Acoustic and Linguistic Analysis for Early Dementia Detection using Machine Learning

Marcel Seitz & Philip Werz

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Who we are

Marcel Seitz

Philip Werz

Agenda

1. Motivation and Relevance
2. Research Gap & Research Questions
3. Theoretical Background
4. Methodology
5. Outlook
6. Timeline

1. Motivation and Relevance

Dementia

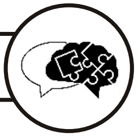
Challenges of Dementia

- Rising global prevalence of dementia, especially Alzheimer's Disease
- AD affected ~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

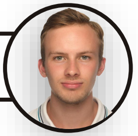
Early Markers and Assessment Tools

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

Cookie Theft Picture

- Widely used neuropsychological instrument

Free Speech



- Naturalistic 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/DM

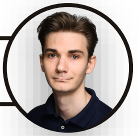
Lack of Multimodal Analysis

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

Combining acoustic and linguistic features via <u>multimodal</u> ML remains largely unexplored

Research Questions

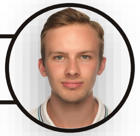
Cookie Theft Picture



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

II Does combining audio and text features from Cookie Theft descriptions enhance early dementia classification compared to single-modality models?

Free Speech



I How well can ML models using acoustic and linguistic features from **Alexa conversations** differentiate HC and DM/MCI patients?

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

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

3.1 Theoretical Background

DM vs MCI

Clinical Background

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

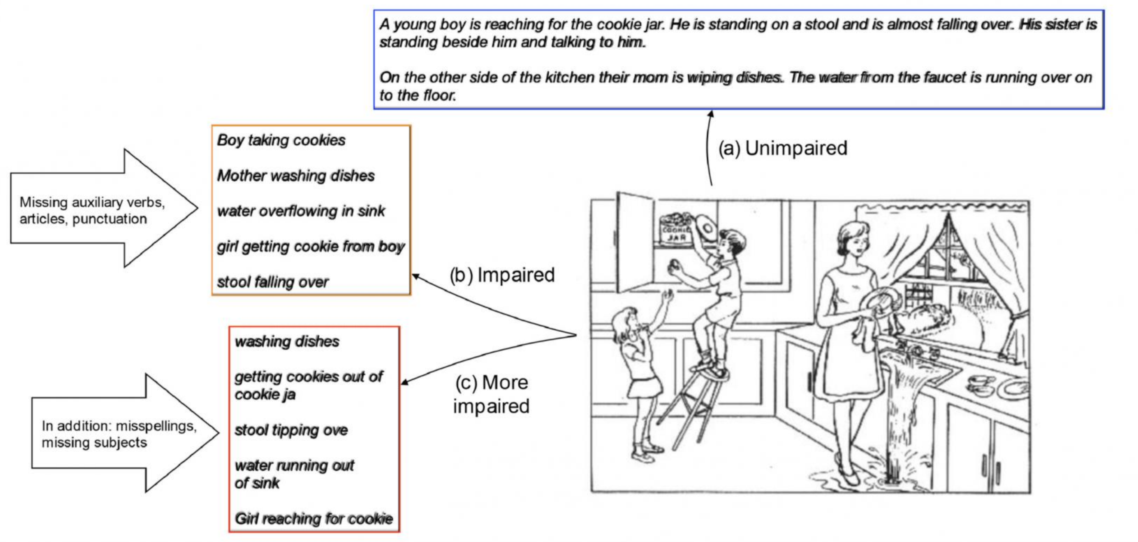
Early Biomarkers of Cognitive Decline

- **Speech as Cognitive Marker**: 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



Sources: [7-21], [27]; Abbreviations: AD = Alzheimer's disease, MCI = Mild Cognitive Impairment, DM = Dementia, HC = Healthy

Source: Figure 1

3.2 Theoretical Background

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Speech

Source: Figure 2

Free Speech (Amazon Alexa)

- **Free speech** (e.g., Alexa) offers 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

