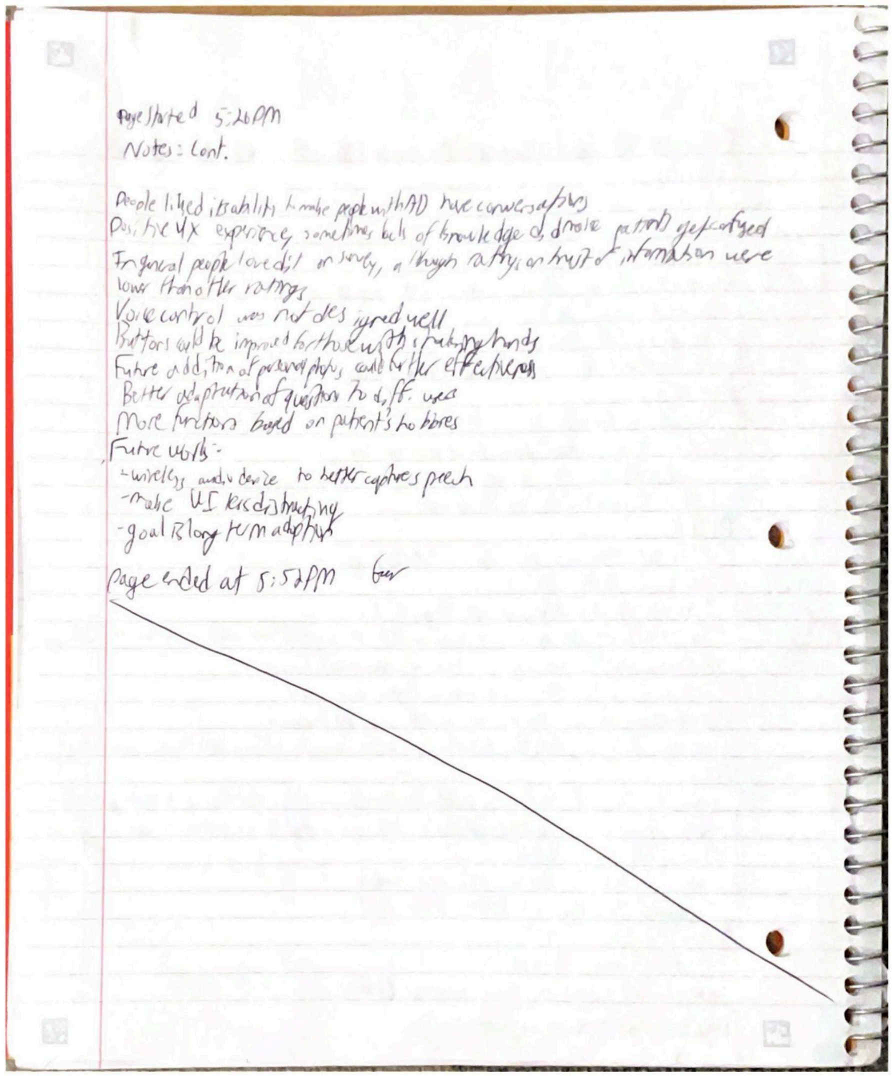
<tr><td></td><td>
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Notes: Cont.
People liked its ability to make people with AD have conversations
Positive UX experience, sometimes lack of knowledge of device patients get confused
In general people loved it on survey, although rating on trust of information were lower than other ratings
Voice control was not designed well
Buttons could be improved for those with shaking hands
Future addition of personal photos could further effectiveness
Better adaptation of questions to diff. users
More functions based on patient's hobbies
Future work:
- wireless audio device to better capture speech
- make UI less distracting
- goal is long term adoption
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-Gustavo Rodriguez
Added at 3:12 AM on 10/13/2023</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>How can the standard of living of an Alzheimer's patient be improved?</td></tr>
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Important Figures

Fig. 1. Examples of photos that could be used to assist reminiscing sports (photo courtesy: Tennessee Athletics/UTsports.com). The left and middle photos containing multiple objects could potentially be confusing to PLWD. Comparatively, the picture on the right is more appropriate for PLWD during reminiscence.

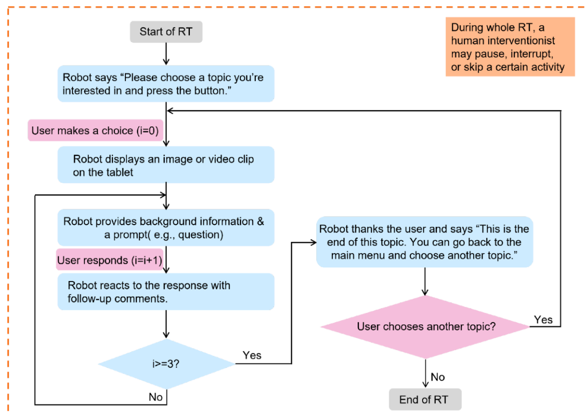

Fig. 3. Flowchart of the robot-mediated reminiscence activity. If the user does not make a choice (or does not respond), the human interventionist will verbally invite the user to make a choice (or respond). The interventionist may also help skip the certain activity or end the RT, according to the user's willingness.

VOCAB: (w/definition)

Reminiscence Therapy (RT)-Intervention in dementia care involving discussion of past experiences using prompts
Robot-mediated reminiscence therapy (RMRT)-Reminiscence therapy led by a social robot
Social Robot-A robot meant to interact with the user. This is the type of humanoid robot that was used in this study.
UX-a term describing the user experience using a device or app

Cited references to follow up on

Follow up Questions

How can a technology like this become affordable?
How could people be exposed to this without spending too much money?
Could more functions be added to the robot to make it both a medical and a therapeutic device?

Article #8 Notes: How hyperspectral imaging and artificial intelligence transform Alzheimer’s diagnosis

Article notes should be on separate sheets

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Source Title	How hyperspectral imaging and artificial intelligence transform Alzheimer’s diagnosis
Source citation (APA Format)	Lemmens, S., De Groef, L., Charle, W., Jayapala, M., Theunis, J., Moons, L., De Boever, P., & Stalmans, I. (2021). How hyperspectral imaging and artificial intelligence transform alzheimer’s diagnosis. *Spectroscopy Europe*, 18. https://doi.org/10.1255/sew.2021.a26
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-85153081013&origin=resultslist&sort=r-f&src=s&sid=6f2f77c4ccafab568ec17affa8da68fb&sot=b&sdt=b&s=TITLE-ABS-KEY%28hyperspectral+imaging+AND+alzheimer%27s%29&sl=52&sessionSearchId=6f2f77c4ccafab568ec17affa8da68fb
Source type	Journal Article
Keywords	Retinal imaging AND alzheimer’s
#Tags	#Alzheimer’s #Diagnosis #Eyes
Summary of key points + notes (include methodology)	Hyperspectral imaging can be used to detect spectral changes that could be caused by the amyloid beta protein that is known to be a biomarker of Alzheimer’s disease. In combination with optical coherence tomography, which can be used to obtain cross sections of the retina, there is potential to detect Alzheimer’s using uninvasive more affordable means. This study creates a machine learning model that uses both means to detect Alzheimer’s with 75% accuracy.

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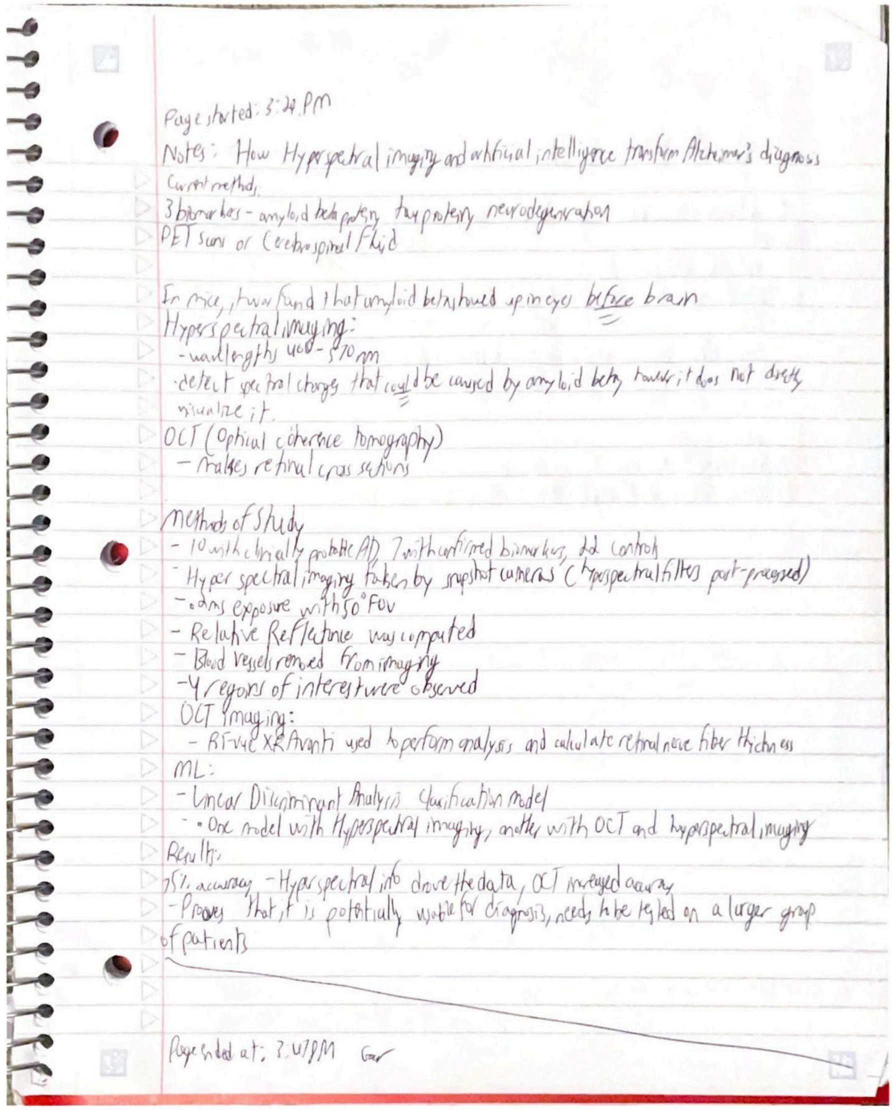

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Notes: How Hyperspectral imaging and artificial intelligence transform Alzheimer's diagnosis

Current methods:

3 biomarkers - amyloid beta protein, tau protein, neurodegeneration

PET scans or Cerebrospinal Fluid

In mice, it was found that amyloid beta showed up in eyes before brain

Hyperspectral imaging:

- wavelengths 460-570 nm

- detect spectral changes that could be caused by amyloid beta, however it does not directly visualize it.

OCT (Optical coherence tomography)

- makes retinal cross sections

Methods of Study

- 10 with clinically probable AD, 7 with confirmed biomarkers, 22 controls

- Hyper spectral imaging taken by snapshot cameras (hyperspectral filters post-processed)

- 0.4ms exposure with 50° FOV

- Relative Reflectance was computed

- Blood vessels removed from imaging

- 4 regions of interest were observed

OCT Imaging:

- RTVue XR Avanti used to perform analysis and calculate retinal nerve fiber thickness

ML:

- Linear Discriminant Analysis Classification model

- One model with Hyperspectral imaging, another with OCT and hyperspectral imaging

Results:

75% accuracy - Hyperspectral info drove the data, OCT increased accuracy

- Proves that it is potentially usable for diagnosis, needs to be tested on a larger group of patients

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-Gustavo Rodriguez
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<td>How can Alzheimer’s Disease be detected in an affordable, unintrusive, reliable way?</td>
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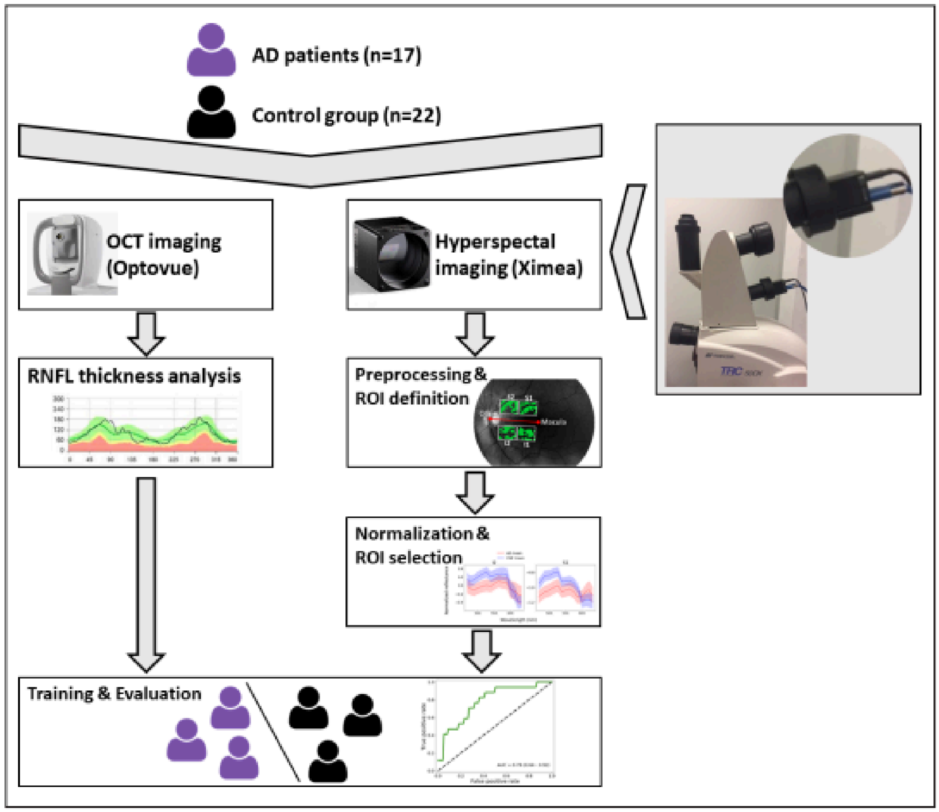
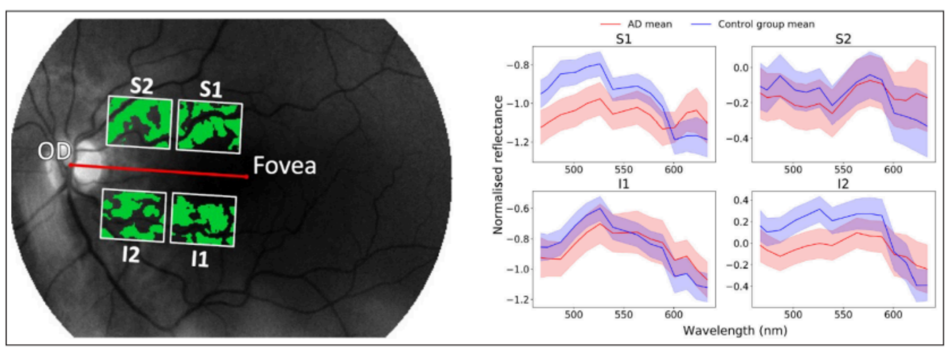
Important Figures	 **Figure 2.** Study set-up.  **Figure 3.** Left: Four regions of interest were defined: superior 1 (S1), superior 2 (S2), inferior 1 (I1) and inferior 2 (I2). The green parts in the image are the ones used for the analysis, with the retinal blood vessels substracted from the image. Right: Mean spectra in the four regions of interest. Shaded areas indicate the mean ± the standard error of the mean.
VOCAB: (w/definition)	Hyperspectral Imaging: A type of imaging of the eye that uses wavelengths of 460-570nm wavelengths to detect spectral changes in the eye. Optical Coherence Tomography: A type of imaging that creates a cross section of the retina that can be used to find retinal nerve fiber thickness Linear Discrimination Analysis: A type of classification model. In this study it was used to create a model that could predict Alzheimer's with 75% accuracy. Retinal reflectance: The reflectance of the retina that is calculated using data from hyperspectral imaging. It contributed to the model used in this study to predict Alzheimer's.

