Acoustic and Linguistic Analysis for Early Dementia Detection using Machine Learning

Marcel Seitz & Philip Werz

27.10.2025, Final Guided Research Presentation

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Who we are

Marcel Seitz

Philip Werz

Agenda

1. Motivation and Relevance

Dementia

Challenges of Dementia

- Rising global prevalence of dementia, especially Alzheimer's Disease
- Affects ~57 million in 2021, ~10 million new cases/year.
- Major global cause of death & disability.
- Urgent need for early diagnosis & long-term monitoring.

ALPHA-KI

- AI-Based Digital Health Assistant for Elderly & Chronically Ill.

AssistD

- Improving Dementia Care through Adaptive Voice Assistance.

Early Markers and Assessment Tools

- Subtle changes in speech and language are often earliest detectable markers of cognitive decline.

Cookie Theft Picture

- Widely used neuropsychological instrument

Voice Assistant

- Voice assistant interactions

Acoustic and Linguistic Analysis using Machine Learning

Sources: [1-4]

2. Research Gap & Research Questions

Research Gap

ADReSS Challenge

- **AD classification:** Building a model to predict whether a speech session indicates AD or non-AD.
- **MMSE score regression:** Creating a model to infer a subject's Mini Mental State Examination (MMSE) score from speech/language data.

Few studies focus on HC vs. MCI; mostly focused on HC vs. AD

Lack of Multimodal Analysis

- Previous studies mostly use either acoustic (audio) or linguistic (text) features, sometimes both, but treat them separately.
- Shakeri et al. focused on multilingual analysis on unified conversational dataset [5].

Combining acoustic and linguistic features via multimodal ML remains largely unexplored

Research Questions

Cookie Theft Picture

I — How accurately can unimodal ML models based on acoustic or linguistic features from **Cookie Theft Picture descriptions** distinguish between **HC and MCI patients**?

II — Does integrating **audio and linguistic** features from **Cookie Theft descriptions** enhance early dementia classification compared to unimodal approaches?

III — How do different **transcription representations** (orthographic versus phonetic ARPAbet) of Cookie Theft Picture descriptions affect the stability and discriminative power of transformer-based text and multimodal models?

Voice Assistant

I — How well can unimodal ML models using acoustic or linguistic features from **Alexa interactions** differentiate **HC and MCI/D patients**?

II — Does integrating **audio and linguistic** features from **Alexa-based speech interactions** improve early dementia classification compared to unimodal approaches?

III — How do different **transcription representations** (orthographic versus phonetic ARPAbet) of Alexa conversations affect the stability and discriminative power of transformer-based text and multimodal models?

Sources: [5-6]; Abbreviations: AD = Alzheimer's Dementia, MCI = Mild Cognitive Impairment, D = Dementia, HC = Healthy Control

3.1 Theoretical Background

DM vs MCI

Clinical Background

- **Dementia**: Progressive cognitive decline affecting daily life; Alzheimer is the most common cause.
- **MCI**: Intermediate stage between normal aging and Demenita; may progress, stay stable, or revert.
- **Early Detection**: Critical at MCI stage for timely intervention and treatment trials.

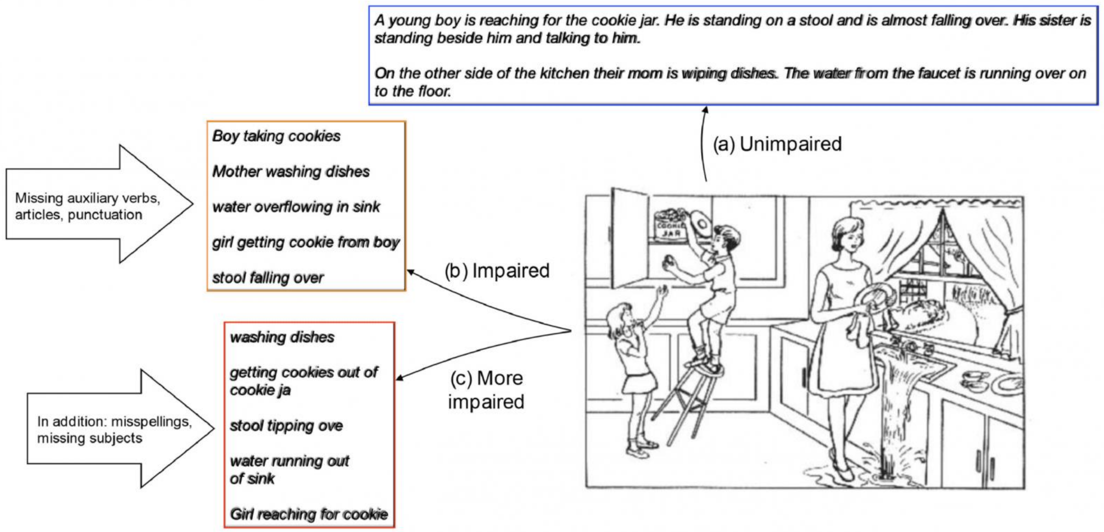
Early Biomarkers of Cognitive Decline

- **Speech as Cognitive Marke**r: Involves memory, attention, and language, sensitive to early decline.
- **Early Language Changes in MCI**: Reduced lexical variety, vague words, and semantic errors.
  - **Simpler Syntax**: Shorter sentences, fewer embedded clauses.
  - **Fluency & Prosody**: More pauses, hesitations, and reduced articulation/emotional tone.

Speech

Standardized (Cookie Theft Picture)

- **Standardized tasks** (e.g., Cookie Theft) guide content and reduce variability, enabling easier feature extraction.
- **Controlled & Natural**: Same visual stimulus enables comparability.
- **Cognitive Support**: Reduces memory/attention demands, suitable for impaired participants.
- **MCI Indicators**: Less detail, low lexical/syntactic complexity, more pronouns, reduced fluency.



Source: Figure 1

Sources: [7-21], [27]; Abbreviations: MCI = Mild Cognitive Impairment

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Interactions

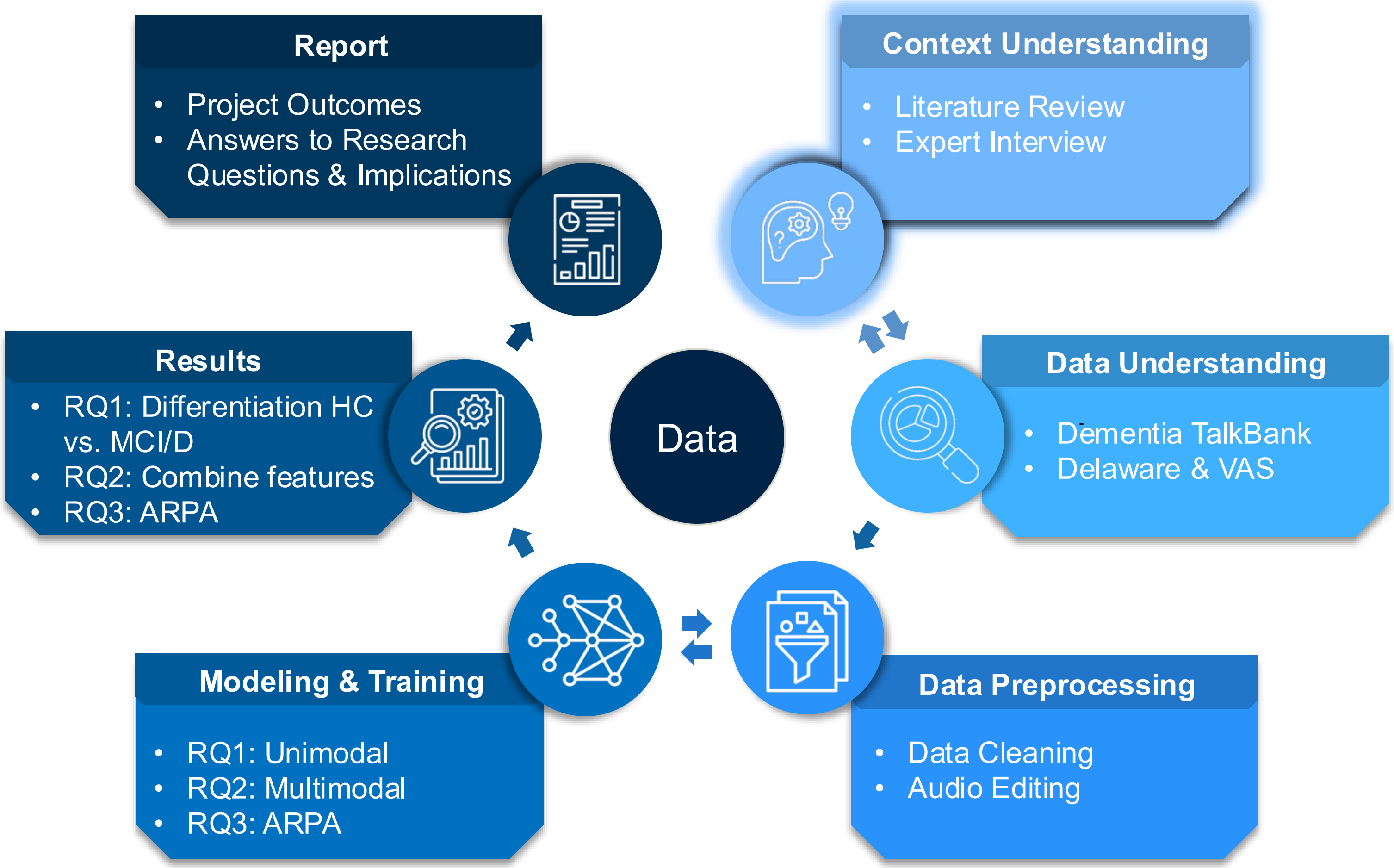
Source: Figure 2

Voice Assistant (Amazon Alexa)

- **Interactions** (e.g., Alexa) can offer more natural data but introduces higher linguistic and acoustic variability, posing challenges for consistent classification.
- **Linguistic Markers**: Less coherence, fewer content words, more pronouns & pauses.
- **Temporal Features**: Slower tempo, more hesitations, altered articulation.