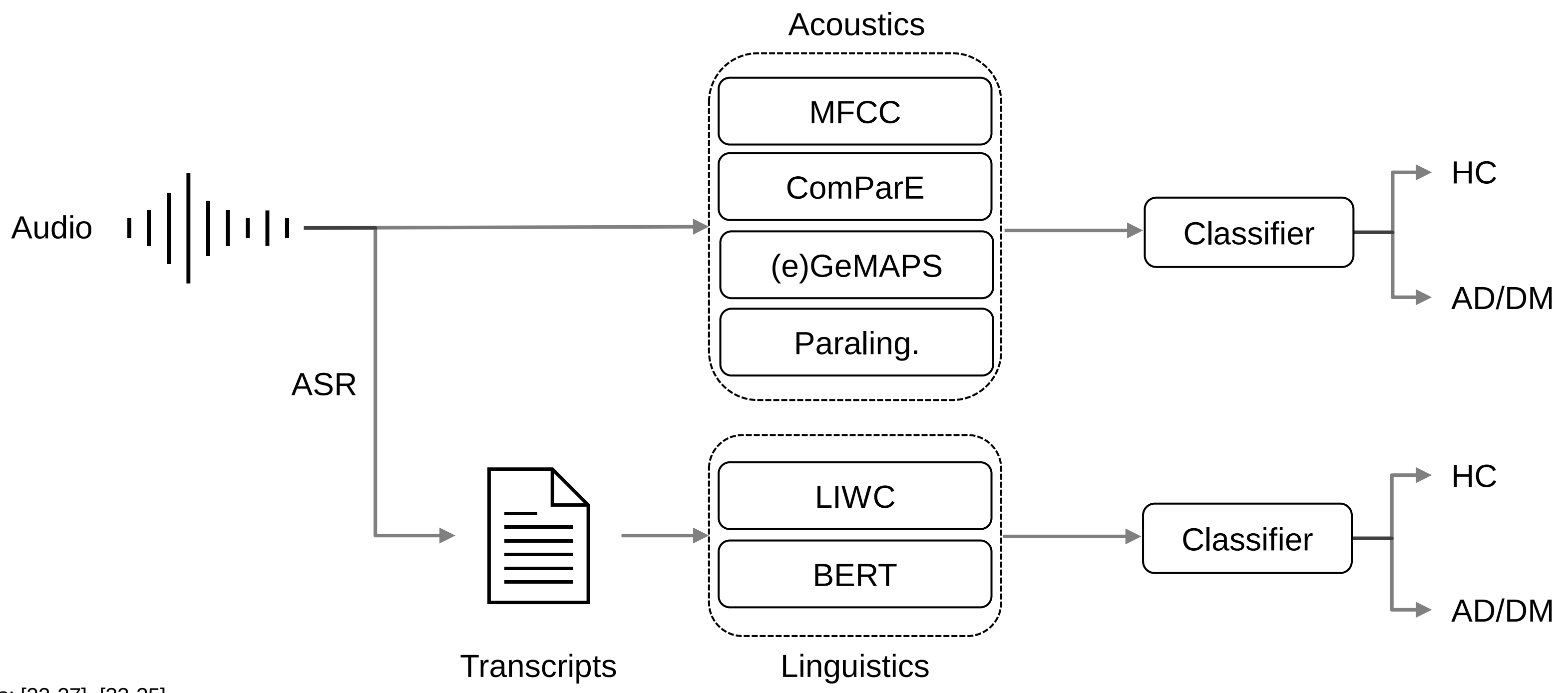
Sources: [7-10], [17-21], [27-32]; Abbreviations: AD = Alzheimer's disease, MCI = Mild Cognitive Impairment, DM = Dementia, HC = Healthy Control

3.3 Theoretical Background

Machine Learning

Cognitive Impairment Detection

- **ML detects cognitive decline**: Scalable, non-invasive alternative to MRI and lab tests
- **Deep learning**: CNNs, RNNs, and Transformers (e.g., BERT, wav2vec2) learn directly from speech/text
- **Key features**: MFCCs, eGeMAPS etc. reflect pitch and pauses



Legend

- **ASR**: Automatic Speech Recognition
- **Acoustics** : Acoustic feature extraction
- **Linguistics**: Text feature extraction

Sources: [22-27], [33-35]