Cited references to follow up on	
Follow up Questions	Could this method of detection be merged with other methods? What improvements could be made to the model used in this study? Are the selected regions representative enough of the presence of the Amyloid Beta protein? What other medical issues may cause the model to appear as though the Amyloid Beta protein is involved?

Article #9 Notes: Novel quantitative electroencephalogram feature image adapted for deep learning: Verification through classification of Alzheimer's disease dementia

Article notes should be on separate sheets

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Source Title	Novel quantitative electroencephalogram feature image adapted for deep learning: Verification through classification of Alzheimer's disease dementia
Source citation (APA Format)	Jeong, T., Park, U., & Kang, S. W. (2022). Novel quantitative electroencephalogram feature image adapted for deep learning: Verification through classification of Alzheimer's disease dementia. *Frontiers in neuroscience*, *16*, 1033379. https://doi.org/10.3389/fnins.2022.1033379
Original URL	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9670114/
Source type	Journal Article
Keywords	Brain waves AND Alzheimer's
#Tags	#Alzheimer's #Diagnosis #EEG
Summary of key points + notes (include methodology)	Quantitative electroencephalography (QEEG) reveals features in electroencephalograms. Features of the brain waves emitted during sleep have been found to connect with Alzheimer's disease. Using QEEG with a deep learning algorithm, this study creates a tool with 97.4% accuracy in predicting Alzheimer's.

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Note: Novel Quantitative electroencephalogram feature image adapted for deep learning: Verification through classification of Alzheimer's disease dementia

Quantitative electroencephalography (QEEG) analysis
- reveals electroencephalogram (EEG) features associated with dysfunctions
- Topographies used to represent EEG characteristics
- due to topographies needed at many different frequencies, using DL to diagnose is difficult
- This study created a method to diagnose ADD (Alzheimer's disease dementia) with 97.4% accuracy using feature images created through complex processing of EEG Data

EEG definition: "electrical pattern measured at multiple channel locations on the scalp, reflecting cortical activities of the underlying brain region"
QEEG - mapping function based on features taken from EEG
QEEG has been used to diagnose disorders, and databases to normalize gender and age exist
QEEG is easier to access than PET scan
Methods:
- Data collected while patients were resting (based on frequencies emitted in sleep)
- Bad epoch rejection used to eliminate noise (eye, muscle, heart movement)
- Normalization database with 1289 controls
- 19 electrode locations, many bands observed per electrode
- matrix was created - x axis = frequency, y axis = channels
- 4 types of feature images were made
Classification Data:
- used community and subjective cognitive decline data
- comparing QEEG data of ADD vs NADD controls shows progression
MCI was considered not ADD (even as some MCI turns into AD)
137 ADD, 628 NADD, 10% excluded to be used as test data
Verification of no overfitting was used
Models were trained from scratch (pretrained means model typically already made for that type of data)
Tools helped infer what features were used
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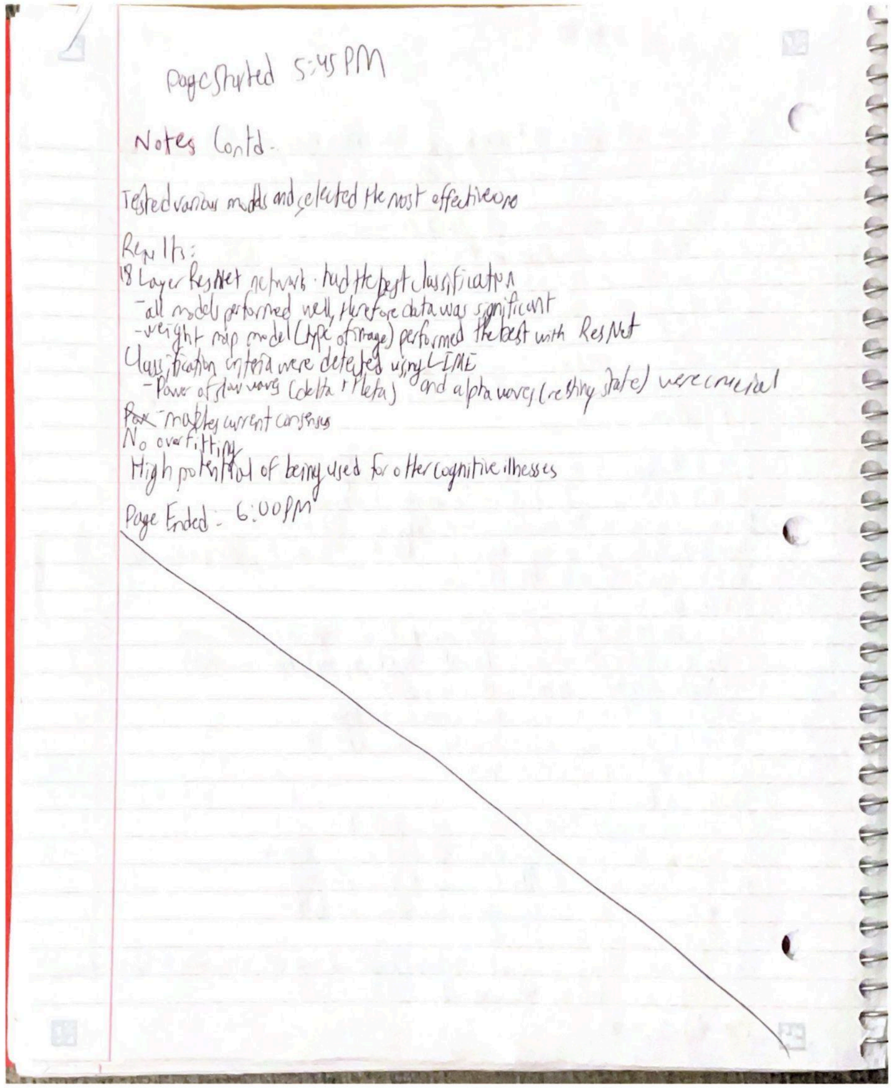
<td>
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Notes Contd.
Tested various models and selected the most effective one
Results:
18 Layer ResNet network · had the best classification
- all models performed well, therefore data was significant
- weight map model (type of image) performed the best with ResNet
Classification criteria were detected using LIME
- Power of slow waves (delta + theta) and alpha waves (resting state) were crucial
~~Pox~~ - matches current consensus
No overfitting
High potential of being used for other cognitive illnesses
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-Gustavo Rodriguez
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<tr>
<td>Research Question/Problem/ Need</td>
<td>How can Alzheimer’s disease be predicted in a cost effective, unintrusive, effective way?</td>
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Important Figures

Models	ADD classification criteria	Non-ADD classification criteria
1. Nearest	High power of slower waves (delta-theta).	High power of alpha waves and low power of slower waves (delta-theta).
2. Bicubic	High power of slower waves (delta-theta).	High power of alpha waves.
3. Weight map	High power of slower waves (delta-theta).	High power of alpha waves and low power of slower waves (delta-theta).
4. Rescaled	Low power of faster waves (beta 2) and high power of slower waves (delta-theta).	Low power of slower waves (delta-theta).

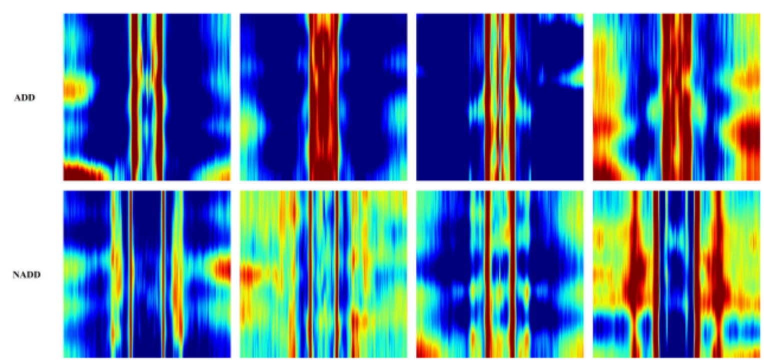

FIGURE 6
Typical feature images representing the classes Alzheimer's disease dementia (ADD) and non-Alzheimer's disease dementia (NADD).

VOCAB: (w/definition)

Electroencephalography (EEG):"Electrical pattern measured at multiple channel locations on the scalp, reflecting cortical activities of the underlying brain regions"
Quantitative Electroencephalography (QEEG) Analysis: a type of analysis that uses topographies to represent EEG characteristics
Bad Epoch Rejection: The process of eliminating noise from EEG recordings.
Overfitting: When a deep learning or machine learning model tailors itself too much to the data provided, making it only function for that data and make false assumptions that do not apply to the broader field.
Topograph: A graphical representation of EEGs. They are created to make the data accessible to a deep learning or machine learning model.

Cited references to follow up on

Follow up Questions

How might this algorithm be improved?
Could this same form of detection be done in a waking state?
Would it be less cost effective but more invasive

	Since it requires a patient to be sleeping, would this model be cost effective for areas with fewer doctors or hospitals? Could a low cost EEG recorder be developed to allow people to collect data from home?

Article #10 Notes: WavBERT: Exploiting Semantic and Non-semantic Speech using

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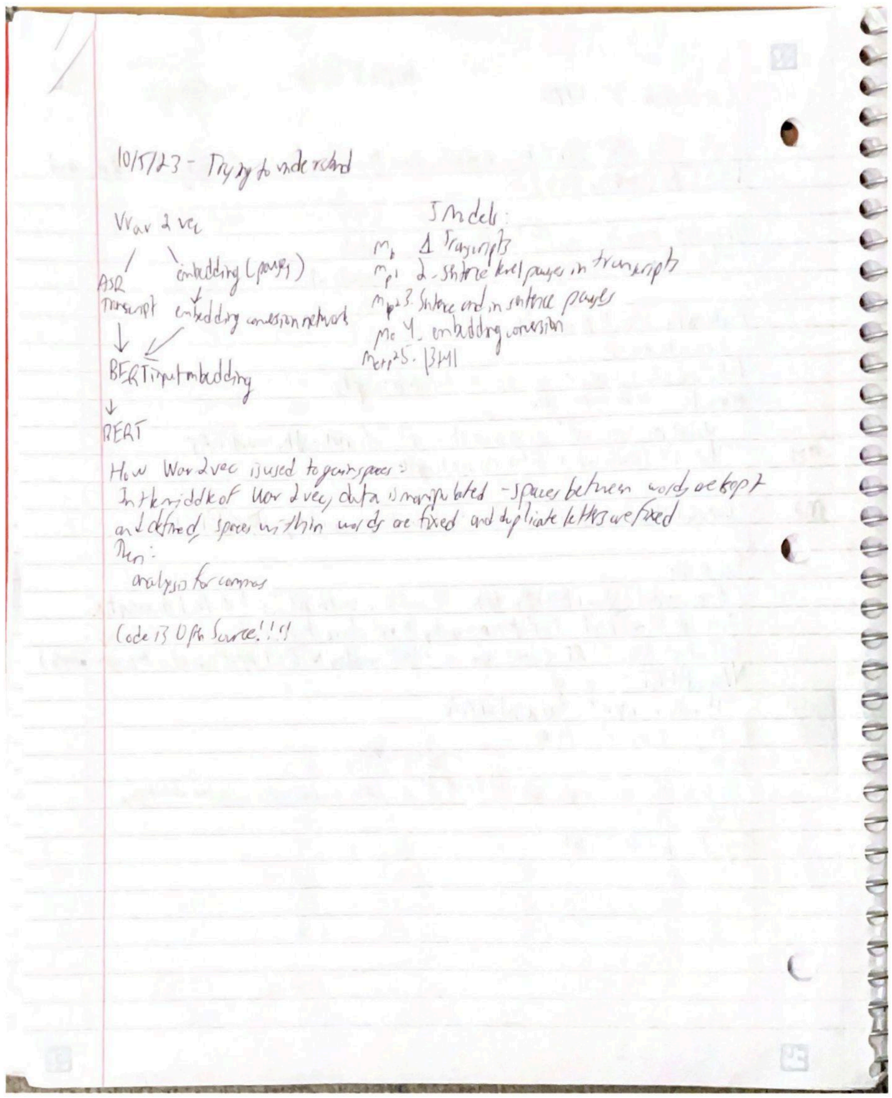
Source Title	WavBERT: Exploiting Semantic and Non-semantic Speech using Wav2vec and BERT for Dementia Detection
Source citation (APA Format)	Zhu, Y., Obyat, A., Liang, X., Batsis, J. A., & Roth, R. M. (2021). WavBERT: Exploiting Semantic and Non-semantic Speech using Wav2vec and BERT for Dementia Detection. *Interspeech, 2021*, 3790–3794. https://doi.org/10.21437/interspeech.2021-332
Original URL	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10102979/
Source type	Journal Article
Keywords	speech detection of alzheimer's bert
#Tags	#Alzheimer’s #Detection #DL #ML
Summary of key points + notes (include methodology)	This work aims to create a Deep Learning model that can accurately detect Dementia by accurately recording pauses as punctuation such as periods or commas in a sentence. This is done by running the data through Wav2vec, then converting that data into usable data that can be merged with the current transcript-like data and then fed into the BERT model. This allows for a BERT model that is pre-trained on a language to use the normality or abnormality of pauses directly in conjunction with factors such as vocabulary or repetitiveness.