Sources: [7-10], [17-21], [27-32]; Abbreviations: MCI = Mild Cognitive Impairment

4.1 Methodology – Context Understanding



Abbreviations: MCI = Mild Cognitive Impairment, D = Dementia, HC = Healthy Control, ARPA = Advanced Research Projects Agency

4.2 Methodology – Data Understanding

Report
- Project Outcomes
- Answers to Research Questions & Implications

Context Understanding
- Literature Review
- Expert Interview

Results
- RQ1: Differentiation HC vs. MCI/D
- RQ2: Combine features
- RQ3: ARPA

Data

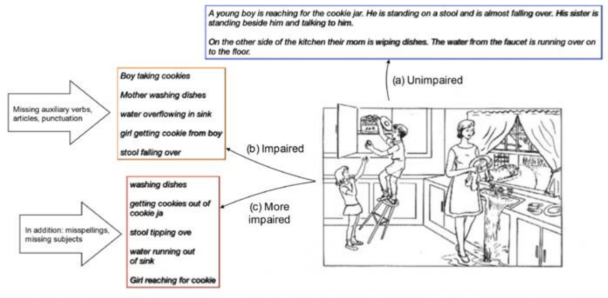
Data Understanding
- Dementia TalkBank
- Delaware & VAS

Modeling & Training
- RQ1: Unimodal
- RQ2: Multimodal
- RQ3: ARPA

Data Preprocessing
- Data Cleaning
- Audio Editing

Delaware

- Standardized dataset.
- Picture descriptions; Story-, Procedural-, Personal-Narratives
- Participants: older adults (60-90).
- Audio recordings and manually transcribed and annotated speech data (CHAT format, 112 Participants).
- Includes data from a control group and individuals diagnosed with MCI (64 MCI, 48 HC).
- Total Length: 18 h.
- Data Collection Ongoing.



Source: Figure 1

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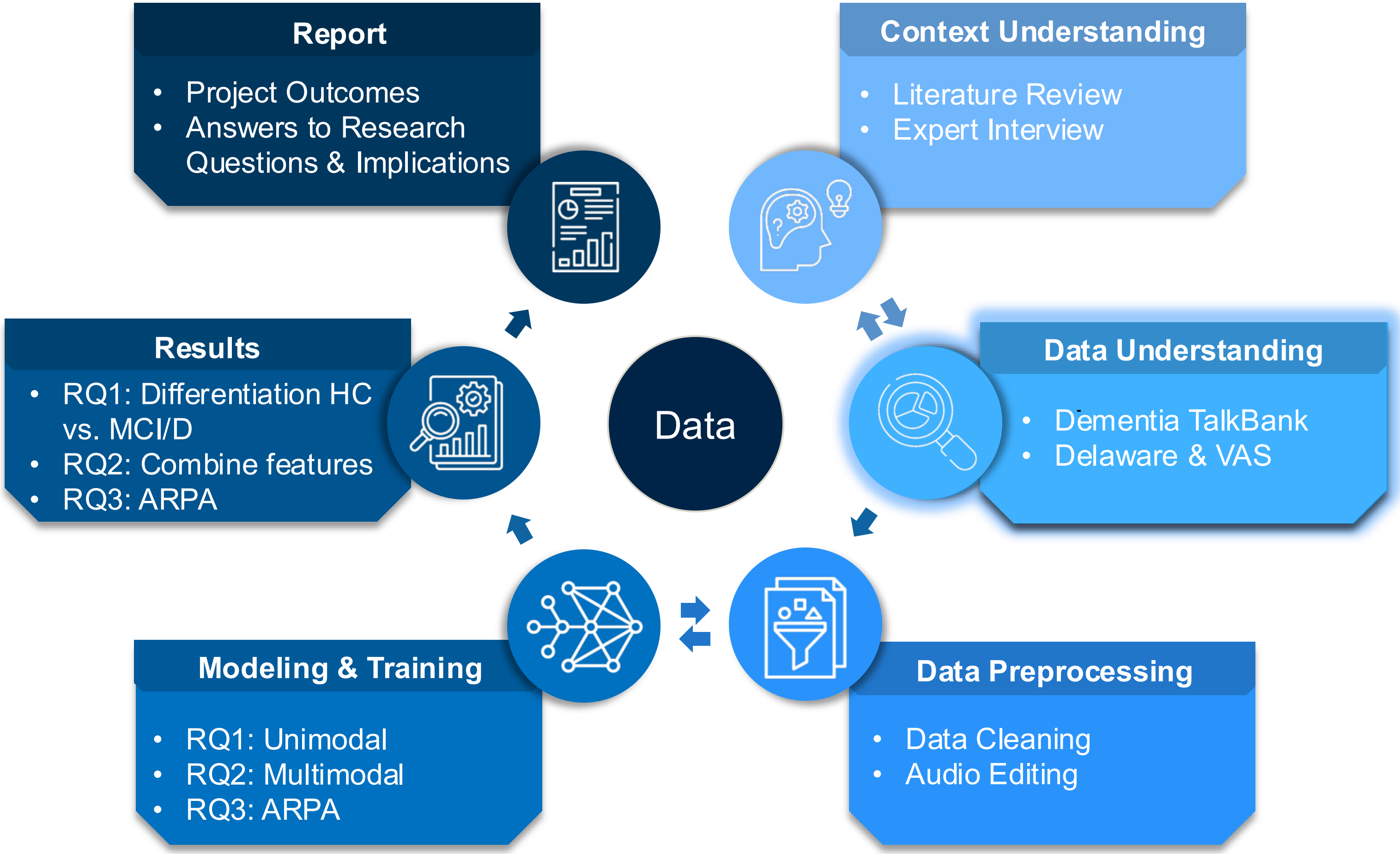
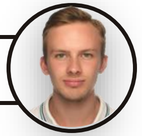


VAS

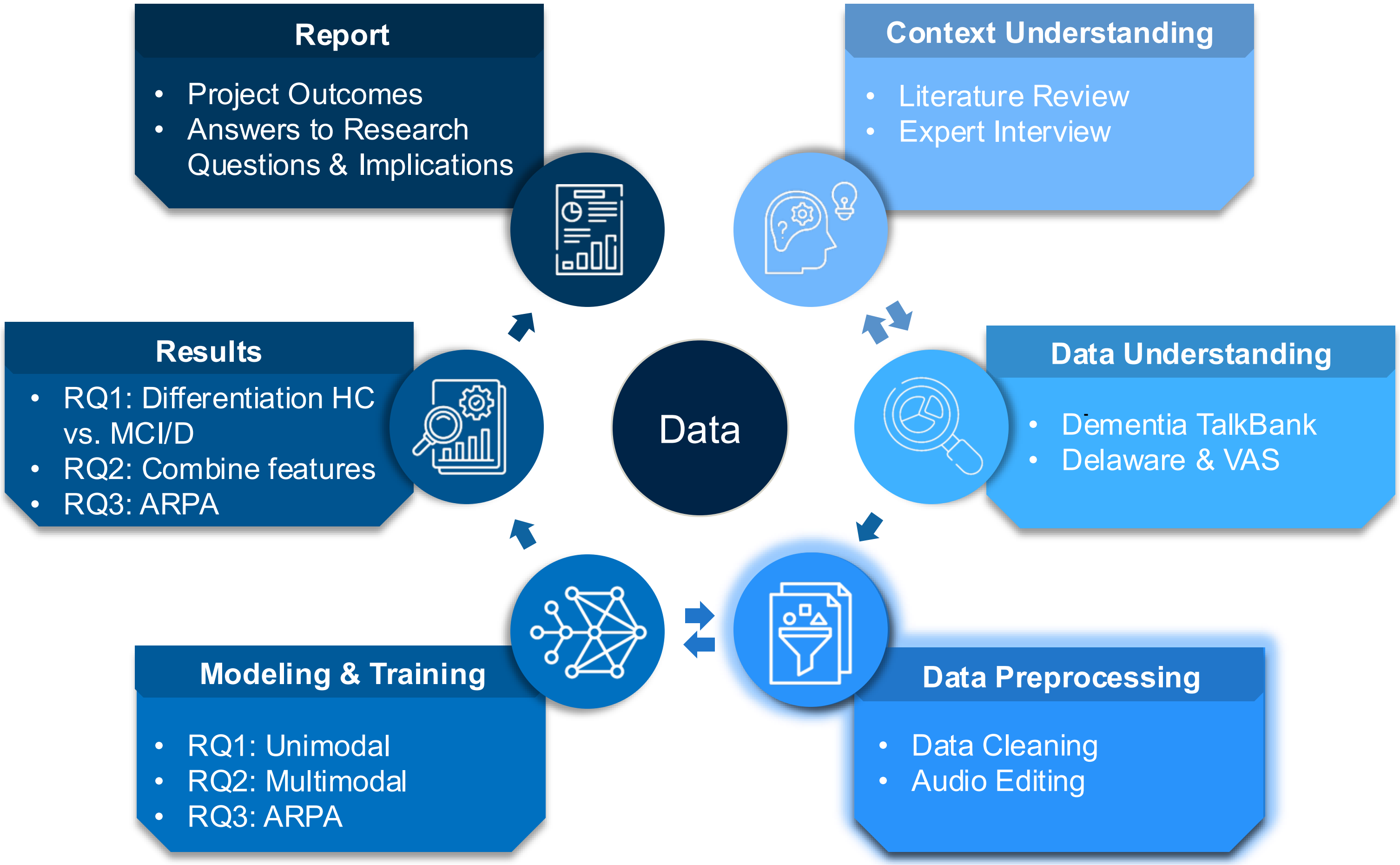


- Dataset of voice interactions from older adults (64-94).
- Audio recordings and text transcripts from Amazon Alexa (CHAT format, 100 Participants).
- Includes data from a control group and individuals diagnosed with dementia (D:29, HC: 36, MCI: 35).
- Total Length: 3.5h.