3.3 Theoretical Background

Machine Learning

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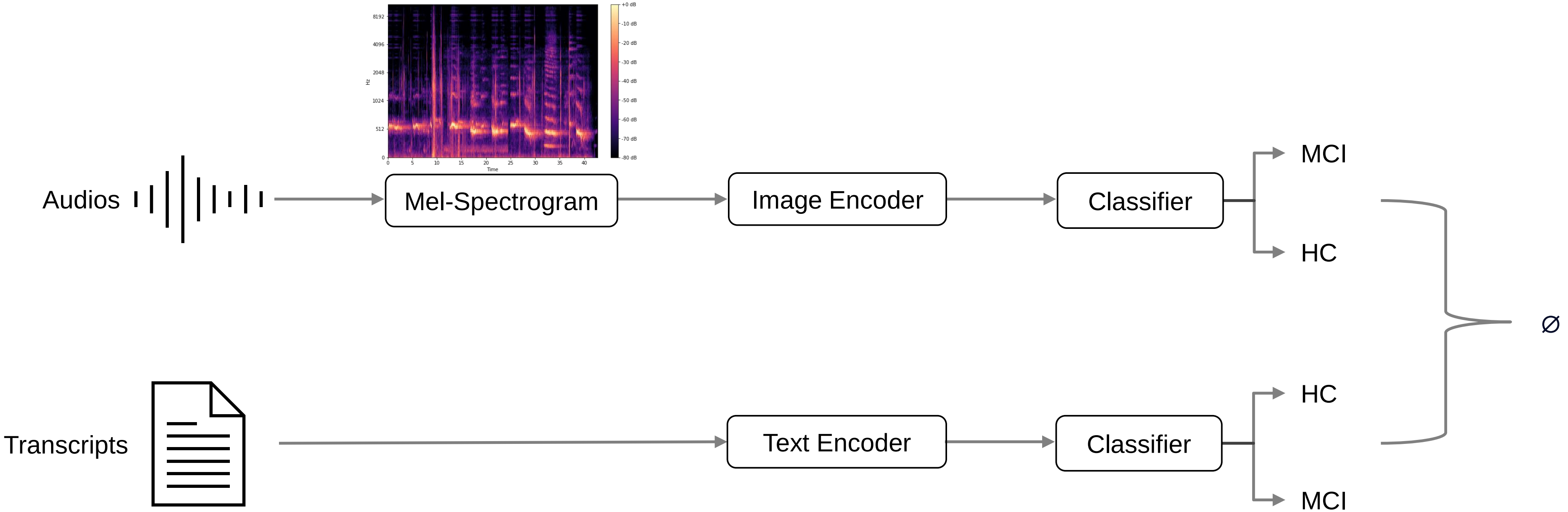
Multimodal Fusion

- **Multimodal Fusion**: Combines speech and text for better dementia detection
  - **Late-Level Fusion:** Combines modalities after individual classification; processes each modality separately



Sources: [22-27], [33-35], Mel-Spectrogram: Figure 3

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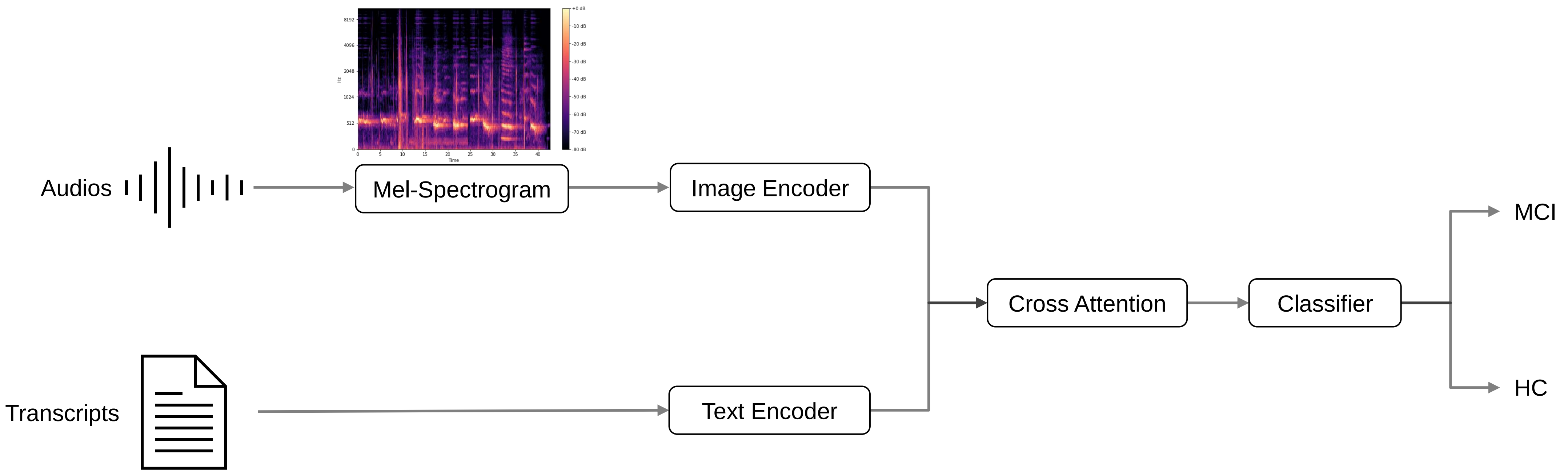
Multimodal Fusion