10/5/23 - Trying to understand

Wav 2 vec

ASR Transcript

embedding (pauses)

embedding conversion network

BERT input embedding

BERT

5 Models:

M 1 Transcripts

M 2 - Sentence level pauses in transcripts

M 3. Sentence and in sentence pauses

M 4. embedding conversion

M 5. BERT

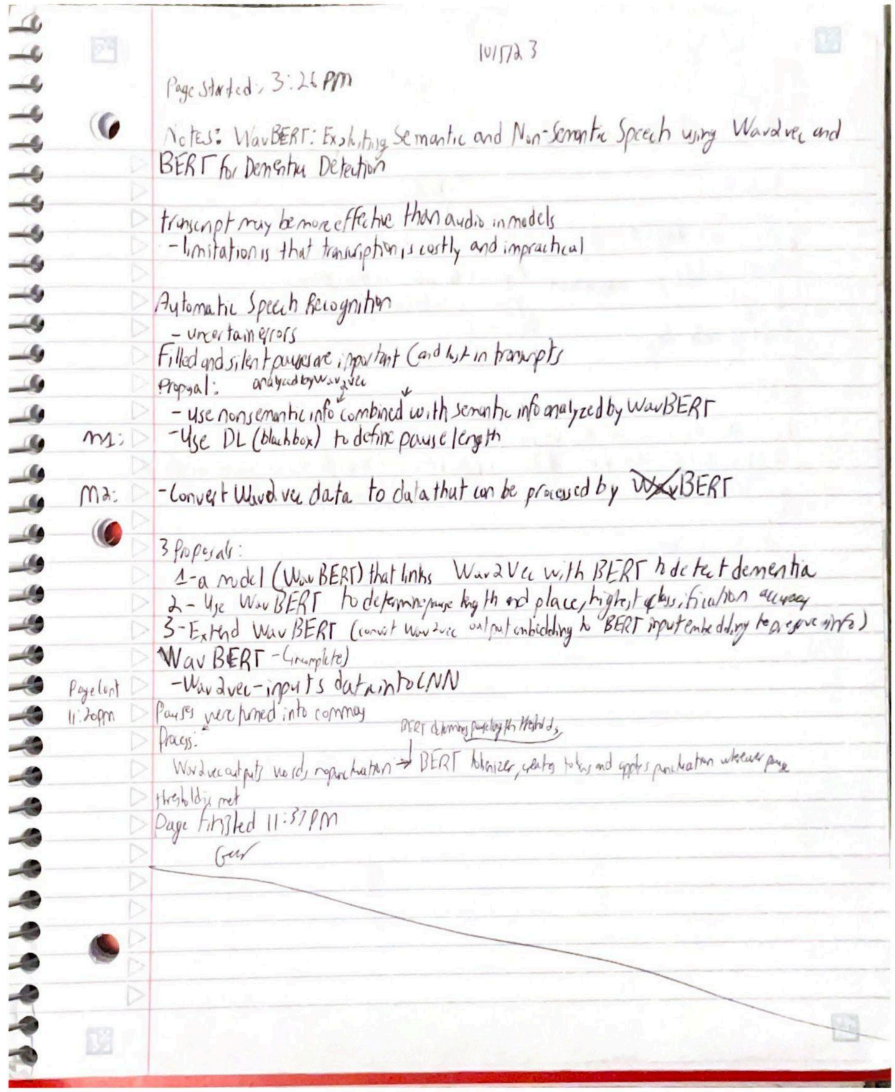
How Wor2vec is used to gain spaces:

In the middle of Wor2vec, data is manipulated - spaces between words are kept and defined, spaces within words are fixed and duplicate letters are fixed

Then:

analysis for commas

Code is Open Source!!!



10/5/23

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Notes: WavBERT: Exploiting Semantic and Non-Semantic Speech using Wav2vec and BERT for Dementia Detection

transcript may be more effective than audio in models
- limitation is that transcription is costly and impractical

Automatic Speech Recognition
- uncertain errors

Filled and silent pauses are important (and lost in transcripts)

Proposal: (analyzed by Wav2vec)
- use nonsemantic info combined with semantic info analyzed by WavBERT

m1: - Use DL (blackbox) to define pause length

m2: - Convert Wav2vec data to data that can be processed by ~~Wav~~BERT

3 Proposals:
1 - a model (WavBERT) that links Wav2Vec with BERT to detect dementia
2 - Use WavBERT to determine pause length and place, highest classification accuracy
3 - Extend WavBERT (convert Wav2vec output embedding to BERT input embedding to preserve info)

WavBERT - (incomplete)
- Wav2vec - inputs data into CNN

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Pauses were turned into commas

Process:
Wav2vec outputs words, no punctuation → BERT tokenizer, creates tokens and applies punctuation wherever pause threshold is met (BERT determines pause length thresholds)

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-Gustavo Rodriguez
Added on 10/13/2023 at 3:22 AM

Research Question/Problem/ Need	How can Alzheimer’s Disease be detected in a cost effective, unobtrusive manner?

Important Figures

Table 1:

Results of classification, regression, and progression tasks over ADReSSo testing dataset. The design of the baseline linguistic model and the definitions of precision, recall, F1, mean F1, accuracy, and RMSE can be found at the baseline paper [10].

Task	1. Classification (%)						2. Regression	3. Progression (%)					
	Class	Precision	Recall	F1	Mean F1	Accuracy	RMSE	Class	Precision	Recall	F1	Mean F1	Accuracy
Baseline [10]	non-AD AD	80.00 77.80	77.80 80.00	78.87 78.87	78.87	78.87	5.28	non-decline decline	83.30 50.00	68.20 70.00	75.00 58.30	66.67	68.75
M_b	non-AD AD	71.79 75.00	77.78 68.57	74.67 71.64	73.16	73.24	4.60	non-decline decline	64.00 14.29	72.73 10.00	68.09 11.76	39.92	53.13
M_{p1}	non-AD AD	80.00 87.10	88.89 77.14	84.21 81.82	83.02	**83.10**	4.45	non-decline decline	62.96 0	77.27 0	69.39 0	34.69	53.13
M_{p2}	non-AD AD	77.50 83.87	86.11 74.29	81.58 78.79	80.19	80.28	**4.44**	non-decline decline	64.29 0	81.82 0	72.00 0	36.00	56.25
M_e	non-AD AD	78.95 81.82	83.33 77.14	81.08 79.41	80.25	80.28	4.46	non-decline decline	79.17 62.50	86.36 50.00	82.61 55.56	69.08	75.00
M_{e+p2}	non-AD AD	77.78 77.14	77.78 77.14	77.78 77.14	77.46	77.46	4.47	non-decline decline	81.82 60.00	81.82 60.00	81.82 60.00	**70.91**	75.00

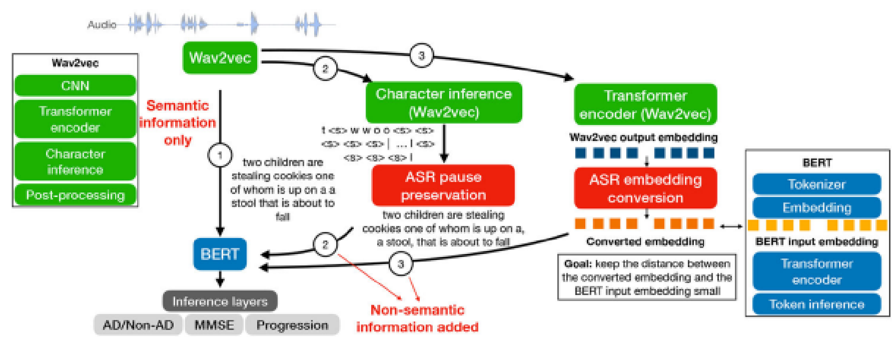

Figure 1:

VOCAB: (w/definition)

Wav2vec- A tool that analyzes speech input and creates transcripts that lack punctuation
BERT- A pre trained deep learning model used for natural language processing
WavBERT- The combined use of Wav2vec and BERT that was used in this study in order to turn spoken data into data that can be analyzed deeply. An extended version of WavBert was used in order to incorporate punctuation.

Cited references to follow up on

Follow up Questions

Are there parts of this study that are universal across all languages?
Could BERT be trained on languages other than English?

Article #11 Notes: Automatic Assessment of Alzheimer's across Three Languages Using Speech and Language Features

Article notes should be on separate sheets

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Source Title	**Automatic Assessment of Alzheimer's across Three Languages Using Speech and Language Features**
Source citation (APA Format)	Pérez-Toro, P. A., Arias-Vergara, T., Braun, F., Hönig, F., Tobón-Quintero, C. A., Aguillón, D., Lopera, F., Hincapié-Henao, L., Schuster, M., Riedhammer, K., Maier, A., Nöth, E., & Orozco-Arroyave, J. R. (2023). Automatic assessment of alzheimer's across three languages using speech and language features. *INTERSPEECH 2023*. https://doi.org/10.21437/interspeech.2023-2079
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-85171523943&origin=resultslist&sort=plf-f&src=s&sid=4bc41d7089b0377b2c1b95dfa588f3e6&sot=b&sdt=b&s=TITLE-ABS-KEY%28Alzheimer%27s+AND+Deep+Learning+AND+Spanish%29&sl=24&sessionSearchId=4bc41d7089b0377b2c1b95dfa588f3e6
Source type	Journal Article
Keywords	automatic AND assessment AND of AND alzheimer's AND across AND three AND languages AND using AND speech AND language AND features
#Tags	#Alzheimer's #Detection #ML #MultiLang
Summary of key points + notes (include methodology)	This study attempted various methods of detecting Alzheimer's Disease across multiple languages using a variety of features including word embeddings, acoustic features, pleasure arousal dominance, and acoustic embeddings in Wav2Vec. These methods were used in models that were trained on an individual language and then tested, and compared to those that were trained on one language and tested on another, with the goal of finding a universal feature that could be used across all languages. This was not the case with English, Spanish, and German, as each language had its own significant determining factors, although English and

	German both valued acoustic embeddings.
Research Question/Problem/ Need	How can Alzheimer's Disease be detected across multiple languages?

Important Figures

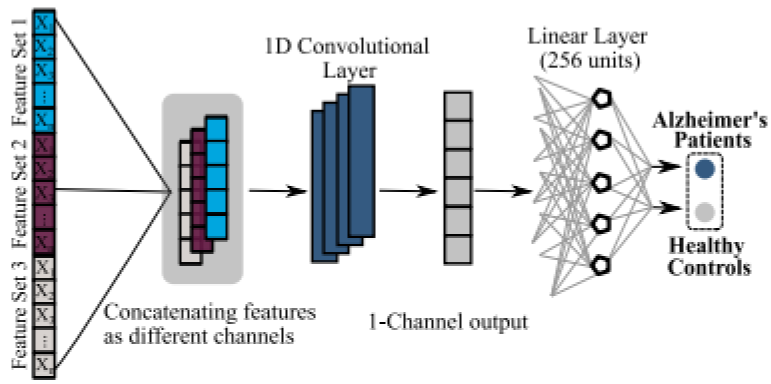

Figure 1: *Architecture of the ANN proposed to perform classification and feature fusion.*

Table 1: *Demographic information of the subjects for each language*

	AD Patients F/M	HC Subjects F/M
English Corpus		
Number of Subjects	33/60	37/56
Age [years]	66.5 (7.8)/70.0 (7.3)	64.5 (8.1)/63.3 (8.0)
Spanish Corpus		
Number of Subjects	14/15	15/12
Age [years]	48.2 (5.7)/50.7 (7.1)	49.5 (7.7)/ 53.2 (7.1)
German Corpus		
Number of Subjects	83/64	26/32
Age [years]	70.1 (8.4)/70.6 (8.2)	68.6 (8.5)/ 72.6 (7.8)

Values are expressed as mean (standard deviation). F: female. M: male. Age is given in years.

Table 2: *Best classification results obtained for each language and possible combinations.* ***UAR:*** *Unweighted Average Recall.* ***Sens:*** *Sensitivity.* ***Spe:*** *Specificity.*

Language	Feature Fusion	Classifier	UAR	Sens	Spe
EN	WV1 + WV12	SVM	70	58	82
	BERT + WV1	ANN	**82**	**89**	**74**
ES	PAD + Rhythm	SVM	75	79	70
	Gr + WV12	ANN	**78**	**76**	**80**
DE	Rhythm + WV1 + WV9 + WV12	SVM	65	55	74
	BERT + WV1 + WV9	ANN	**70**	**79**	**62**
EN+ES	PAD + Dur + WV1 + WV12 + WV9	SVM	72	64	79
	BERT + Rhythm + Gr + WV12	ANN	**78**	**70**	**86**
EN+DE	Rhythm	SVM	55	44	66
	BERT + PAD + Rhythm + WV1 + WV9	ANN	67	65	70
ES+DE	PAD + WV9	SVM	66	65	67
	Dur + PAD + Rhythm + WV1 + WV9	ANN	68	72	64
EN + ES + DE	Rhythm	SVM	55	45	65
	Rhythm + WV1 + WV9	ANN	**73**	**81**	**66**

WVi: Wav2Vec i-th layer of the transformer. PAD: Pleasure Arousal Dominance posteriors. Dur: Duration features. Gr: Grammar features.

The results for the first classification approach are shown

Table 3: *Best classification results obtained while training in one language and testing in another.* ***UAR:*** *Unweighted Average Recall.* ***Sens:*** *Sensitivity.* ***Spe:*** *Specificity.*

Train	Test	Feature Fusion	Classifier	UAR	Sens	Spe
EN	ES	BERT+WV1	SVM	60	34	85
		PAD+Dur+Rhythm+ WV1+WV9	ANN	65	70	59
	DE	PAD+Rhythm	SVM	55	45	66
		PAD+Rhythm	ANN	57	26	88
ES	EN	PAD+Dur+WV9+ WV12	SVM	67	68	67
		WV1	ANN	64	74	54
	DE	Dur+Rhythm+WV1+ WV12	SVM	56	27	84
		BERT+WV9	ANN	59	50	67
DE	EN	PAD+Dur+WV1+ WV9+WV12	SVM	62	32	92
		Dur+Rhythm	ANN	64	69	60
	ES	WV12	SVM	56	31	81
		Dur+Rhythm	ANN	**70**	**78**	**62**

WVi: Wav2Vec i-th layer of the transformer. PAD: Pleasure Arousal Dominance posteriors. Dur: Duration features. Gr: Grammar features.

VOCAB: (w/definition) Pleasure Arousal Dominance- A set of features revolving around the pleasantness,

	agitation, and control of an individual in speech. These features are defined using a deep neural network. Artificial Neural Network - The type of neural network used in the study. Inputs were taken in channels that would all contribute towards the output of the model. Rhythm - A set of variables that are based on the timing of word pronunciation.
Cited references to follow up on	
Follow up Questions	What is the difference between using a 102 language BERT and a 1 language BERT? Could people be trained to train models using inauthentic writing (not from natural interactions)?