Source: Figure 2

Source: [6], Abbreviations: MCI = Mild Cognitive Impairment, D = Dementia, HC = Healthy Control, ARPA = Advanced Research Projects Agency

4.3 Methodology – Data Preprocessing



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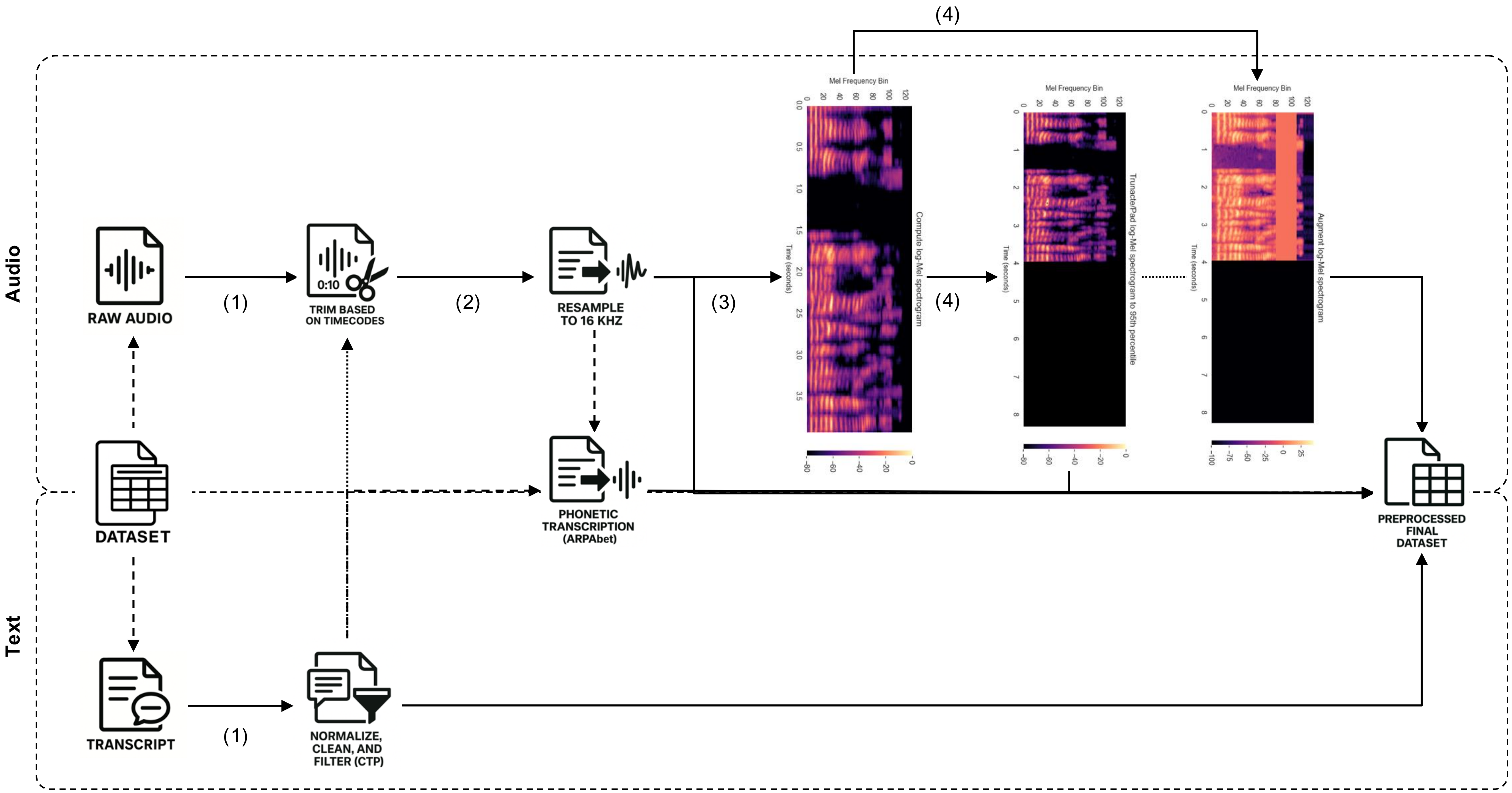
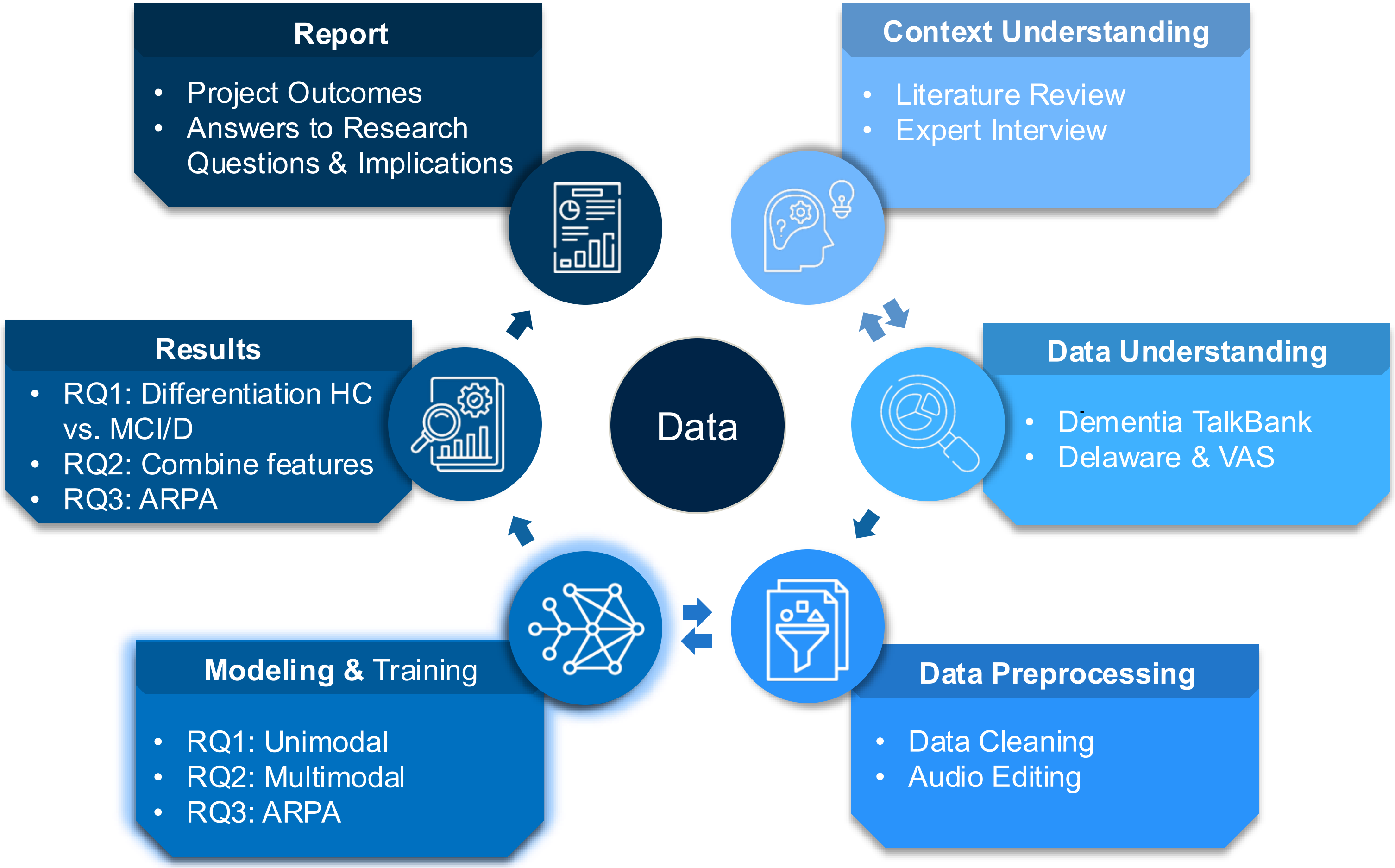


Data Preprocessing

Abbreviations: ARPA = Advanced Research Projects Agency, CTP = Cookie Theft Picture