Article #12 Notes: To BERT or Not To BERT: Comparing Speech and Language-based Approaches for Alzheimers Disease Detection

Article notes should be on separate sheets

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Source Title	To BERT or Not To BERT: Comparing Speech and Language-based Approaches for Alzheimers Disease Detection
Source citation (APA Format)	Balagopalan, A., Eyre, B., Rudzicz, F., & Novikova, J. (2020). To BERT or not to BERT: comparing speech and language-based approaches for Alzheimer's disease detection. *arXiv preprint arXiv:2008.01551*.
Original URL	https://arxiv.org/abs/2008.01551
Source type	Journal Article
Keywords	None (Found through another article)
#Tags	#BERT #Alzheimer's
Summary of key points + notes (include methodology)	Feature based machine learning models and deep learning models both offer various strengths. This study aims to determine which model can provide the better accuracy when detecting Alzheimer's Disease through speech. Although deep learning performed the best in terms of accuracy, it is more difficult to analyze and it could be used as a value in a traditional machine learning model in the feature for improved accuracy.
Research Question/Problem/ Need	What is the best type of model for Alzheimer's Disease Detection using speech (transcripts included)

Important Figures	

Table 3: *10-fold CV results averaged across 3 runs with different random seeds on the ADReSS train set. Accuracy for BERT is higher, but not significantly so from SVM ($H = 0.4838, p > 0.05$ Kruskal-Wallis H test). Bold indicates the best result.*

Model	#Features	Accuracy	Precision	Recall	Specificity	F1
SVM	10	0.796	0.81	0.78	0.82	0.79
NN	10	0.762	0.77	0.75	0.77	0.76
RF	50	0.738	0.73	0.76	0.72	0.74
NB	80	0.750	0.76	0.74	0.76	0.75
BERT	-	**0.818**	**0.84**	**0.79**	**0.85**	**0.81**

VOCAB: (w/definition)	Mini-Mental State Examination (MMSE) scores - A score determined for a patient based on their state of mind at the time of testing. Transfer Learning - The use of an already created model as a stepping stone for further fine tuning for a given task Seed - a method of retaining a set of random numbers. Since computers cannot exhibit true random, a seed can be used in order to allow the same set of random numbers to be generated in future applications of code (running an already trained model as opposed to retraining it every time it is needed)
Cited references to follow up on	
Follow up Questions	How pre-trained was the model used in the study? Was it pre-trained with any Alzheimer's data, or just with standard English?

Article #13 Notes: Cross-lingual Features for Alzheimer's Dementia Detection from Speech

Article notes should be on separate sheets

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Source Title	Cross-lingual Features for Alzheimer's Dementia Detection from Speech
Source citation (APA Format)	Melistas, T., Kapelonis, L., Antoniou, N., Mitseas, P., Sgouropoulos, D., Giannakopoulos, T., Katsamanis, A., Narayanan, S. (2023) Cross-Lingual Features for Alzheimer's Dementia Detection from Speech. Proc. *INTERSPEECH 2023*, 3008-3012, doi: 10.21437/Interspeech.2023-1934
Original URL	https://www.isca-speech.org/archive/pdfs/interspeech_2023/melistas23_interspeech.pdf

Source type	Journal Article
Keywords	Alzheimer's Disease, Multilingual, Machine Learning
#Tags	#Multilingual #Alzheimer's #Detection
Summary of key points + notes (include methodology)	This article proposes the use of a machine learning model with certain features to diagnose Alzheimer's Disease in a multilingual aspect. Transcripts were obtained using a whisper model. These transcripts would be analyzed for many features including: resulting in accuracy above 75%.
Research Question/Problem/ Need	What are features that can be used to detect Alzheimer's Disease?

Important Figures

Lang.		Count	Years	Education Years	MMSE
ENG	AD Label - F/M	79/43	69.92 (6.36) / 68.37 (7.59)	11.51 (2.37) / 12.79 (2.85)	17.36 (5.07) / 18.72 (6.01)
	HC Label - F/M	75/40	65.62 (6.18) / 66.86 (6.40)	14.02 (2.67) / 13.92 (2.56)	29.00 (1.29) / 28.90 (0.9)
GR (val.)	AD Label - F/M	3/1	78.67 (1.70) / 69 (-)	7.67 (7.04) / 16 (-)	23.67 (2.87) / 29 (-)
	HC Label - F/M	3/1	66.33 (6.34) / 69 (-)	8.33 (3.30) / 16 (-)	29.33 (0.47) / 26 (-)
GR (test.)	F/M (No labels)	35/11	69.43 (7.28) / 67.55 (9.13)	11.57 (3.90) / 10.73 (3.86)	-
SP	AD Label - F/M	44/30	79.70 (7.98) / 79.17 (7.69)	7.78 (3.05) / 10.27 (4.80)	18.91 (4.66) / 21.53 (5.40)
	HC Label - F/M	139/58	75.62 (7.39) / 75.22 (9.03)	9.41 (3.77) / 9.97 (3.96)	28.18 (1.97) / 28.43 (1.64)

Table 1: *Mean (std) values for metadata information. F (M) stands for Female (Male), AD for Alzheimer's Dementia, HC for Healthy Control. We report these values per AD label (AD or HC), except for the Greek test set, for which the label information isn't available.*

Attempt	Model	ASR	Utt	Au:H	Au:Tr	Au:Sr	MD	F1-CV (%)	Acc-Val (%)	Acc-Test (%)
Attempt 1	SVM	✓				✓	✓	72.1	75.0	63.0
Attempt 2	SVM	✓	✓				✓	77.6	87.5	63.0
Attempt 3	XGB	✓		✓	✓	✓	✓	70.5	50.0	69.6
Attempt 4	XGB	✓	✓			✓	✓	74.3	75.0	71.7
Attempt 5	Majority Vote							-	75.0	78.3

Table 2: *Cross-Validation F1 on English train set (F1-CV), Accuracy on Greek validation and test sets.*

VOCAB: (w/definition)	Interaction Dynamics features-Extracted features related to timestamps of when a patient talks Stop-word ratio- The number of words where a patient stops. This was compared to common words that had pauses to help calibrate the judgement of the system. Metadata- all of the data known about the demographics of the patients being assessed. Zero-Shot Evaluation - When a machine learning model sees none of the type of the data it is being tested on in training.
Cited references to follow up on	
Follow up Questions	Why might some features work better than others? What aspects of languages allow for some to synthesize stronger than others? How might these models be implemented?

Article #14 Notes: Predicting dementia from spontaneous speech using large language models

Article notes should be on separate sheets

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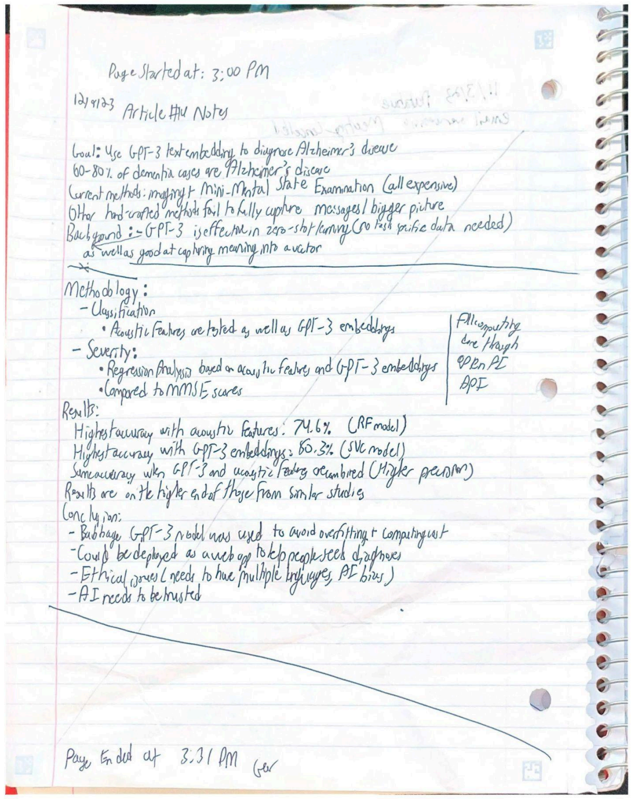
Source Title	Predicting dementia from spontaneous speech using large language models
Source citation (APA Format)	Agbavor, F., & Liang, H. (2022). Predicting dementia from spontaneous speech using large language models. *PLOS Digital Health*, *1*(12). https://doi.org/10.1371/journal.pdig.0000168
Original URL	https://journals.plos.org/digitalhealth/article?id=10.1371/journal.pdig.0000168
Source type	Journal Article
Keywords	Alzheimer's Disease, Deep Learning
#Tags	#Alzheimer's #Detection #GPT
Summary of key points + notes (include methodology)	This article tests the use of a GPT-3 based model in order to detect Alzheimer's disease. Both GPT (weaker model version Babbage) embeddings and acoustic features were tested in isolation and in combination. The peak accuracy using GPT was around 80%, whereas that of the acoustic features hovered around 75%. When combined, the features still retained similar accuracy. These results are generally on the higher end of comparable studies. The model was also able to predict an MMSE score more accurately than the current testing procedures.

	 Page Started at: 3:00 PM 12/4/23 Article #4 Notes Goal: Use GPT-3 text embedding to diagnose Alzheimer's disease 60-80% of dementia cases are Alzheimer's disease Current methods: imaging + Mini-Mental State Examination (all expensive) Other hand-crafted methods fail to fully capture messages/bigger picture Background: - GPT-3 is effective in zero-shot learning (no task specific data needed) as well as good at capturing meaning into a vector Methodology: - Classification • Acoustic Features are tested as well as GPT-3 embeddings - Severity: • Regression Analysis based on acoustic features and GPT-3 embeddings • Compared to MMSE scores All computing done through OpenAI API Results: Highest accuracy with acoustic features: 74.6% (RF model) Highest accuracy with GPT-3 embeddings: 80.3% (SVC model) Same accuracy when GPT-3 and acoustic features are combined (Higher precision) Results are on the higher end of those from similar studies Conclusion: - Babbage GPT-3 model was used to avoid overfitting + computing cost - Could be deployed as a web app to help people seek diagnoses - Ethical issues (needs to have multiple languages, AI bias) - AI needs to be trusted Page Ended at 3:31 PM -Gustavo Rodriguez Added on 10/15/2023 at 1:15 PM
Research Question/Problem/ Need	What are the best models for Alzheimer's/Dementia detection?
Important Figures	(table below)
VOCAB: (w/definition)	Mini Mental State Examination (MMSE)- A MMSE is a lengthy test done that is used to provide a benchmark as to the current mental state of a patient. This test provides a number that can help quantify how serious cognitive illness is for the patient

	Embeddings	Model	Accuracy	Precision	Recall	F1
10-fold CV	Ada	SVC	0.788 (0.075)	0.798 (0.109)	0.819 (0.098)	0.799 (0.066)
		LR	0.796 (0.107)	0.798 (0.126)	**0.835 (0.129)**	0.808 (0.100)
		RF	0.734 (0.090)	0.738 (0.109)	0.763 (0.149)	0.743 (0.103)
	Babbage	SVC	0.802 (0.054)	0.823 (0.092)	0.804 (0.103)	0.806 (0.053)
		LR	**0.809 (0.112)**	**0.843 (0.148)**	0.811 (0.091)	**0.818 (0.091)**
		RF	0.760 (0.052)	0.780 (0.102)	0.781 (0.110)	0.770 (0.047)
Test Set	Ada	SVC	0.788	0.708	**0.971**	0.819
		LR	0.718	0.653	0.914	0.762
		RF	0.732	0.690	0.829	0.753
	Babbage	SVC	**0.803**	**0.723**	**0.971**	**0.829**
		LR	0.718	0.647	0.943	0.767
		RF	0.761	0.714	0.857	0.779

https://doi.org/10.1371/journal.pdig.0000168.t002

	Generative Pre-trained Transformers (GPT) - The type of model that was used to train the deep learning feature for the model. GPT is a large language model which has typically been used for text generation in various applications. Embeddings - Values generated by a deep learning model. Embeddings from the GPT model used in the study were used to diagnose Alzheimer’s disease.
Cited references to follow up on	
Follow up Questions	Why might a model such as this one be less effective than BERT? How does this model’s generative abilities aid or degrade the model’s ability?

Article #15 Notes: Multilingual word embeddings for the assessment of narrative speech in mild cognitive impairment

Article notes should be on separate sheets

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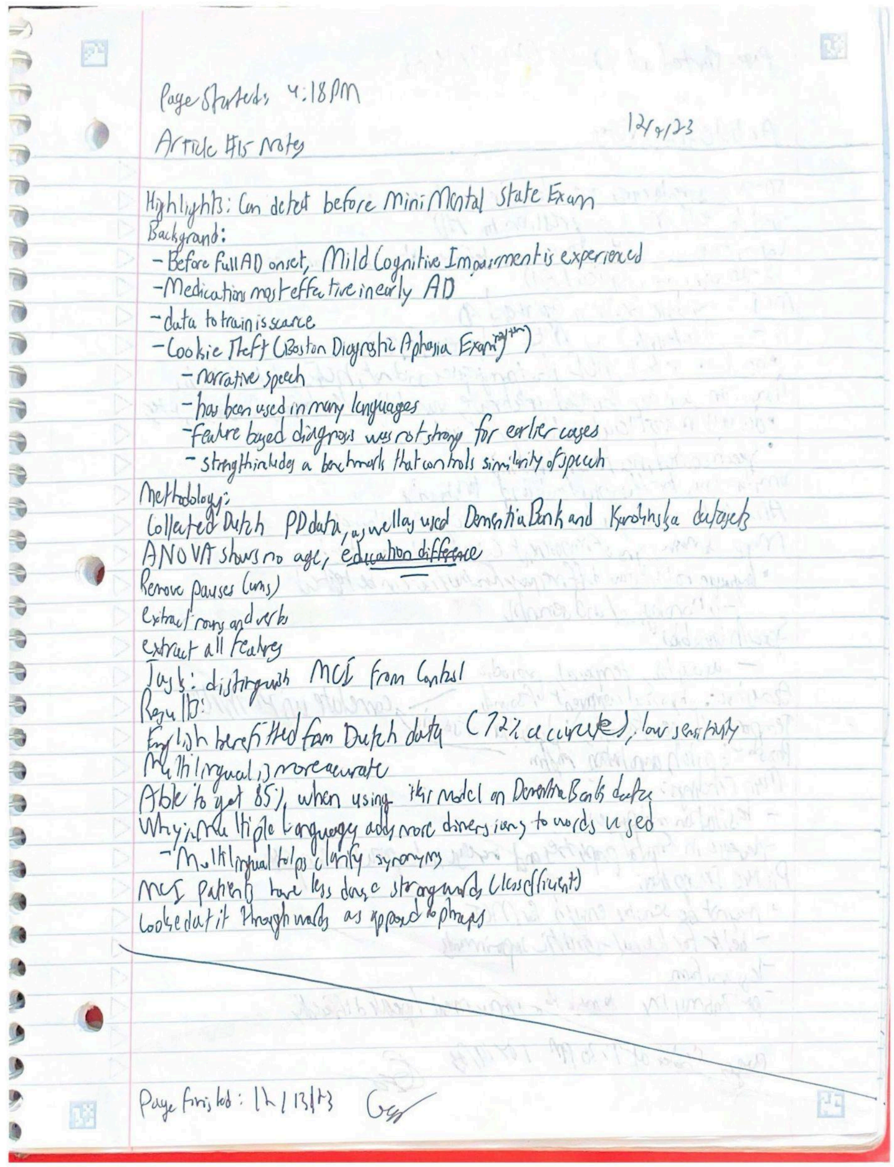
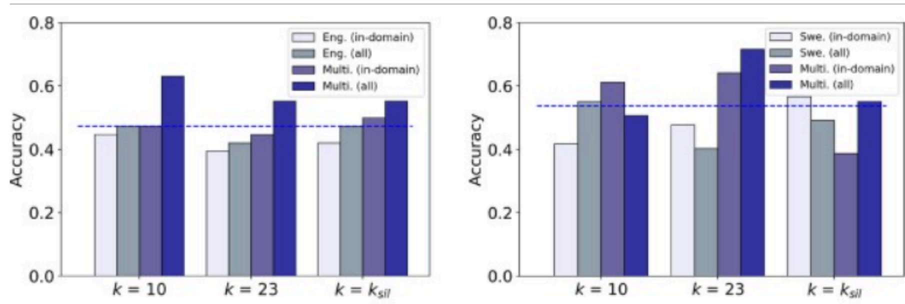
Source Title	Multilingual word embeddings for the assessment of narrative speech in mild cognitive impairment
Source citation (APA Format)	Fraser, K. C., Lundholm Fors, K., & Kokkinakis, D. (2019). Multilingual word embeddings for the assessment of narrative speech in mild cognitive impairment. *Computer Speech & Language*, *53*, 121–139. https://doi.org/10.1016/j.csl.2018.07.005
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-85092014864&origin=resultslist&sort=plf-f&src=s&sid=09e878460dc411eb8d58ed61ebbd9cae&sot=b&sdt=cl&cluster=scolang%2C"Chinese"%2Ct%2C"German"%2Ct%2C"Korean"%2Ct&s=TITLE-ABS-KEY%28cookie+theft+AND+Alzheimer%27s%29&sl=43&sessionSearchId=09e878460dc411eb8d58ed61ebbd9cae
Source type	Journal Article
Keywords	Alzheimer’s Disease, Multilingual, Machine Learning
#Tags	#Multilingual #Alzheimer’s #Detection
Summary of key points + notes	This article looks into the diagnosis of Dementia using word level analysis.

(include methodology)	Specifically, 300D vectors are generated for each word to provide more detail into the diagnosis of a patient. This analysis is then applied to a multilingual lens. The multilingual aspect of the model made it more accurate, as it either provided more options for words or made synonyms less likely to be misinterpreted.  Page Started: 4:18 PM 12/8/23 Article #15 Notes Highlights: Can detect before Mini Mental State Exam Background: - Before full AD onset, Mild Cognitive Impairment is experienced - Medications most effective in early AD - data to train is scarce - Cookie Theft (Boston Diagnostic Aphasia Examination) - narrative speech - has been used in many languages - Feature based diagnosis was not strong for earlier cases - strength includes a benchmark that controls similarity of speech Methodology: Collected Dutch PD data, as well as used Dementia Bank and Karolinska datasets ANOVA shows no age, education difference Remove pauses (ums) Extract nouns and verbs extract all features Task: distinguish MCI from Control Results: English benefitted from Dutch data (72% accurate), low sensitivity Multilingual is more accurate Able to get 85% when using their model on Dementia Bank's data Why: multiple languages adds more dimensions to words used - Multilingual helps clarify synonyms MCI patients have less dense strong words (less fluent) Looked at it through words as opposed to phrases Page Finished: 12/13/23 GR -Gustavo Rodriguez Added on 10/15/2023 at 1:15 PM
Research Question/Problem/ Need	What are features that can be used to detect Alzheimer's Disease?

Important Figures

	In-domain				Out-domain	
Dataset	**Gothenburg**		**DementiaBank**		**Karolinska**	**DementiaBank**
Group label	**MCI**	**HC**	**MCI**	**HC**	**HC**	**HC**
N	31	36	19	19	96	78
Age (years)	70.1 (5.6)	67.9 (7.2)	66.7 (8.5)	66.4 (9.2)	57.2 (19.9)	63.9 (7.8)
Educ. (years)	14.1 (3.6)	13.1 (3.4)	14.9 (3.1)	14.2 (2.3)	13.0 (4.0)	13.9 (2.5)
Sex (M / F)	15 / 16	13 / 23	9 / 10	9 / 10	44 / 52	30 / 48
MMSE (/30)	28.2 (1.4)	29.6 (0.6)	27.4 (1.8)	29.1 (1.2)	–	29.1 (1.1)*
Task type	Spoken	Spoken	Spoken	Spoken	Written	Spoken
Language	Swedish	Swedish	English	English	Swedish	English



(a) English MCI vs HC. (b) Swedish MCI vs HC.

VOCAB: (w/definition)

FastTexts Embedding - The model used to gain the embeddings for the words analyzed. These embeddings were used to get 300D vectors which could then be compared in between words and in between patients to find key differences that can be used for diagnosis.

Cited references to follow up on

Follow up Questions

Can these analyses be synthesized with other methods in order to form a more cohesive model?
Do the same principles about multilingual accuracy apply to other models?

Article #16 Notes:Discriminating speech traits of Alzheimer’s disease assessed through a corpus of reading task for Spanish language

Article notes should be on separate sheets

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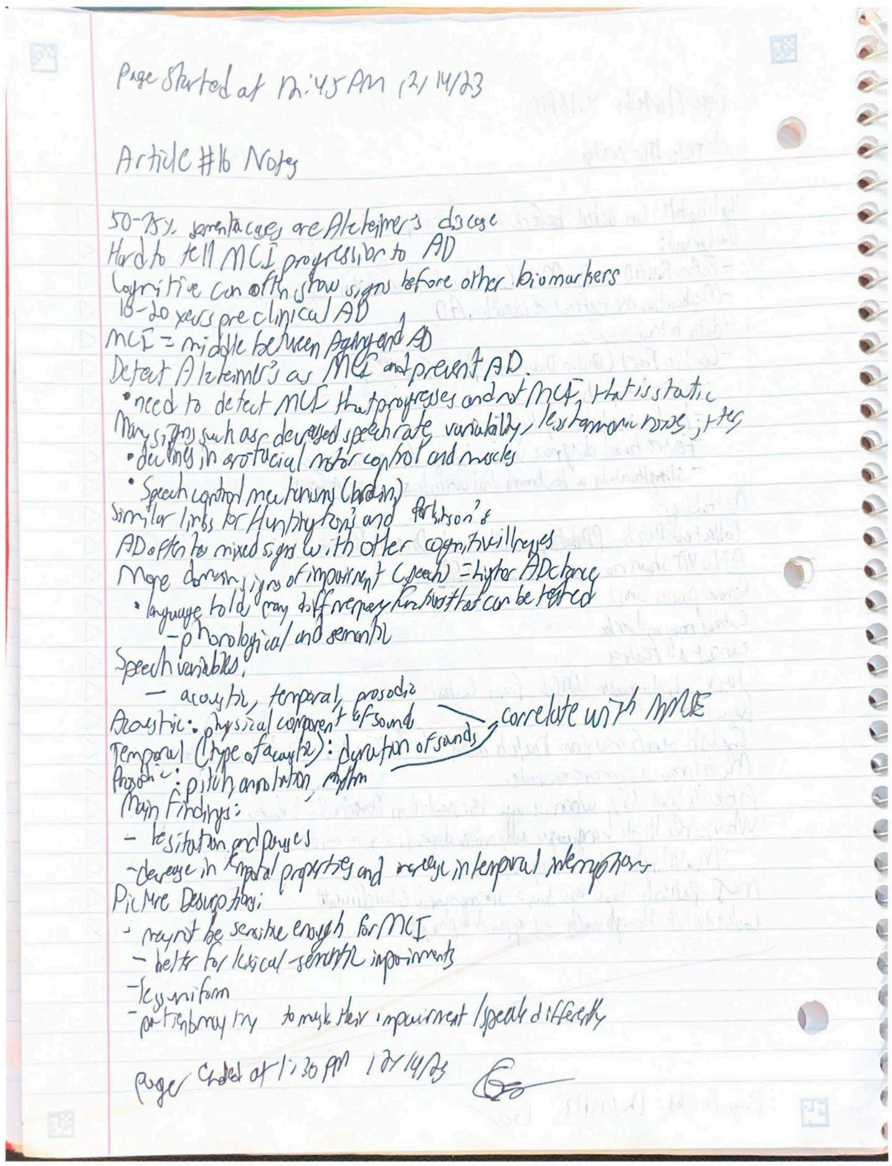
Source Title	Discriminating speech traits of Alzheimer’s disease assessed through a corpus of reading task for Spanish language
Source citation (APA Format)	Ivanova, O., Meilán, J. J., Martínez-Sánchez, F., Martínez-Nicolás, I., Llorente, T. E., & González, N. C. (2022). Discriminating speech traits of alzheimer’s disease assessed through a corpus of reading task for Spanish language. *Computer Speech & Language*, *73*, 101341. https://doi.org/10.1016/j.csl.2021.101341
Original URL	https://www.sciencedirect.com/science/article/pii/S0885230821001340?via%3Dihub
Source type	Journal Article
Keywords	Mild Cognitive Impairment, Reading task, Automatic speech analysis, Corpus
#Tags	#Spanish #Alzheimer’s #Detection #Speech
Summary of key points + notes (include methodology)	This article proposes the use of a standard testing procedure to analyze speech of patients by having each patient read the same set of two sentences in spanish. The main benefit to this method is its level of control over the situation, as there is little variance in between the contents of the speech which can aid with analysis of cognitive impacts that can decipher between various stages of dementia. The main difference aimed to be established was a difference between Mild Cognitive Impairment that advances to Alzheimer’s and Mild Cognitive Impairment that does not advance any further.

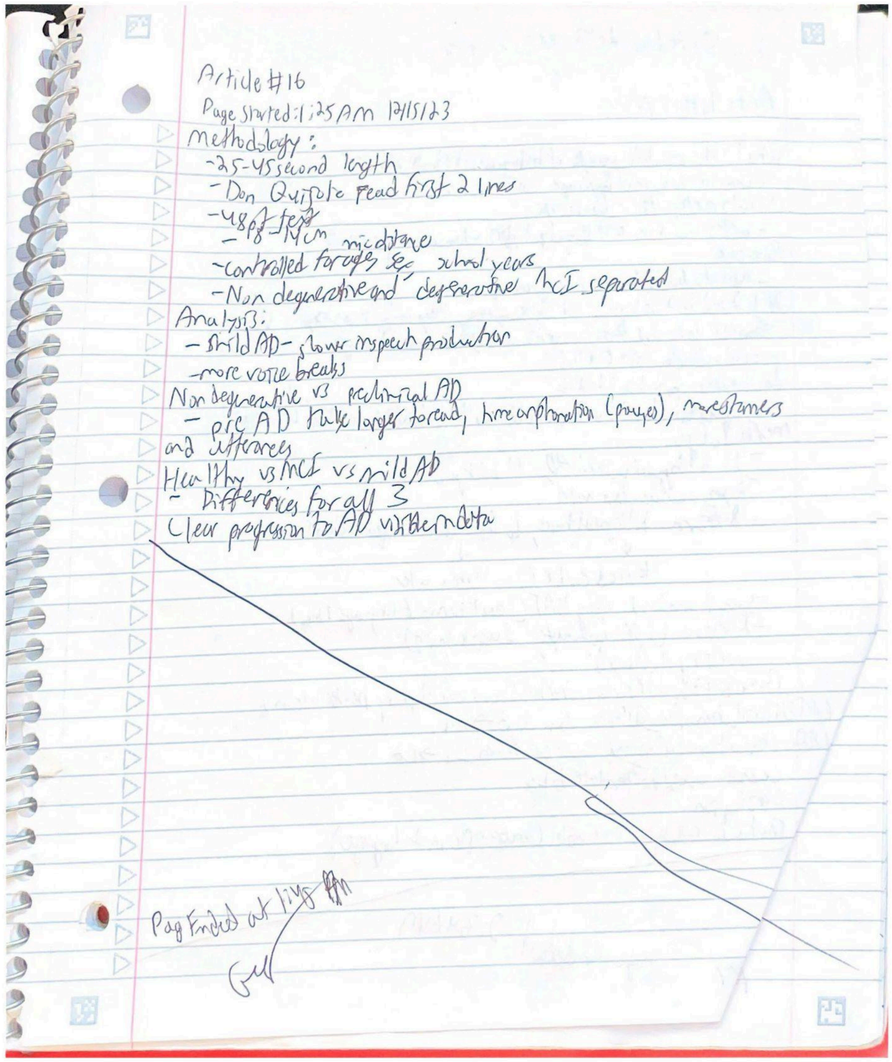
	-Gustavo Rodriguez Added on 10/15/2023 at 1:15 PM 

Page Started at 12:45 AM 12/14/23

Article #16 Notes

50-75% dementia cases are Alzheimer's disease
Hard to tell MCI progression to AD
Cognitive can often show signs before other biomarkers
10-20 years preclinical AD
MCI = middle between Aging and AD
Detect Alzheimer's as MCI and prevent AD.
• need to detect MCI that progresses and not MCI that is static
Many signs such as decreased speech rate variability, less harmonic noise, etc
• declines in orofacial motor control and muscles
• Speech control mechanisms (brain)
Similar links for Huntington's and Parkinson's
AD often has mixed signs with other cognitive illnesses
More domain signs of impairment (speech) = higher AD chance
• language told many different features that can be tested
– phonological and semantic
Speech variables:
– acoustic, temporal, prosodic
Acoustic: physical component of sound → correlate with MMSE
Temporal (type of acoustic): duration of sounds
Prosodic: pitch, annotation, rhythm
Main Findings:
– hesitation and pauses
– decrease in temporal properties and increase in temporal interruptions
Picture Descriptions:
– may not be sensitive enough for MCI
– better for lexical-semantic impairments
– less uniform
– patients may try to mask their impairment / speak differently

Page Ended at 1:30 AM 12/14/23


Article #16
Page Started: 1:25 AM 12/15/23
Methodology:
-25-45 second length
-Don Quijote read first 2 lines
-48 pt text
- 18-14 cm mic distance
-controlled for age, sex, school years
-Non degenerative and degenerative MCI separated
Analysis:
- Mild AD - slower in speech production
-more voice breaks
Non degenerative vs preclinical AD
- pre AD take longer to read, time on phonation (pauses), more stammers and utterances
Healthy vs MCI vs mild AD
- Differences for all 3
Clear progression to AD with the data
Page Ended at 1:49 AM

Research Question/Problem/ Need

What is the best method of testing speech for Alzheimer's detection and distinction from Mild Cognitive Impairment?

Important Figures

Table 3
Reading corpus metadata.