4.3 Methodology – Data Modeling



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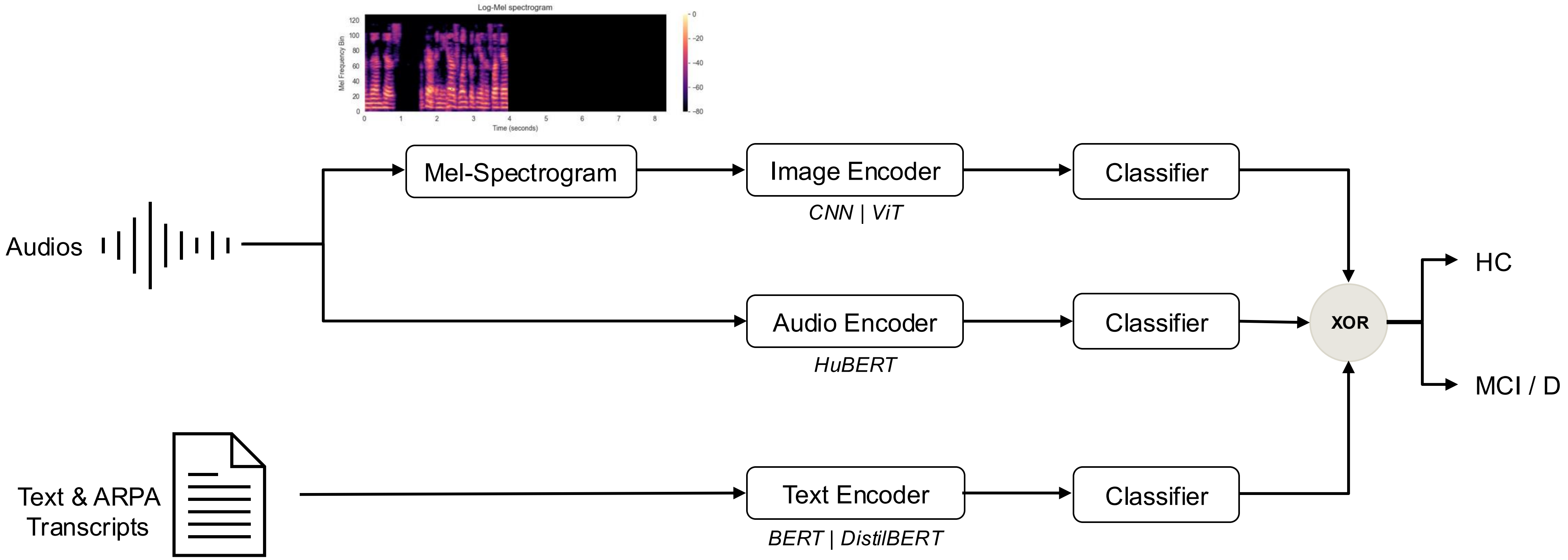
4.4 Methodology – Modeling | Unimodal



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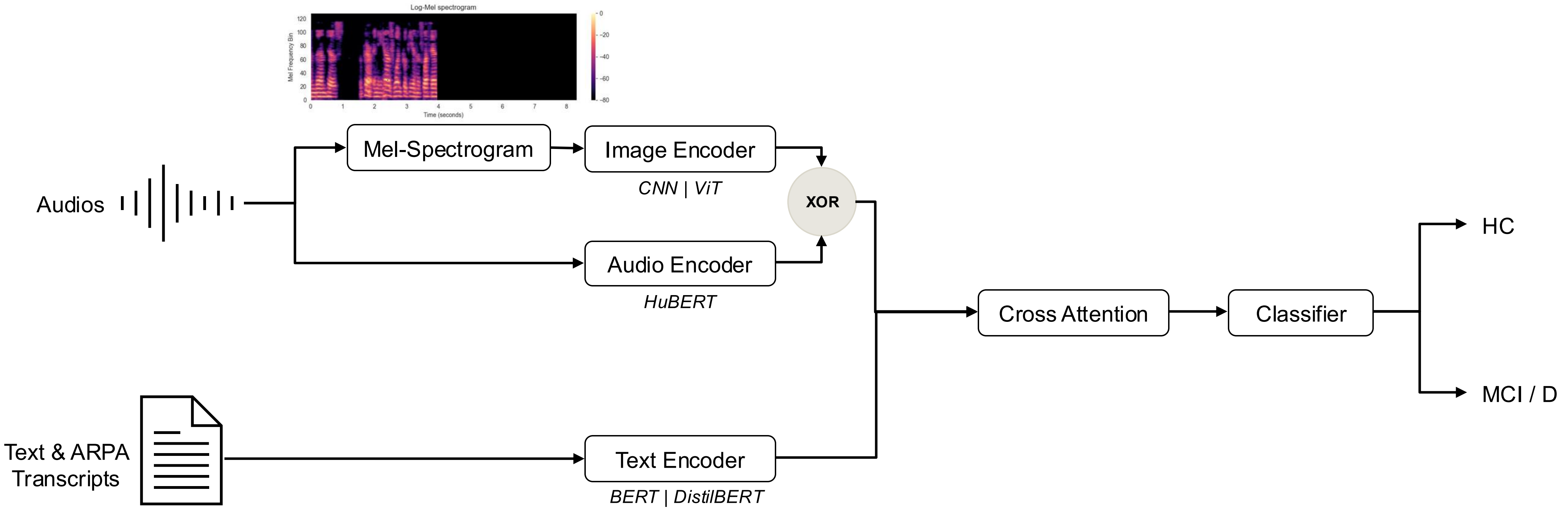
4.4 Methodology – Modeling | Multimodal



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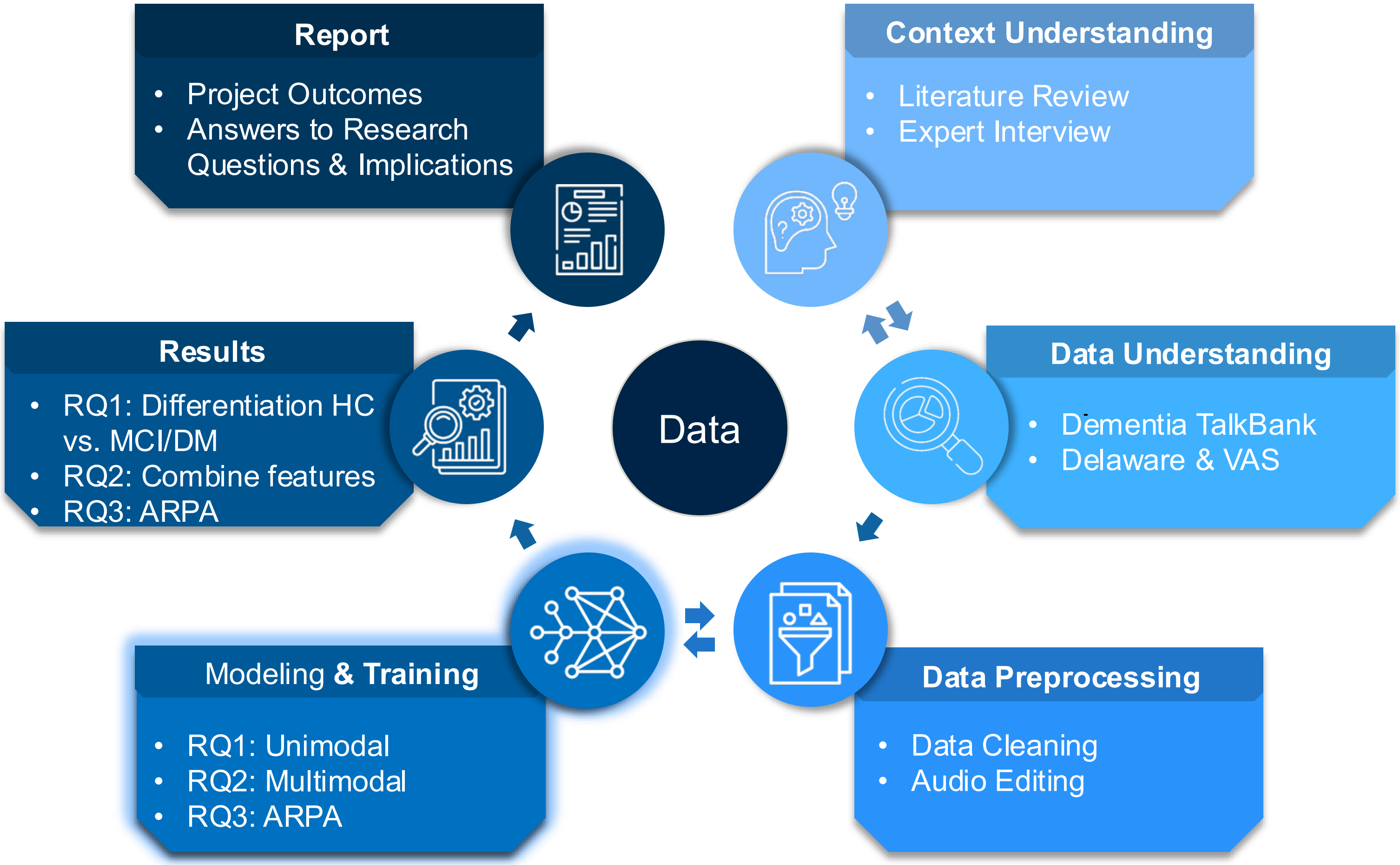
4.4 Methodology – Training

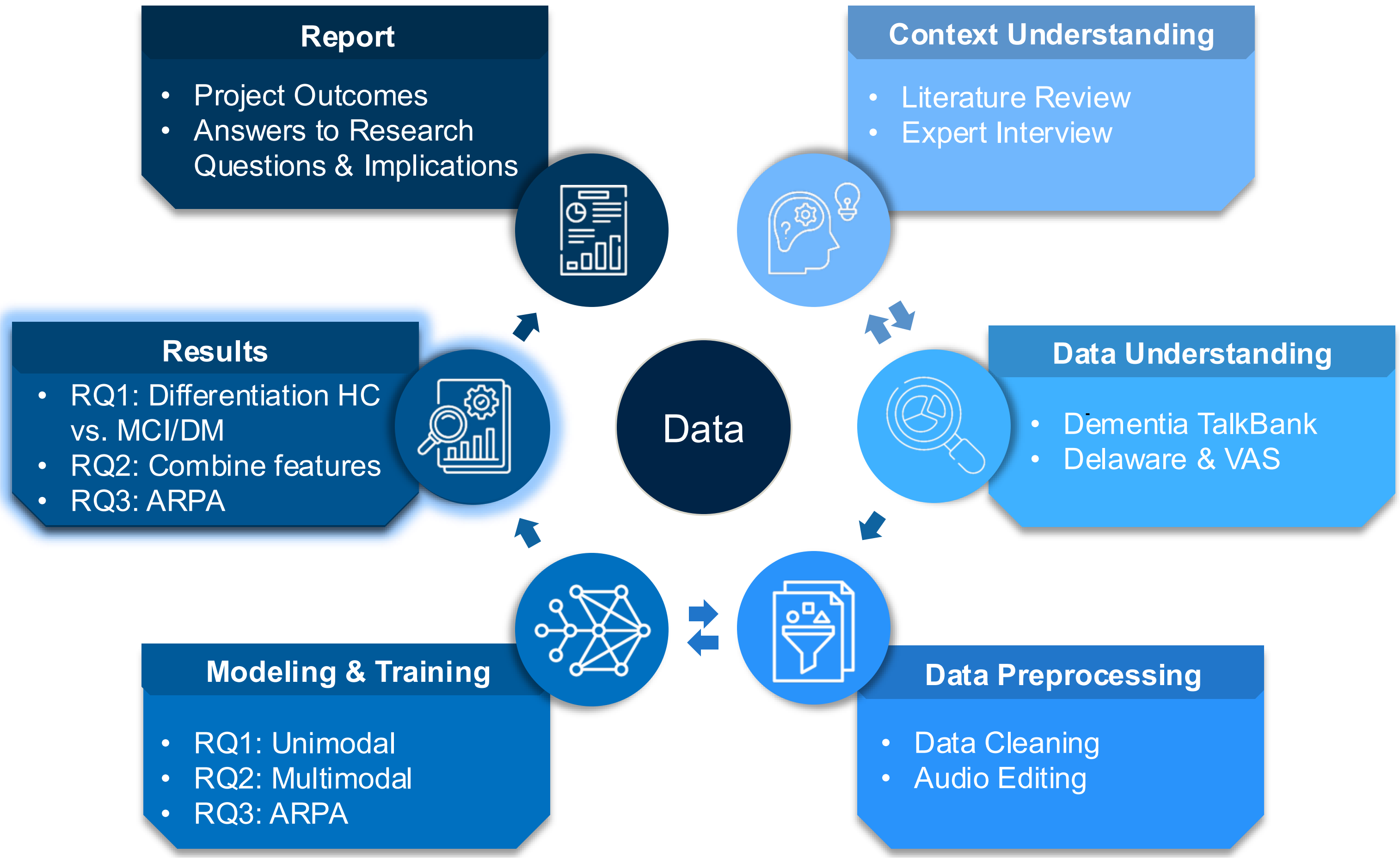


Training

- **Bayesian Optimization with the Optuna library** for efficient search
- **Objective**: Maximize validation F1
- **Tuned hyperparameters**
- **Early stopping & pruning** for stability and efficiency
- **Automatic logging (CSV)**: hyperparameters, metrics of all model configurations

Abbreviations: MCI = Mild Cognitive Impairment, D = Dementia, HC = Healthy Control

4.5 Results



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4.5 Results - Delaware

Domain	Best Configuration	F1	Bal. Acc.	Comment
Audio (unimodal)	ViT-tiny	0.77	0.65	• Indicates that transformer-style patch embeddings (ViT) capture **long-range spectro-temporal dependencies**. • **HuBERT** showed signs of **overfitting** to waveform variability.
Text (unimodal)	BERT (ARPA)	0.73	0.59	• **ARPAbet transcriptions improved BERT's** stability. • **DistilBERT** gained **little benefit due to its compressed architecture**, performing best on orthographic text.
Multimodal	CNN + BERT (non-ARPA)	0.76	0.65	• Gains remained modest due to **limited dataset size.**

I

How accurately can unimodal ML models based on acoustic or linguistic features from **Cookie Theft Picture descriptions** distinguish between **HC and MCI patients**?

- **ViT-tiny** (audio) achieved the highest F1 and balanced accuracy, significantly **outperforming CNN and HuBERT.**
- **BERT-based** text models reached moderate accuracy.
- **DistilBERT** performed **comparably** but with slightly lower stability.

II

Does integrating **audio and linguistic** features from **Cookie Theft descriptions** enhance early dementia classification compared to single-modality models?

- **CNN + BERT (non-ARPA)** achieved the highest multimodal balanced accuracy.
- **Multimodal fusion** provided **complementary (not superior)** diagnostic information compared to ViT.

III

How do different **transcription representations** (orthographic versus phonetic ARPAbet) of Cookie Theft Picture descriptions affect the stability and discriminative power of transformer-based text and multimodal models?

- **ARPAbet improved BERT's** stability and performance.
- In **multimodal setups**, ARPAbet **enhanced** linguistic–acoustic alignment for **spectrogram-based models** (ViT, CNN) but showed negligible effect for waveform-level HuBERT.
- Indicates that **phonetic abstraction benefits large transformers** and **supports cross-modal synchronization.**

Abbreviations: Bal. Acc. = Balanced Accuracy

4.5 Results – VAS

	H vs. MCI			H vs. D		
Domain	**Best Configuration**	**F1**	**Bal. Acc.**	**Best Configuration**	**F1**	**Bal. Acc.**
Audio (unimodal)	ViT-Small	0.65	0.65	ViT-Tiny	0.92	0.92
Text (unimodal)	BERT (Text)	0.71	0.52	BERT (Text)	0.68	0.58
Multimodal	CNN + BERT (Text)	0.59	0.59	ViT-Small + BERT	0.87	0.88

I

How well can unimodal ML models using acoustic or linguistic features from **Alexa interactions** differentiate **HC and MCI/D** patients?

- **ViT-Small (audio)** achieved the best balanced accuracy (0.65) for *H vs. MCI*, outperforming CNN and ViT-Tiny.
- **All audio models** reached high performance for H vs. D (F1 ≈ 0.91–0.92).
- Text-based BERT models showed **moderate results** (F1 ≈ 0.68–0.71), with **DistilBERT slightly less stable**.

II

Does integrating **audio and linguistic** features from **Alexa-based speech interactions** improve early dementia classification compared to unimodal approaches?

- **BERT + CNN** achieved the highest multimodal balanced accuracy = 0.59 for *H vs. MCI* and **DistilBERT + ViT-Tiny** reached 0.88 for *H vs. D*.
- Multimodal fusion provided **complementary (but not superior)** diagnostic information compared to unimodal ViT models.

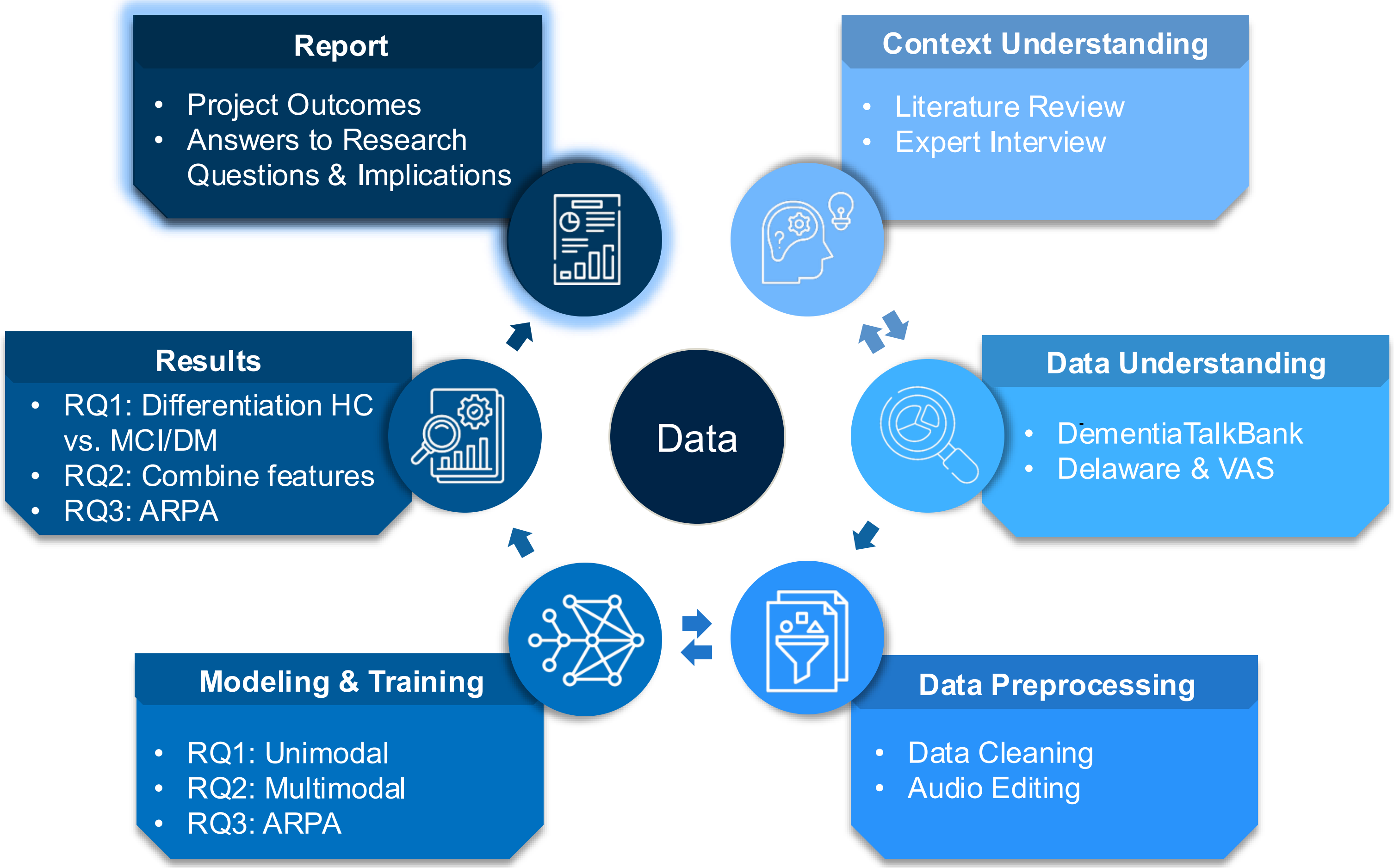
III

How do different **transcription representations** (orthographic versus phonetic ARPAbet) of Alexa conversations affect the stability and discriminative power of transformer-based text and multimodal models?