Corpus metadata Total number of subjects = 361 Diagnostic group	n of subjects	MMSE (SD)	Gender	Age	Schooling years
Healthy speakers	*n* = 197	28.26 (1.890)	Men = 58, Women = 139	75.5 (7.929)	9.58 (3.848)
MCI	*n* = 90	23.89 (4.082)	Men = 25, Women = 65	79.49 (9.605)	8.67 (3.938)
Dementia	*n* = 74	19.97 (5.174)	Men = 30, Women = 44	79.49 (7.921)	8.81 (4.095)

VOCAB: (w/definition)

Acoustic Features: Features based on the physical component of speech

	Temporal Features: Features based on the duration of speech Prosodic Features: Features based on the pitch, annotation, or rhythm of speech.
Cited references to follow up on	
Follow up Questions	Could this data be used to supplement a model that focuses on the embeddings of the words themselves? Could a test like this be conducted in addition to an interview/picture description task?

Article #17 Notes: Language impairment in Catalan-Spanish bilinguals with Alzheimer's disease

Article notes should be on separate sheets

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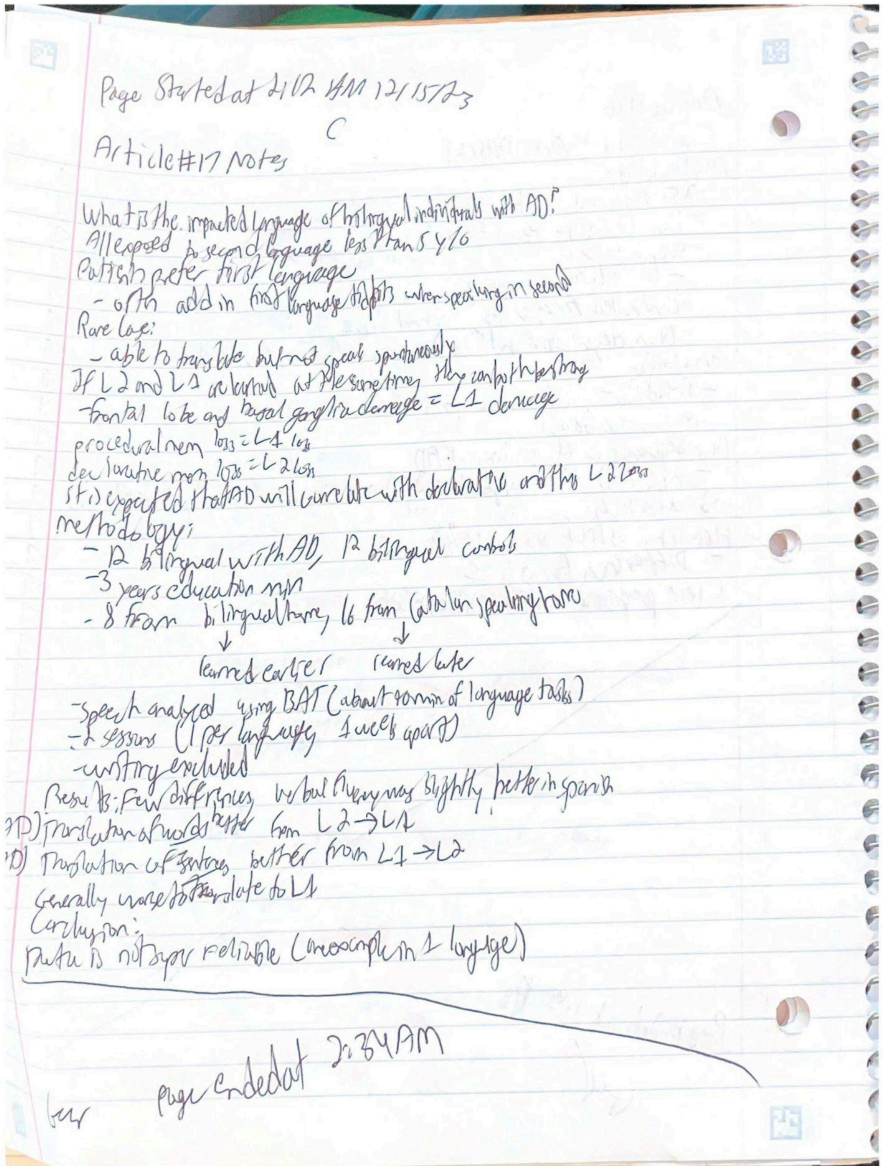
Source Title	Language impairment in Catalan-Spanish bilinguals with Alzheimer's disease
Source citation (APA Format)	Gómez-Ruiz, I., Aguilar-Alonso, Á., & Espasa, M. A. (2012). Language impairment in Catalan-Spanish bilinguals with alzheimer's disease. Journal of Neurolinguistics, 25(6), 552–566. https://doi.org/10.1016/j.jneuroling.2011.06.003
Original URL	https://www.scopus.com/record/display.uri?eid=2-s2.0-84866630452&origin=resultslist&sort=r-f&src=s&sid=b2767e9f8b924e4463d55273f417f2b5&sot=b&sdt=b&s=TITLE-ABS-KEY%28alzheimer%27s+AND+speech+AND+spanish%29&sl=37&sessionSearchId=b2767e9f8b924e4463d55273f417f2b5&relpos=2
Source type	Journal Article
Keywords	Alzheimer's Disease, Multilingual, Machine Learning
#Tags	#Multilingual #Alzheimer's #Detection
Summary of key points + notes (include methodology)	This article tests the differences in how language is affected in the first and second languages of individuals with Alzheimer's disease. The experiment looked at 24 individuals and tested their abilities in Spanish and in Catalan. It found few differences in between the effects between both languages, although they both had significant differences compared to people without Alzheimer's disease. The main noticeable difference between the first language and the second language

	was the ability to translate in between the languages.  Page Started at 2:12 AM 12/15/23 C Article#17 Notes What is the impacted language of bilingual individuals with AD? All exposed to second language less than 5 y/o Patients prefer first language - often add in first language tidbits when speaking in second Rare case: - able to translate but not speak spontaneously If L2 and L1 are learned at the same time they can both be strong -frontal lobe and basal ganglia damage = L1 damage procedural mem loss = L1 loss declarative mem loss = L2 loss it is expected that AD will correlate with declarative and thus L2 loss methodology: - 12 bilingual with AD, 12 bilingual controls -3 years education min - 8 from bilingual home, 16 from Catalan speaking home ↓ learned earlier ↓ learned later -Speech analyzed using BAT (about 90 min of language tasks) -2 sessions (1 per language 1 week apart) -writing excluded Results: Few differences, verbal fluency was slightly better in Spanish AD) Translation of words better from L2→L1 AD) Translation of sentences better from L1→L2 Generally worse to translate to L1 Conclusion: Data is not super reliable (one example in 1 language) Page ended at 2:34AM -Gustavo Rodriguez Added on 10/15/2023 at 1:15 PM
Research Question/Problem/ Need	What is the impacted language on bilingual individuals with Alzheimer's disease?

Important Figures

Table 2
Subtest scores on the BAT for the healthy controls and the AD patients: intra- and intergroup comparisons.

Subtests	Number of items	Healthy controls			AD patients		
		N	L1	L2	N	L1	L2
Pointing	5	12	10.00 (0.00)	10.00 (0.00)	12	10.00 (0.00)	10.00 (0.00)
Commands	15	12	14,75 (0.62)	14.83 (0.38)	12	11.75 (1.71)[b]	11.75 (1.76)[b]
Verbal auditory discrimination	18	12	17.92 (0.28)	17.75 (0.45)	12	16.33 (2.01)[b]	16.92 (1.20)[b]
Syntactic comprehension	87	12	82.50 (3.11)	83.00 (3.38)	12	65.42 (9.04)[b]	67.83 (5.73)[b]
Semantic categories	5	12	4.75 (0.45)	4.92 (0.28)	12	3.25 (1.35)[b]	3.25 (1.05)[b]
Synonyms	5	12	5.00 (0.00)	4.92 (0.28)	12	4.42 (0.99)[b]	4.50 (0.79)
Antonyms	10	12	9.33 (0.88)	9.83 (0.38)	12	6.25 (2.45)[b]	7.00 (1.53)[b]
Grammaticality judgments	10	12	9.83 (0.57)	9.67 (0.49)	12	7.17 (1.74)[b]	7.25 (0.86)[b]
Semantic acceptability	10	12	10.00 (0.00)	9.83 (0.57)	12	8.33 (1.96)[b]	8.83 (1.74)[a]
Repetition of words	30	12	29.92 (0.28)	29.92 (0.28)	12	29.42 (0.79)	29.50 (0.79)
Lexical decision	30	12	29.42 (0.79)	29.33 (0.88)	12	27.17 (1.19)[b]	27.67 (2.70)
Repetition of sentences	7	12	6.42 (0.66)	6.67 (0.92)	12	5.83 (0.71)	5.83 (0.71)[b]
Series	3	12	3.00 (0.00)	3.00 (0.00)	12	2.58 (0.51)[b]	2.92 (0.28)[a b]
Verbal fluency (sound/p/)	–	12	11.00 (2.89)	13.83 (4.68)[a]	12	4.83 (3.40)[b]	8.00 (3.66)[a b]
Verbal fluency (sound/f/)	–	12	8.50 (3.23)	8.92 (2.61)	12	4.25 (2.22)[b]	5.08 (3.23)[b]
Verbal fluency (sound/k/)	–	12	9.92 (3.98)	11.33 (4.49)	12	4.58 (2.81)[b]	6.83 (3.35)[a b]
Verbal fluency (/p/+/f/+/k/)	–	12	29.42 (8.94)	33.83 (10.73)	12	13.66 (7.07)[b]	19.91 (8.73)[a b]
Naming	20	12	19.92 (0.28)	20.00 (0.00)	12	17.25 (4.37)[b]	16.75 (4.61)[b]
Sentence construction	15	12	14.75 (0.45)	14.75 (0.45)	12	10.00 (4.67)[b]	10.50 (4.75)[b]
Semantic opposites	10	12	10.00 (0.00)	9.92 (0.28)	12	7.83 (1.94)[b]	8.00 (2.52)[b]
Derivational morphology	10	12	8.67 (1.77)	9.75 (0.45)	12	6.58 (3.08)[b]	6.17 (3.27)[b]
Morphological opposites	10	12	9.33 (0.78)	9.42 (0.90)	12	6.33 (3.11)[b]	6.00 (2.92)[b]
Description	3	12	3.00 (0.00)	3.00 (0.00)	12	1.42 (0.90)[b]	1.25 (1.05)[b]
Mental arithmetic	15	12	12.25 (1.91)	12.67 (2.01)	12	6.17 (3.88)[b]	7.08 (3.96)[b]
Listening comprehension	5	12	4.58 (0.51)	4.92 (0.28)[a]	12	2.50 (0.52)[b]	3.17 (1.26)[b]
Reading words aloud	10	10	10.00 (0.00)	10.00 (0.00)	8	9.75 (0.46)	10.00 (0.00)
Reading sentences aloud	10	10	9.33 (0.77)	9.25 (0.45)	8	9.00 (0.92)	9.33 (0.77)
Reading comprehension (paragraph)	6	10	5.92 (0.28)	5.75 (0.45)	8	3.13 (1.24)[b]	3.42 (1.50)[b]
Reading comprehension of words	10	10	9.75 (0.45)	9.83 (0.38)	7	9.43 (0.53)	9.50 (0.90)
Reading comprehension of sentences	10	10	8.92 (1.08)	9.17 (0.83)	7	7.00 (1.52)[b]	7.25 (1.71)[b]

L1: Catalan; L2: Spanish.
[a] Differences between Catalan and Spanish mean scores for each group ($p < 0.05$).
[b] Differences between healthy controls and AD patients ($p < 0.05$).

VOCAB: (w/definition)

Bilingual Aphasia Test (BAT) - a test used to gain speech data from patients. The test is split up into three parts.
L1 - Language 1. Used to represent the language that was learned first by the patient
L2 - Language 2. Used to represent the language that is learned second by the patient

Cited references to follow up on

Follow up Questions

Why might so much be similar between the two languages? Would picking languages that are not as attached to each other (Spanish and English, etc.) lead to different results?

Article #18 Notes: Recognition of Alzheimer's Dementia From the Transcriptions of Spontaneous Speech Using fastText and CNN Models