- **Phonetic ARPAbet transcriptions** did not improve performance or stability of transformer-based models.
- **ARPA-based models** (e.g., ViT-Small + BERT: Bal. Acc. = 0.55; 0.84 for *H vs. D*) performed similar to orthographic versions.
- The **limited length** of Alexa interactions **may have constrained** both ARPA and standard text representations, reducing their discriminative power.

Abbreviations: Bal. Acc. = Balanced Accuracy

4.6 Methodology – Report



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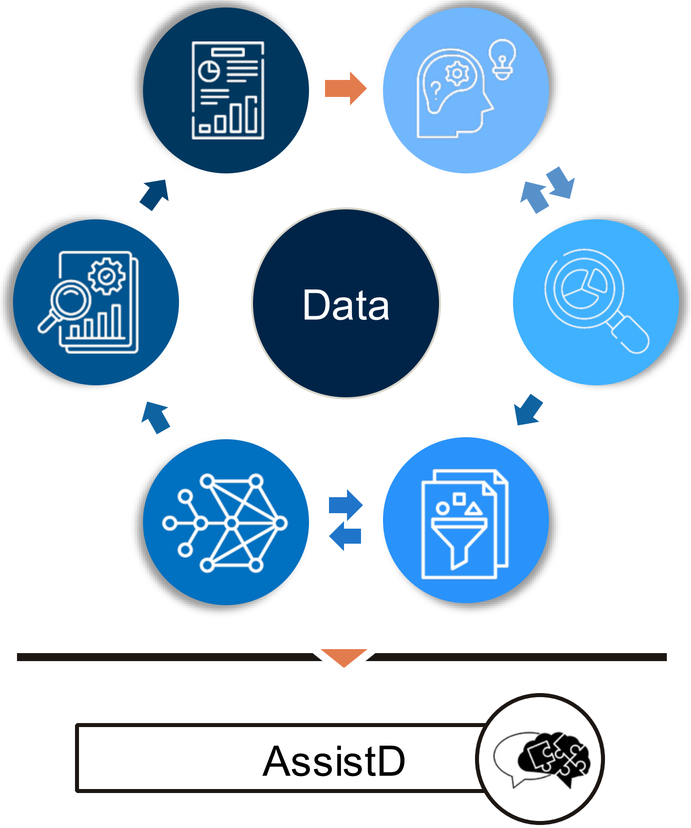
4.7 Methodology – Next Steps



Source: [4]

5. Outlook

Contribution

Academic Insights

- **Unimodal ViT** achieved best performance
- **Multimodal integration yields complementary**, not superior, diagnostic information.
- **Phonetic abstraction** (ARPAbet) stabilizes transformer-based language models (in case of CTP, not for Alexa conversations).
- **Unified framework** for flexible unimodal and multimodal experimentation (audio, text, and fusion).

Future Research

- *k*-fold cross validation (resource intensive).
- Develop a **larger and more balanced** dataset.
- Establish a **consistent transcription protocol.**
- Incorporate diverse AI Assistant interactions to increase variability
- **Employ IPA** (incl. German) for finer phonetic granularity, compared to ARPAbet (English-only, lower granularity, suitable for smaller datasets).
- **LLM-based CTP Analysis (LLM as a Judge):**
  - Extract clinically relevant cues (e.g., clockwise / anti-clockwise actions).

Additional Step

Provide supplementary documents containing further findings and relevant details

Abbreviations: CTP = Cookie Theft Picture, IPA = International Phonetic Alphabet, ARPA = Advanced Research Projects Agency

7.1 Sources

Literature:

[1] WHO. "Dementia Fact Sheet." https://www.who.int/news-room/fact-sheets/detail/dementia (accessed 21 April, 2025).

[2] A. Wimo et al., "The worldwide costs of dementia in 2019," Alzheimer's & Dementia, vol. 19, no. 7, pp. 2865-2873, 2023, doi: https://doi.org/10.1002/alz.12901.

[3] Silva, C. d. M. G. Loures, L. C. V. Alves, L. C. de Souza, K. B. G. Borges, and M. d. G. Carvalho, "Alzheimer's disease: risk factors and potentially protective measures," Journal of Biomedical Science, vol. 26, no. 1, p. 33, 2019/05/09 2019, doi: 10.1186/s12929-019-0524-y.

[4] Sebis Chair, "Sebis Workshop – 4. Juli 2024," Technical University of Munich, 2024. [Online]. Available: https://wwwmatthes.in.tum.de/pages/z5zeisq60d7t/Sebis-Workshop-4.-Juli-2024

[5] A. Shakeri, M. Farmanbar, and K. Balog, "MultiConAD: A Unified Multilingual Conversational Dataset for Early Alzheimer's Detection," *arXiv preprint arXiv:2502.19208*, 2025.

[6] B. MacWhinney, "DementiaBank," TalkBank, Carnegie Mellon University, 2024. [Online]. Available: https://talkbank.org/dementia/

[7] H. Linus, "Exploring key areas of cognitive function: Memory, attention, & more," 2023/01/31 2023. [Online]. Available: https://linushealth.com/blog/exploring-key-areas-of-cognitive-function.

[8] C. De Looze *et al.*, "Cognitive and Structural Correlates of Conversational Speech Timing in Mild Cognitive Impairment and Mild-to-Moderate Alzheimer's Disease: Relevance for Early Detection Approaches," (in English), *Frontiers in Aging Neuroscience,* Original Research vol. Volume 13 - 2021, 2021-April-27 2021, doi: 10.3389/fnagi.2021.637404.

[9] V. Taler and N. A. Phillips, "Language performance in Alzheimer's disease and mild cognitive impairment: a comparative review," (in eng), *J Clin Exp Neuropsychol,* vol. 30, no. 5, pp. 501-56, Jul 2008, doi: 10.1080/13803390701550128.

[10] L. Toth *et al.*, "A Speech Recognition-based Solution for the Automatic Detection of Mild Cognitive Impairment from Spontaneous Speech," (in eng), *Curr Alzheimer Res,* vol. 15, no. 2, pp. 130-138, 2018, doi: 10.2174/1567205014666171121114930.

[11] K. D. Mueller, B. Hermann, J. Mecollari, and L. S. Turkstra, "Connected speech and language in mild cognitive impairment and Alzheimer's disease: A review of picture description tasks," (in eng), *J Clin Exp Neuropsychol,* vol. 40, no. 9, pp. 917-939, Nov 2018, doi: 10.1080/13803395.2018.1446513.

[12] K. C. Fraser, J. A. Meltzer, F. Rudzicz, and P. Garrard, "Linguistic Features Identify Alzheimer's Disease in Narrative Speech," *Journal of Alzheimer's Disease,* vol. 49, no. 2, pp. 407-422, 2016, doi: 10.3233/jad-150520.

[13] S. Reeves *et al.*, "Narrative video scene description task discriminates between levels of cognitive impairment in Alzheimer's disease," (in eng), *Neuropsychology,* vol. 34, no. 4, pp. 437-446, May 2020, doi: 10.1037/neu0000621.

[14] C. Roth, "Boston Diagnostic Aphasia Examination," in *Encyclopedia of Clinical Neuropsychology*, J. S. Kreutzer, J. DeLuca, and B. Caplan Eds. New York, NY: Springer New York, 2011, pp. 428-430.

[15] P. S. Ambadi, K. Basche, R. L. Koscik, V. Berisha, J. M. Liss, and K. D. Mueller, "Spatio-Semantic Graphs From Picture Description: Applications to Detection of Cognitive Impairment," (in eng), *Front Neurol,* vol. 12, p. 795374, 2021, doi: 10.3389/fneur.2021.795374.

[16] L. Cummings, "Describing the Cookie Theft picture: Sources of breakdown in Alzheimer's dementia," *Pragmatics and Society,* vol. 10, pp. 151-174, 03/28 2019, doi: 10.1075/ps.17011.cum.

[17] H. Chertkow, "Mild cognitive impairment," Current Opinion in Neurology, vol. 15, no. 4, pp. 401–407, 2002. [Online]. Available: https://journals.lww.com/co-neurology/abstract/2002/08000/mild_cognitive_impairment.1.aspx

[18] S. Gauthier, B. Reisberg, M. Zaudig, R. C. Petersen, K. Ritchie, K. Broich, et al., "Mild cognitive impairment," The Lancet, vol. 367, pp. 1262–1270, 2006. [Online]. Available: https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(06)68542-5/abstract

[19] D. Knopman, B. Boeve, and R. C. Petersen, "Essentials of the proper diagnoses of mild cognitive impairment, dementia, and major subtypes of dementia," Mayo Clinic Proceedings, vol. 78, no. 10, pp. 1290–1308, 2003. [Online]. Available: https://www.mayoclinicproceedings.org/article/S0025-6196(11)62851-6/abstract

[20] D. Knopman and R. C. Petersen, "Mild cognitive impairment and mild dementia: a clinical perspective," Mayo Clinic Proceedings, vol. 89, no. 10, pp. 1452–1459, 2014. [Online]. Available: https://www.mayoclinicproceedings.org/article/S0025-6196(14)00622-3/fulltext

[21] J. Morris, "Mild cognitive impairment and preclinical Alzheimer's disease," Geriatrics, Suppl, pp. 9–14, 2005. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/16025770/

[22] V. Diaz and G. H. Rodríguez, "Machine learning for detection of cognitive impairment," 2022.

7.2 Sources

Literature:

[23] A. P. Fard, M. H. Mahoor, M. Alsuhaibani, and H. H. Dodge, "Linguistic-based mild cognitive impairment detection using informative loss," *Computers in Biology and Medicine,* vol. 176, p. 108606, 2024.