Article notes should be on separate sheets

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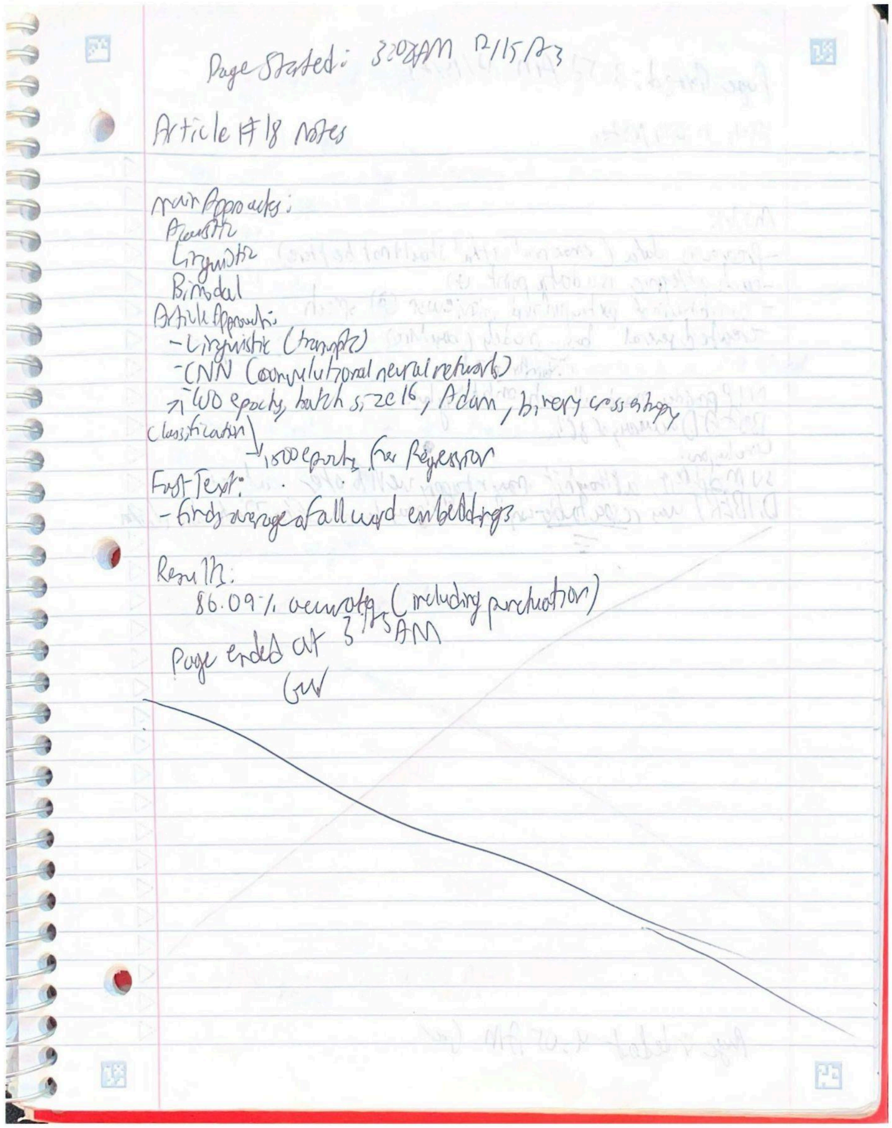
<table>
<tr><td>Source Title</td><td>Recognition of Alzheimer’s Dementia From the Transcriptions of Spontaneous Speech Using fastText and CNN Models</td></tr>
<tr><td>Source citation (APA Format)</td><td>Meghanani, A., Anoop, C. S., & Ramakrishnan, A. G. (2021). Recognition of alzheimer’s dementia from the transcriptions of spontaneous speech using fasttext and CNN Models. Frontiers in Computer Science, 3. https://doi.org/10.3389/fcomp.2021.624558</td></tr>
<tr><td>Original URL</td><td>https://www.frontiersin.org/articles/10.3389/fcomp.2021.624558/full</td></tr>
<tr><td>Source type</td><td>Journal Article</td></tr>
<tr><td>Keywords</td><td>Alzheimer’s Disease, Machine Learning</td></tr>
<tr><td>#Tags</td><td>#Alzheimer’s #Detection</td></tr>
<tr><td>Summary of key points + notes (include methodology)</td><td>This article proposes the use of a much more standard machine learning strategy to diagnose Alzheimer’s. The researches test both a Convolutional Neural network and the use of FastText Embeddings. The FastText embeddings were the most effective with an accuracy of 86%.</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>What is the best model to diagnose Alzheimer’s Disease?</td></tr>
<tr><td>Important Figures</td><td>
<table>
<tr><th>Dataset</th><th>Model</th><th>Accuracy</th><th>RMSE</th></tr>
<tr><td>PAR</td><td>CNN, bi+tri+4 gram</td><td>73.91</td><td>4.55</td></tr>
<tr><td>PAR</td><td>CNN, tri+4+5 gram</td><td>77.54</td><td>4.41</td></tr>
<tr><td>PAR</td><td>CNN, bi+tri+4+5 gram</td><td>76.54</td><td>4.65</td></tr>
<tr><td>PAR</td><td>fastText, bigram</td><td>80.54</td><td>5.43</td></tr>
<tr><td>PAR</td><td>fastText, bi + trigram</td><td>82.36</td><td>5.40</td></tr>
<tr><td>PAR + INV</td><td>CNN, bi+tri+4 gram</td><td>80.18</td><td>4.63</td></tr>
<tr><td>PAR + INV</td><td>CNN, tri+4+5 gram</td><td>81.27</td><td>4.53</td></tr>
<tr><td>PAR + INV</td><td>CNN, bi+tri+4+5 gram</td><td>80.36</td><td>4.38</td></tr>
<tr><td>PAR + INV</td><td>fastText, bigram</td><td>86.09</td><td>4.66</td></tr>
<tr><td>PAR + INV</td><td>fastText, bi + trigram</td><td>85.90</td><td>4.81</td></tr>
</table>
</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>Convolutional Neural Network- a neural network that takes input and passes it through several layers of neurons to output a value.
FastText- A model that creates a 100D vector for each word in a set and then compiles all of the vectors to arrive on a value for the set.</td></tr>
</table>

	 Page Started: 3:20AM 12/15/23 Article #18 Notes Main Approaches: Acoustic Linguistic Bimodal Article Approach: - Linguistic (transcripts) - CNN (convolutional neural network) -> 100 epochs, batch size 16, Adam, binary cross entropy (classification) -> 1500 epochs for Regression Fast Text: - finds average of all word embeddings Results: 86.09% accuracy (including punctuation) Page ended at 3:45AM GV -Gustavo Rodriguez Added on 10/15/2023 at 1:15 PM
Cited references to follow up on	
Follow up Questions	Why might some features work better than others? Could these features be synthesized with other figures to make a more accurate model?

Article #19 Notes: Comparing Natural Language Processing Techniques for Alzheimer's Dementia Prediction in Spontaneous Speech

Article notes should be on separate sheets

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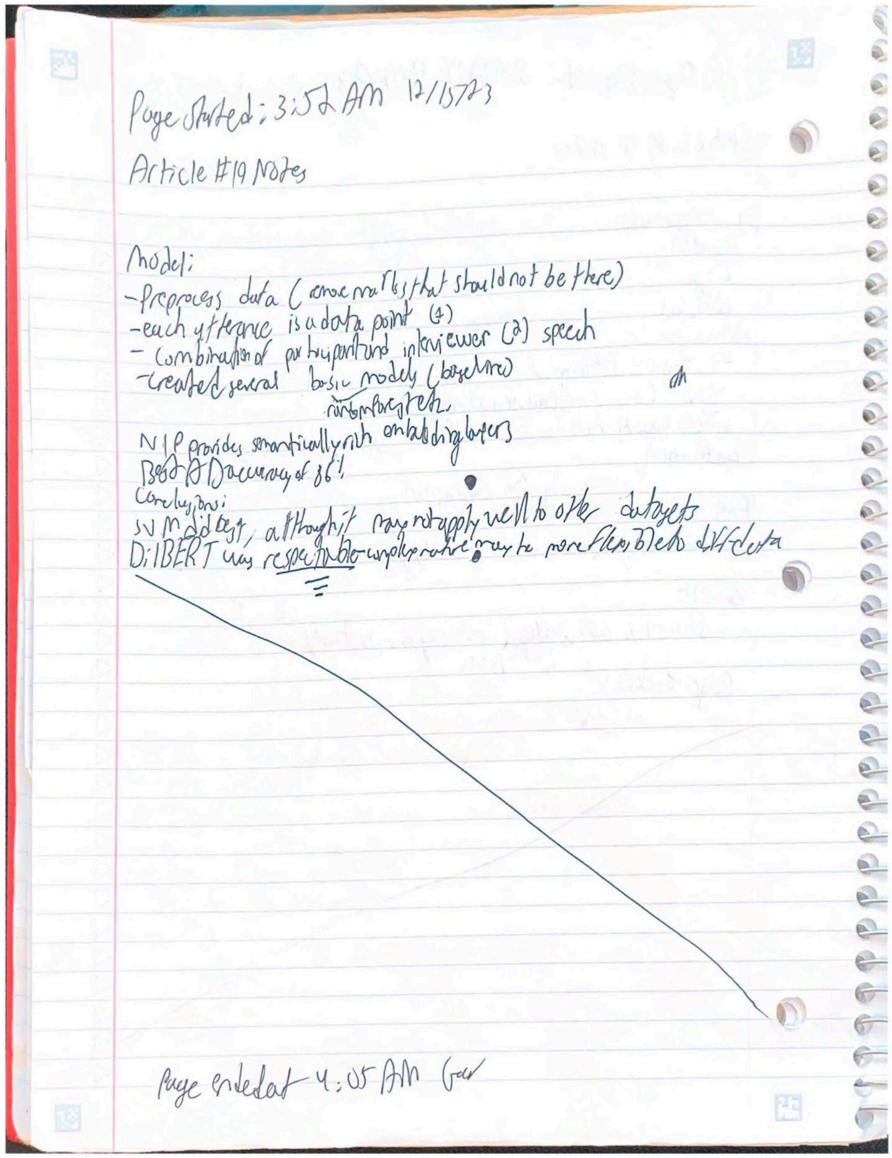
Source Title	Comparing Natural Language Processing Techniques for Alzheimer's Dementia Prediction in Spontaneous Speech
Source citation (APA Format)	Searle, T., Ibrahim, Z., & Dobson, R. (2020). Comparing natural language processing techniques for alzheimer's dementia prediction in spontaneous speech. *Interspeech 2020*. https://doi.org/10.21437/interspeech.2020-2729
Original URL	https://wpi.primo.exlibrisgroup.com/discovery/openurl?institution=01WPI_INST&vid=01WPI_INST:Default&date=2020&artnum=&aulast=Searle&issue=&isbn=&spage=2192&title=Proceedings%20of%20the%20Annual%20Conference%20of%20the%20International%20Speech%20Communication%20Association,%20INTERSPEECH&auinit=T.&atitle=Comparing%20natural%20language%20processing%20techniques%20for%20Alzheimer%27s%20dementia%20prediction%20in%20spontaneous%20speech&aufirst=T.&sid=Elsevier:Scopus&volume=2020-October&pages=2192-2196&auinit1=T&issn=2308457X&epage=2196&genre=proceeding&id=doi:10.21437%2FInterspeech.2020-2729
Source type	Journal Article
Keywords	Alzheimer's Disease, Natural Language Processing
#Tags	#Alzheimer's #Detection #NLP
Summary of key points + notes (include methodology)	This article compares many standard machine learning models to natural language processing methods. It found that some of the best models were the SVM model and the Random Forest model. These models, however, are suspected to not expand beyond the training set. DilBERT, a deep learning model, had slightly lower results but BERT is typically better at understanding meaning and could be more accurate on other datasets.

	 Page Started: 3:52 AM 12/15/23 Article #19 Notes Model: -Preprocess data (remove marks that should not be there) -each utterance is a data point (1) - combination of participant and interviewer (2) speech -created several basic models (baseline) [illegible] NLP provides semantically rich embedding layers Best AD accuracy of 86% Conclusions: SVM did best, although it may not apply well to other datasets DistilBERT was respectable [illegible] may be more flexible to diff data Page ended at 4:05 AM [illegible] -Gustavo Rodriguez Added on 10/15/2023 at 1:15 PM
Research Question/Problem/ Need	What is the best model to diagnose Alzheimer's disease using speech?

Important Figures	

Dataset / Model	Class	Prec	Recall	F1	Acc
PAR / DistilBERT	Non-AD	0.76	0.79	0.78	0.77
	AD	0.783	0.75	0.77	
PAR+INV / DistilBERT	Non-AD	**0.83**	0.79	0.81	**0.81**
	AD	0.80	**0.83**	**0.82**	
PAR / TF-IDF/SVM	Non-AD	0.70	0.83	0.75	0.73
	AD	0.79	0.63	0.70	
PAR_SPLT / SVM+CRF	Non-AD	0.78	0.88	**0.82**	**0.81**
	AD	**0.86**	0.75	0.80	
PAR_SPLT+T / SVM+CRF	Non-AD	0.75	**0.88**	0.81	0.79
	AD	0.85	0.71	0.77	

VOCAB: (w/definition)	Conditional Random Field (CRF) - A model that uses graphical representations to draw conclusions on the data. Mini Mental State Exam (MMSE) - The test used to gain a baseline as to patient condition. One of the goals of the paper was to create a model to predict the MMSE.
Cited references to follow up on	
Follow up Questions	In the past, has anyone tried to apply the SVM model to multiple databases to see if it functions?

Article #20 Notes: The efficacy of memory load on speech-based detection of Alzheimer's disease

Article notes should be on separate sheets

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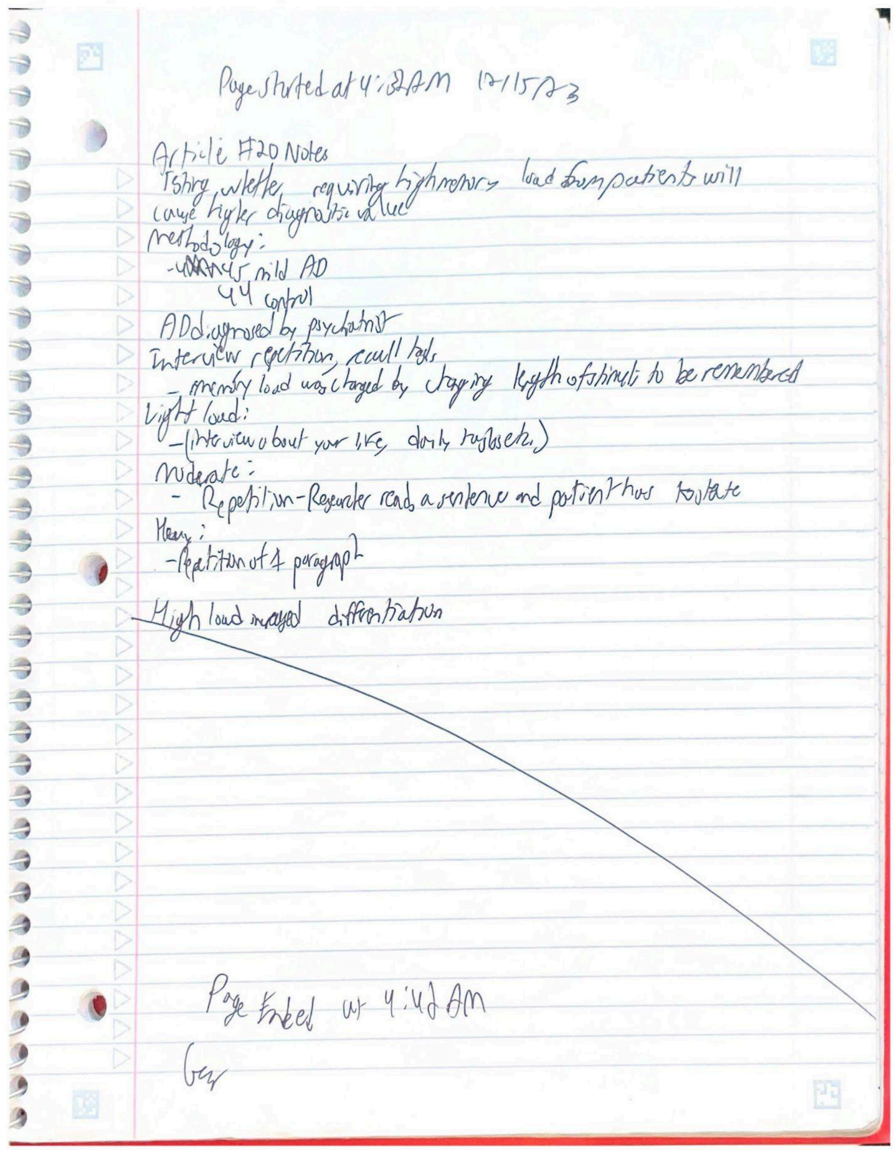
Source Title	The efficacy of memory load on speech-based detection of Alzheimer's disease
Source citation (APA Format)	Bae, M., Seo, M.-G., Ko, H., Ham, H., Kim, K. Y., & Lee, J.-Y. (2023). The efficacy of memory load on speech-based detection of alzheimer's disease. Frontiers in Aging Neuroscience, 15. https://doi.org/10.3389/fnagi.2023.1186786
Original URL	https://www.frontiersin.org/articles/10.3389/fnagi.2023.1186786/full
Source type	Journal Article

Keywords	Alzheimer’s Disease, Machine Learning
#Tags	#Alzheimer’s #Detection
Summary of key points + notes (include methodology)	Alzheimer’s disease affects memory, especially in the short term and working memory. By increasing the memory needed to accomplish a speech task, it is predicted that the effects of Alzheimer’s on speech will be exacerbated, making it easier for a model to detect. The researchers ran a study that proved that heavy repetition makes speech data of Alzheimer’s patients more decipherable.  Page started at 4:32AM 12/15/23 Article #20 Notes Testing whether requiring high memory load from patients will cause higher diagnostic value methodology: -45 mild AD 44 control AD diagnosed by psychiatrist Interview, repetition, recall tasks - memory load was changed by changing length of stimuli to be remembered Light load: -(interview about your life, daily routine) Moderate: - Repetition-Researcher reads a sentence and patient has to state Heavy: -Repetition of a paragraph High load increased differentiation Page Ended at 4:48 AM Gus -Gustavo Rodriguez

	Added on 10/15/2023 at 1:15 PM
Research Question/Problem/ Need	How can high accuracy for speech diagnosis of Alzheimer's be achieved?