[24] R. Shankar, A. Bundele, and A. Mukhopadhyay, "A Systematic Review of Natural Language Processing Techniques for Early Detection of Cognitive Impairment," *Mayo Clinic Proceedings: Digital Health,* p. 100205, 2025.

[25] M. Alsuhaibani, A. P. Fard, J. Sun, F. F. Poor, P. S. Pressman, and M. H. Mahoor, "A Review of Deep Learning Approaches for Non-Invasive Cognitive Impairment Detection," *arXiv preprint arXiv:2410.19898,* 2024.

[26] M. Niemelä, M. von Bonsdorff, S. Äyrämö, and T. Kärkkäinen, "Dementia Classification Using Acoustic Speech and Feature Selection," *arXiv preprint arXiv:2502.03484,* 2025.

[27] J. C. Morris, M. Storandt, J. P. Miller, D. W. McKeel, J. L. Price, E. H. Rubin, and L. Berg, "Mild cognitive impairment represents early-stage Alzheimer disease," Archives of Neurology, vol. 58, no. 3, pp. 397–405, 2001. [Online]. Available: https://jamanetwork.com/journals/jamaneurology/fullarticle/778838

[28] E. Burke, J. Gunstad, and P. Hamrick, "Global and Local Semantic Coherence of Spontaneous Speech in Persons with Alzheimer's Disease and Healthy Controls," Journal of the International Neuropsychological Society, 2023.

[29] R. Bucks, S. Singh, J. M. Cuerden, and G. K. Wilcock, "Analysis of spontaneous, conversational speech in dementia of Alzheimer type," Aphasiology, vol. 14, pp. 71–91, 2000.

[30] I. Hoffmann, D. Németh, C. D. Dye, M. Pákáski, T. Irinyi, and J. Kálmán, "Temporal parameters of spontaneous speech in Alzheimer's disease," International Journal of Speech-Language Pathology, vol. 12, pp. 29–34, 2010.

[31] M. R. Botezatu, E. Miller, and A. M. Kiselica, "Limited connectedness of spontaneous speech may be a marker of dementia," Frontiers in Aging Neuroscience, 2023.

[32] S. Luz, "Longitudinal Monitoring and Detection of Alzheimer's Type Dementia from Spontaneous Speech Data," in IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS), 2017.

[33] H. Lee, S. Suniljit, and Y. S. Ong, "Dynamic Multimodal Sentiment Analysis: Leveraging Cross-Modal Attention for Enabled Classification," arXiv preprint, 2025. [Online]. Available: https://arxiv.org/abs/2501.08085

[34] B. Mocanu and T. Ruxandra, "Active Speaker Recognition using Cross Attention Audio-Video Fusion," in 2022 10th European Workshop on Visual Information Processing (EUVIP), Lisbon, Portugal, 2022, pp. 1–6, doi: 10.1109/EUVIP53989.2022.9922810.

[35] H. Xue and Z. Zhu, "Research and Future Application Analysis of Multimodal Fusion," Highlights in Science, Engineering and Technology – EMIS, vol. 119, 2024.

Figures:

[Figure 1] T. Geere, “IBM AI model predicts onset of Alzheimer’s disease by analyzing descriptions of a Cookie Theft,” *The Next Web*, Nov. 6, 2020. [Online]. Available: https://thenextweb.com/news/ibm-ai-model-predicts-onset-of-alzheimers-disease-by-analyzing-descriptions-of-a-cookie-theft

[Figure 2] J. Clover, “Alexa Guard Rolls Out to Echo Devices in the U.S.,” *MacRumors*, May 14, 2019. [Online]. Available: https://www.macrumors.com/2019/05/14/alexa-guard-rolls-out-echo-devices-us/

[Figure 3] S. Lee, “Getting to know the Mel spectrogram,” *Medium*, Sep. 5, 2019. [Online]. Available: https://medium.com/data-science/getting-to-know-the-mel-spectrogram-31bca3e2d9d0

ViT vs CNN – Example Slide inspired by: Visual Transformer Meets CutMix for Improved Accuracy, Communication Efficiency, and Data Privacy in Split Learning - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Operation-of-CNN-and-ViT_fig3_361733806 [accessed 25 Oct 2025]

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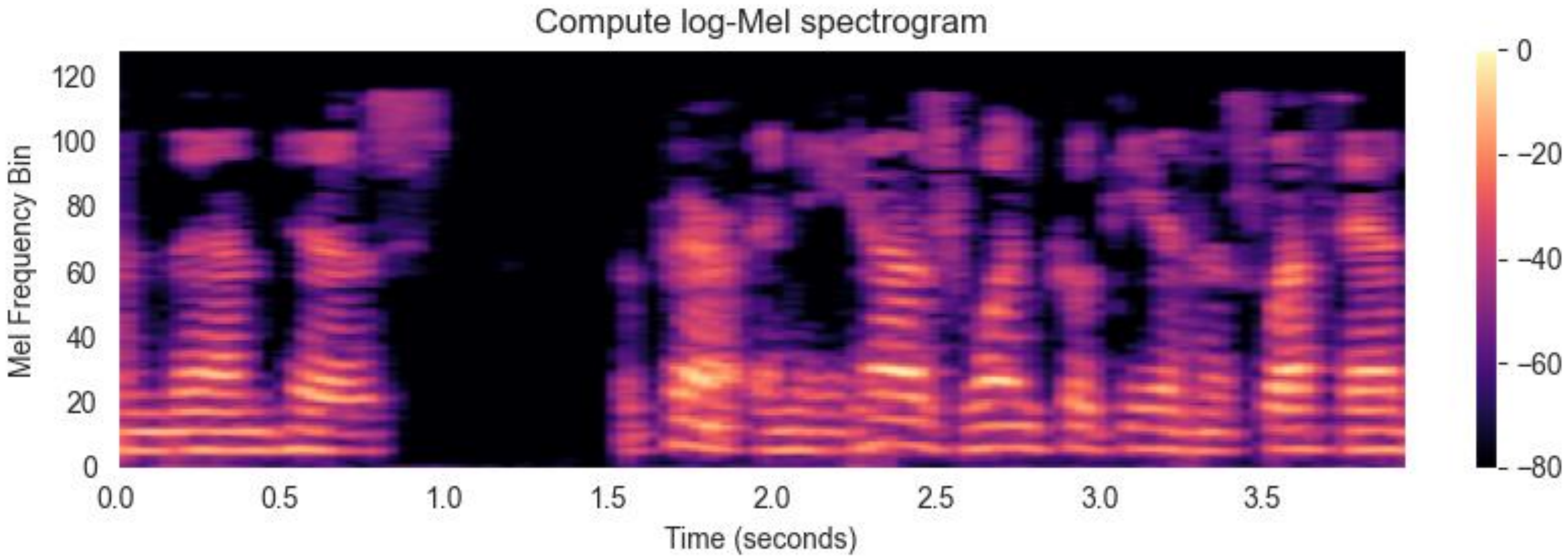
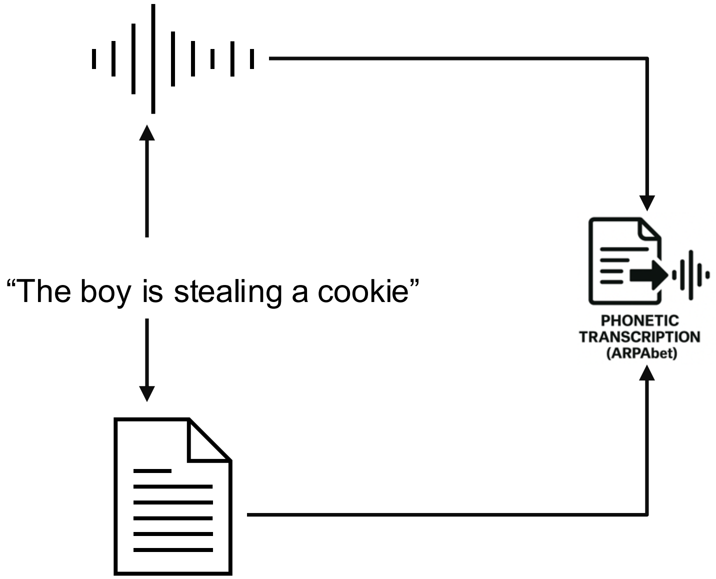
Log-Mel spectrogram – Example



- **Mel Frequency Bin:** represents frequency bands on the perceptual Mel scale
  - (lower bins = lower pitch, higher bins = higher pitch)
- **Color intensity:** indicates signal energy (amplitude) in decibels
  - bright areas mean stronger energy, dark areas mean weaker energy
  - Values are shown relative to the loudest point (0 dB)

Phonetic Transcription (ARPAbet) – Example



Healthy Example:

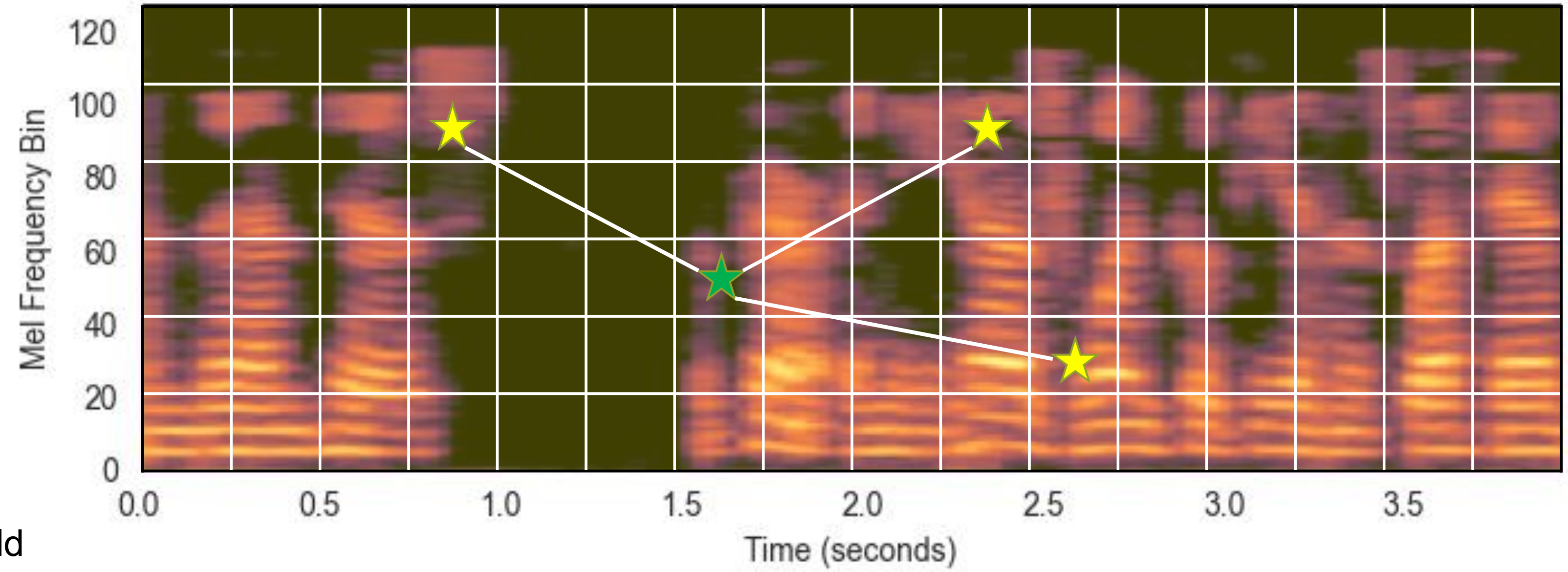
the	dh_**B** ah_**E**
boy	b_**B** oy_**E**
is	ih_**B** z_**E**
stealing	s_**B** t_**I** iy_**I** l_**I** ih_**I** ng_**E**
a	ah_**S**
cookie	k_**B** uh_**I** k_**I** iy_**E**

Dementia Example:

boy → b_B ow_E

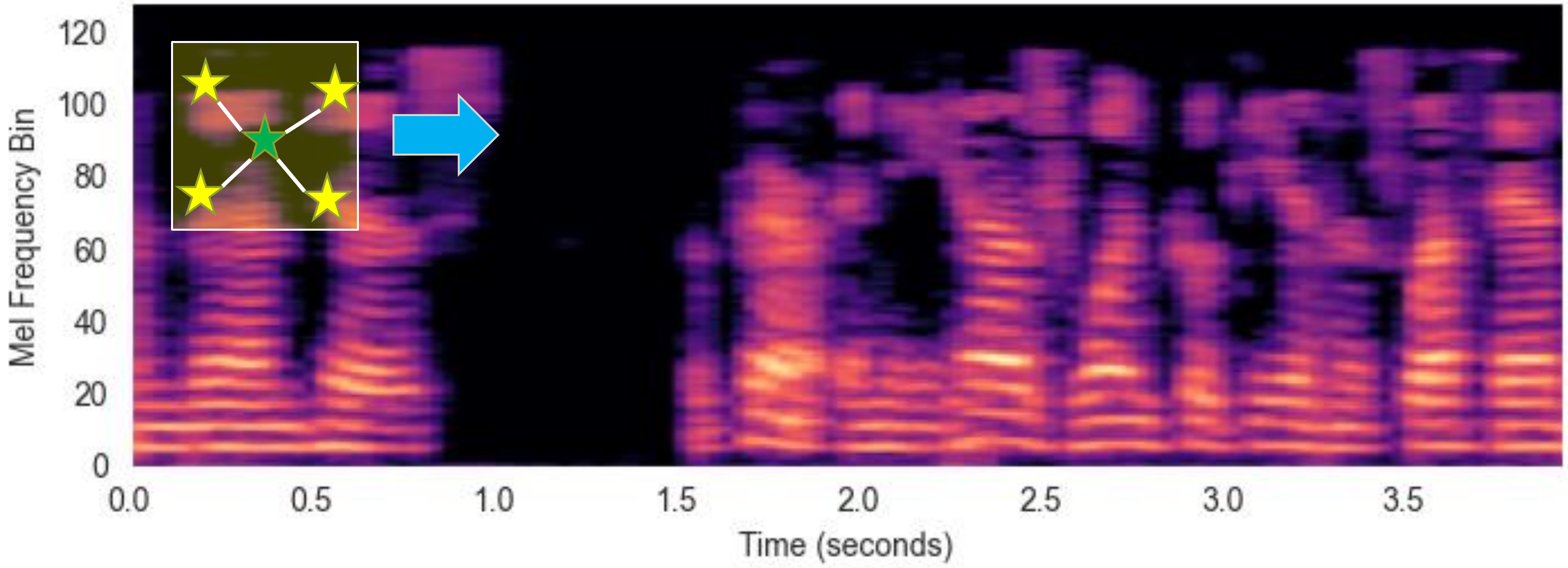
Suffix	Meaning
_B	**Begin**: phoneme is at the start of the word
_I	**Inside**: phoneme is in the middle of the word
_E	**End**: phoneme is at the end of the word
_S	**Single**: the word has only one phoneme

ViT vs. CNN – Example



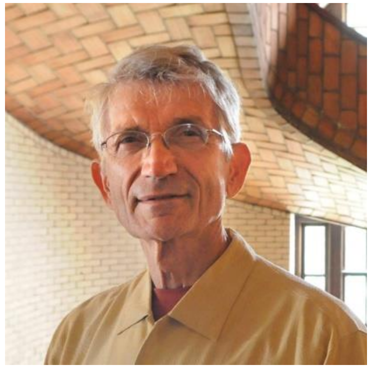
Attention of Vision Transformer

Receptive Field



Convolution of CNN

DementiaBank Overview



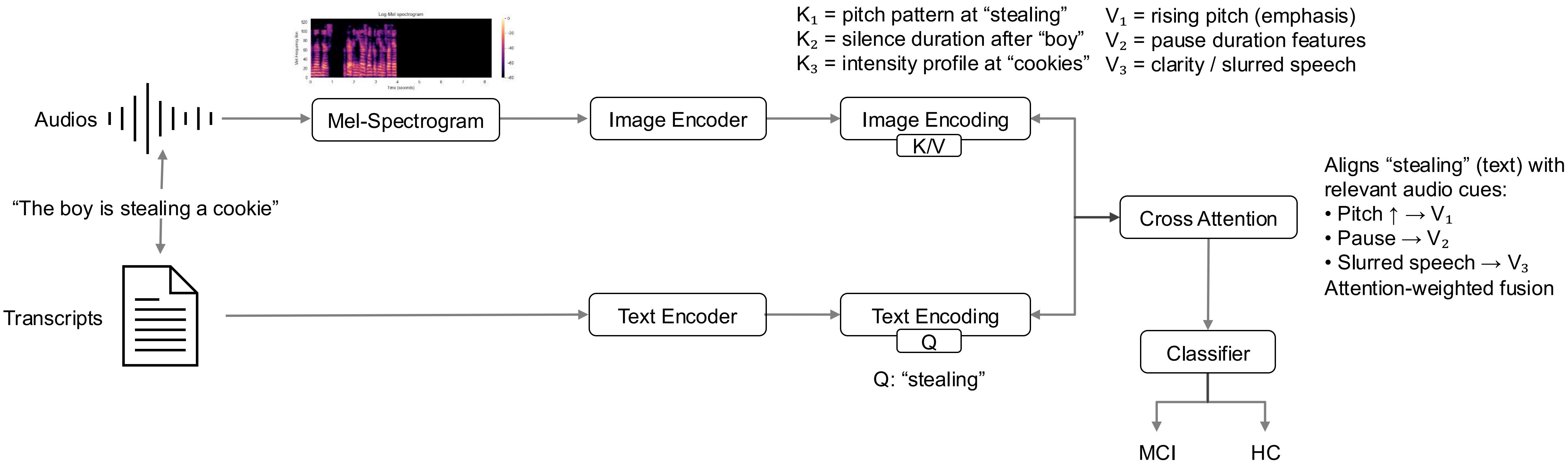
Prof. Brian McWhinney
Carnegie Mellon University

- **What it is**
  - DementiaBank is an online research archive containing transcribed audio and video recordings of conversations and interactions from individuals with dementia, mild cognitive impairment (MCI), and control groups.
- **Purpose**
  - To support research and the development of algorithms that can detect early linguistic signs of cognitive decline, enabling earlier diagnosis and intervention.
- **Content**
  - Includes spoken language samples, CHAT transcripts (compatible with CLAN software), results from clinical tests, and demographic/medical information.
- **Sources & Formats**
  - Data come from several corpora (e.g., Delaware and VAS datasets) and include picture description, storytelling, procedural and personal narratives, and voice commands (e.g., with Alexa).
- **Key Institutions & Funding**
  - Part of the TalkBank system (Carnegie Mellon University). Major contributors include Carnegie Mellon University, University of Pittsburgh, and the TAUKADIAL Challenge consortium (University of Edinburgh, Cardinal Tien Hospital, NCKU).
    Funded by NIH and the EU Horizon 2020 SAAM Project.
- **Access**
  - Restricted to approved researchers and clinicians within the DementiaBank Consortium.

Source: https://talkbank.org/dementia/

Cross Attention – Example

The model looks at: How was this word spoken? (e.g. pitch, pauses)



Inverse Case: Which words (K/V) are most relevant to this audio cue (Q)?