Important Figures

Speech Features		Interview			Repetition			Recall		
		AD	HC	*p*	AD	HC	*p*	AD	HC	*p*
Frequency	Normalized jitter SD	1.54 (0.21)	1.65 (0.2)	**0.011**	1.7 (0.21)	1.74 (0.23)	0.464	1.59 (0.24)	1.77 (0.27)	**<0.001**
	F0 percentile range	8.52 (1.79)	6.53 (3.37)	**<0.001**	6.12 (1.49)	4.8 (2.99)	**0.011**	7.56 (1.62)	5.85 (3.33)	**0.003**
	Jitter mean	0.04 (0.01)	0.04 (0.01)	**0.016**	0.04 (0.01)	0.03 (0.01)	0.101	0.04 (0.01)	0.03 (0.02)	**0.007**
	20th percentile of the F0	26.48 (3.24)	29.14 (5.31)	**0.006**	26.59 (3.19)	28.12 (4.2)	0.059	25.87 (3.01)	28.41 (5.43)	**0.008**
	F0 Rising slope SD	280.29 (133.09)	314.12 (106.09)	0.190	305.72 (139.15)	286.51 (121.58)	0.492	318.75 (182.34)	401.88 (138.27)	**0.018**
	F0 Falling slope SD	129.3 (53.47)	110.27 (81.46)	0.201	126.13 (65.76)	114.29 (64.86)	0.397	133.21 (126.57)	184.22 (75.89)	**0.024**
	F0 mean	30.86 (3.11)	32.52 (4.08)	**0.035**	29.85 (3.1)	30.76 (3.25)	0.181	29.72 (2.99)	31.51 (4.38)	**0.029**
	Normalized F0 SD	0.19 (0.04)	0.16 (0.06)	**0.010**	0.17 (0.04)	0.15 (0.05)	0.105	0.19 (0.04)	0.17 (0.06)	**0.030**
	50th percentile of the F0	30.98 (3.36)	32.31 (4.08)	0.100	30.07 (3.4)	30.54 (3.08)	0.501	29.43 (3.11)	31.12 (4.67)	**0.050**
Loudness	Loudness percentile range	0.49 (0.27)	0.64 (0.28)	**0.016**	0.52 (0.24)	0.6 (0.31)	0.168	0.38 (0.25)	0.64 (0.22)	**<0.001**
	Loudness peaks per second	2.39 (0.53)	2.86 (0.56)	**<0.001**	2.68 (0.51)	2.96 (0.47)	**0.009**	2.05 (0.62)	2.64 (0.55)	**<0.001**
	80th percentile of the loudness	0.58 (0.28)	0.69 (0.28)	0.071	0.61 (0.26)	0.66 (0.31)	0.475	0.46 (0.26)	0.68 (0.21)	**<0.001**
	Loudness mean	0.35 (0.16)	0.39 (0.15)	0.195	0.36 (0.14)	0.36 (0.16)	0.936	0.28 (0.14)	0.37 (0.12)	**0.001**
	Loudness falling slope mean	4.88 (2.37)	6.01 (2.88)	**0.048**	4.45 (2.02)	5.05 (2.49)	0.221	4.46 (2.23)	6.14 (2.58)	**0.002**
	Normalized shimmer SD	0.73 (0.1)	0.8 (0.11)	**0.004**	0.78 (0.09)	0.84 (0.13)	**0.019**	0.75 (0.09)	0.83 (0.12)	**0.002**
	20th percentile of the loudness	0.09 (0.03)	0.06 (0.07)	**0.003**	0.1 (0.03)	0.06 (0.07)	**0.001**	0.08 (0.03)	0.04 (0.07)	**0.003**
	Loudness rising slope mean	5.68 (2.7)	7.03 (3.11)	**0.032**	5.13 (2.34)	5.72 (2.64)	0.272	5.16 (2.65)	6.9 (2.73)	**0.003**
	50th percentile of the loudness	0.22 (0.15)	0.27 (0.12)	0.105	0.27 (0.13)	0.28 (0.13)	0.810	0.17 (0.13)	0.25 (0.1)	**0.004**
	Loudness falling slope SD	3.24 (1.46)	3.71 (1.76)	0.171	2.77 (1.17)	3.01 (1.54)	0.414	3.09 (1.44)	3.95 (1.71)	**0.013**
Temporal	Mean duration of voiced region	0.3 (0.12)	0.38 (0.14)	**0.003**	0.32 (0.09)	0.37 (0.13)	0.059	0.29 (0.1)	0.35 (0.14)	**0.014**
	SD duration of voiced region	0.23 (0.09)	0.28 (0.08)	**0.008**	0.25 (0.05)	0.27 (0.06)	0.067	0.25 (0.08)	0.3 (0.1)	**0.011**

AD, Alzheimer's disease; HC, healthy older adults; *p*, independent *t*-test, or Welch's two-sample test were used as appropriate and a Bonferroni correction for multiple comparisons was applie
eatures are sorted by value of *p*; Statistically significant features are in bold.

VOCAB: (w/definition)

Light Memory Load - A task that does not require significant memory strength. In the article talks about the patient's past were used for this

Moderate Memory Load - A task that requires more memory in order to be completed. For this study, recall of a sentence was use

Heavy Memory Load - A task that requires the most memory to be completed. In this study, it was recall of a paragraph.

Cited references to follow up on

Follow up Questions	Could a new type of test be developed to match the findings of this research? How would this type of data be controlled?

Patent #1 Notes: Speech analysis for monitoring or diagnosis of a health condition

Article notes should be on separate sheets

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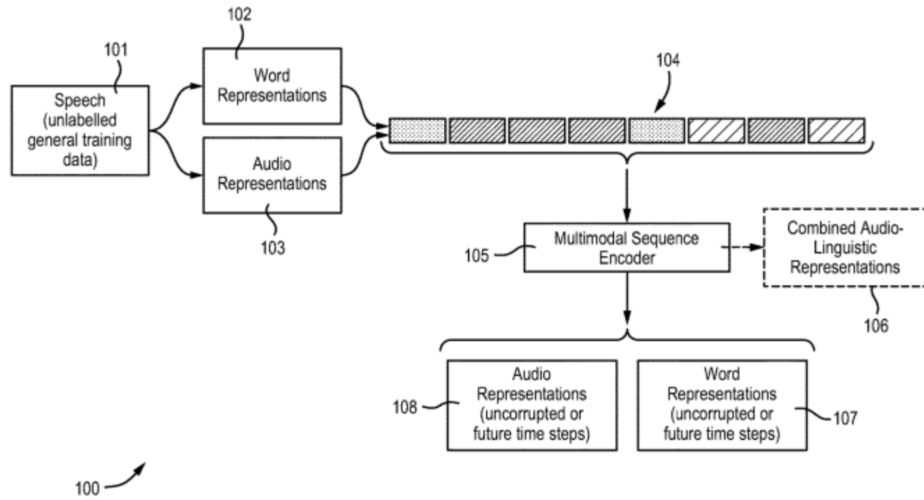
Source Title	Speech analysis for monitoring or diagnosis of a health condition
Source citation (APA Format)	Weston, J., & Fristed, E. (2023). Speech analysis for monitoring or diagnosis of a health condition (Patent No. US202302555553A1). United States Patent and Trademark Office. https://patents.google.com/patent/US20230255553A1/en?q=(Alzheimer%27s+diagnosis+speech)&oq=Alzheimer%27s+diagnosis+speech
Original URL	https://patents.google.com/patent/US20230255553A1/en?q=(Alzheimer%27s+diagnosis+speech)&oq=Alzheimer%27s+diagnosis+speech
Source type	Patent
Keywords	Alzheimer’s Disease, Machine Learning
#Tags	#Alzheimer’s #Detection
Summary of key points + notes (include methodology)	This patent is for a machine learning model that can synthesize the linguistic and audio aspects of speech to deliver an Alzheimer’s diagnosis. This provides a great deal of novelty and strength, as in the past these fields were often separated, but together much stronger connections can be drawn that can deepen the understanding of language and Alzheimer’s disease.
Research Question/Problem/ Need	How can Alzheimer’s disease be diagnosed using speech with high accuracy?

<table>
<tr><td>Important Figures</td><td>
</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>Model pre-training- model pre-training is when a model is fitted to a broader dataset before being streamlined into a specific task. For example, BERT can be pre-trained on all of English before being trained more specifically on Alzheimer’s diagnosis.</td></tr>
<tr><td>Cited references to follow up on</td><td></td></tr>
<tr><td>Follow up Questions</td><td>What are the specifics of the model? What models are synthesized? How effective is the model?</td></tr>
</table>

Patent #2 Notes: Machine Learning Systems and Methods for Multiscale Alzheimer's Dementia Recognition Through Spontaneous Speech

Article notes should be on separate sheets

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Source Title	Machine Learning Systems and Methods for Multiscale Alzheimer's Dementia Recognition Through Spontaneous Speech
Source citation (APA Format)	Edwards, E., Dognin, C., Bollepalli, B., & Singh, M. (20221). *Machine Learning Systems and Methods for Multiscale Alzheimer’s Dementia Recognition Through Spontaneous Speech* (Patent No.

	US20210353218A1). United States Patent and Trademark Office. https://patents.google.com/patent/US20210353218A1/en?q=(Alzheimer%27s+diagnosis+speech)&oq=Alzheimer%27s+diagnosis+speech
Original URL	https://patents.google.com/patent/US20210353218A1/en?q=(Alzheimer%27s+diagnosis+speech)&oq=Alzheimer%27s+diagnosis+speech
Source type	Patent
Keywords	Alzheimer's Disease, Machine Learning
#Tags	#Alzheimer's #Detection
Summary of key points + notes (include methodology)	This patent is for an Alzheimer's detection model based on speech that can extract seven features including vocabulary richness variables, word counts, number of stop words, and other metrics. These variables are then inputted into one of three deep learning models that provide the final diagnosis. The most accurate model was 93% accurate using a fine tuned Word2Vec algorithm. This model hovers around 70% accuracy, which is not an ideal result for detection.
Research Question/Problem/ Need	How can high accuracy for speech diagnosis of Alzheimer's be achieved?

Important Figures	TABLE 4 Best performance after hyper-parameters optimization for each model, metrics are the average of accuracy and f1 scores across 6-fold cross-validation, participant level (soft max average).

Model	Dim.	Accuracy	F1-score
Random (DRF)	11	0.463	0.482
Engineered Feat (DRF)	11	0.704	0.68
Sent2Vec (FT)	600	0.787	0.758
GloVe (FT)	300	0.861	0.865
Word2Vec (FT)	300	0.926	0.923
Word2Vec (DRF)	300	0.787	0.785
GloVe + EF (DRF)	311	0.796	0.792
Sent2Vec (DRF)	600	0.833	0.83
GloVe (DRF)	300	0.824	0.822
FastText (FS)	5	0.796	0.776
Roberta-Base (FT)	768	0.787	0.753
Electra-Base (FT)	768	0.861	0.845

VOCAB: (w/definition)	Fine Tuning - The act of taking a general model and training it to a specific task, such as diagnosing Alzheimer's disease. Training from scratch - Fitting a model using only data from the end goal and not from general means.
Cited references to follow up on	
Follow up Questions	How might this model be improved? How might the model perform on other databases?

Patent #3 Notes: Cognitive Function Evaluation Device, Cognitive Function Evaluation System, and Cognitive Function Evaluation Method

Article notes should be on separate sheets

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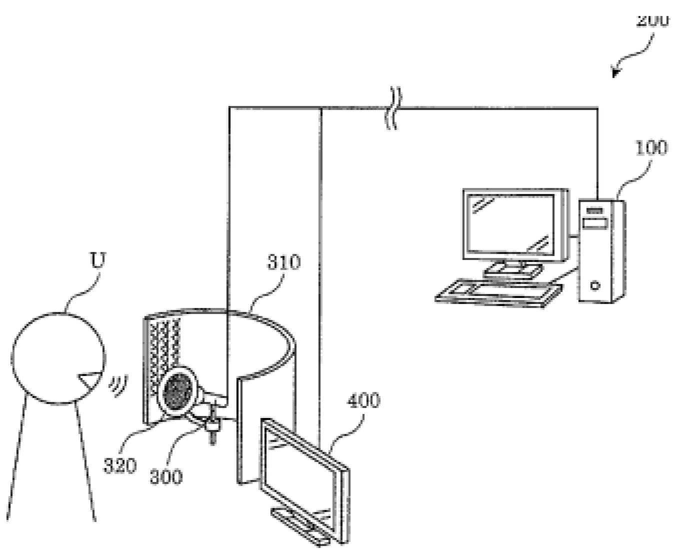
Source Title	Cognitive Function Evaluation Device, Cognitive Function Evaluation System, and Cognitive Function Evaluation Method
Source citation (APA Format)	Sumi, S., Abe, K., Nagumo, R., Nishiyama, T., Matsumura, Y., & Ukeda,

	T. (2019). Cognitive Function Evaluation Device, Cognitive Function Evaluation System, and Cognitive Function Evaluation Method (Patent No. US11766209B2). United States Patent and Trademark Office. https://patentimages.storage.googleapis.com/3b/15/89/ad2942eab5017f/US11766209.pdf
Original URL	https://patentimages.storage.googleapis.com/3b/15/89/ad2942eab5017f/US11766209.pdf
Source type	Patent
Keywords	Alzheimer's Disease, Machine Learning, Applications,
#Tags	#Alzheimer's #Detection
Summary of key points + notes (include methodology)	This patent is for a technology that will track vowel production and use that to detect Alzheimer's disease in Japanese. This method is similar to that of Olga Ivanova which required a standard phrase to be read by various patients. This technology is planned to be implemented as a program that can be easily accessible for diagnostic and/or detection purposes.
Research Question/Problem/ Need	How can Alzheimer's detection become more available?
Important Figures	
VOCAB: (w/definition)	Formant - A band of frequency that determines the quality of a vowel Regression Analysis - The creation of a line of best fit used for binary classification in a machine learning model.
Cited references to follow up on	

Follow up Questions	How effective was this model in diagnosing dementia or predicting MOCA scores? What improvements could be made to the architecture of this model? Would this model still apply to English?