- **Multimodal Fusion**: Combines speech and text for better dementia detection.
  - **Early-Level:** Combines modalities before classification; merges features or embeddings; enables cross-modal interactions; requires synchronized inputs
    - **Cross-Attention:** One modality attends to another; captures inter-modal dependencies



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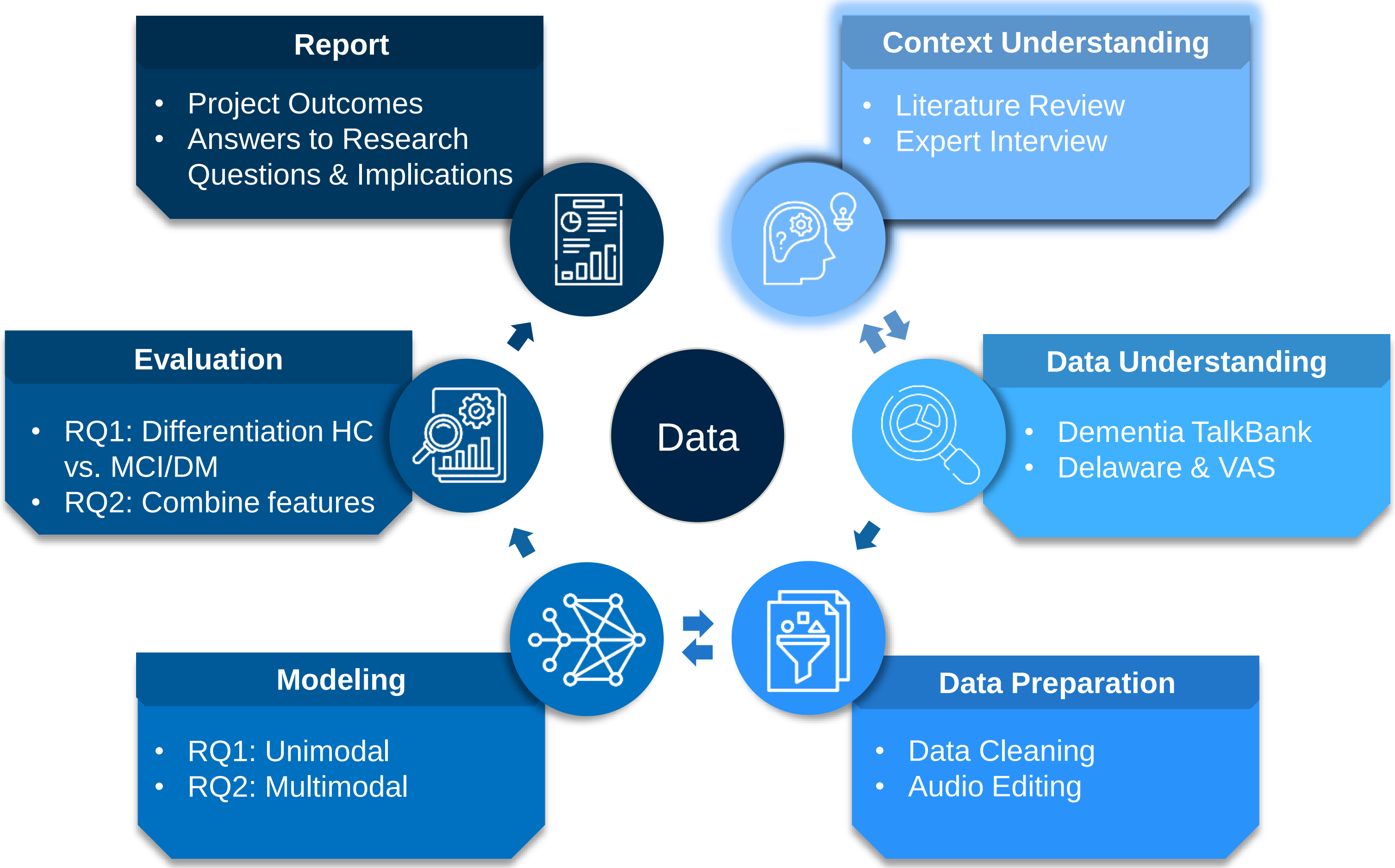
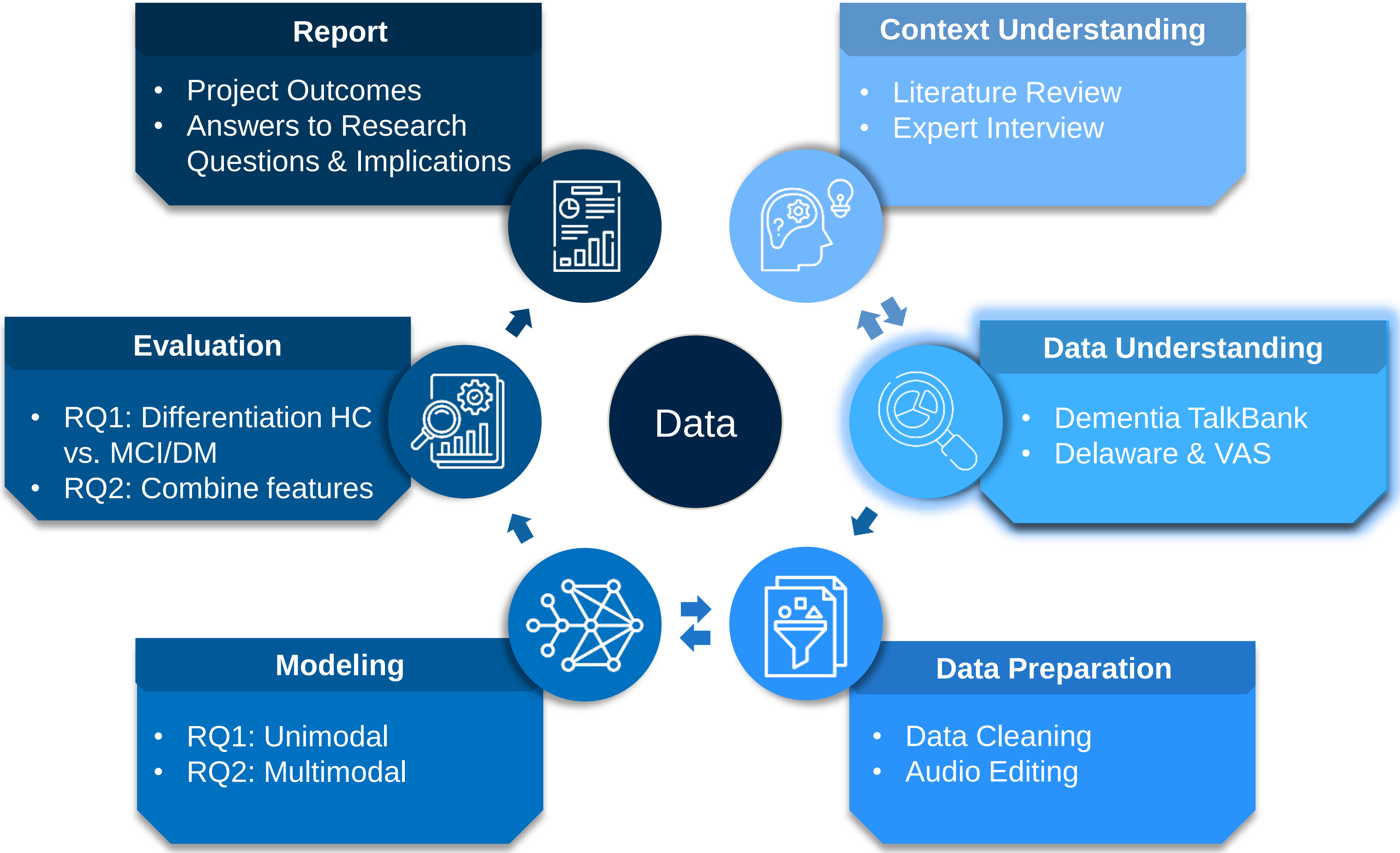
4.1 Methodology – Context Understanding



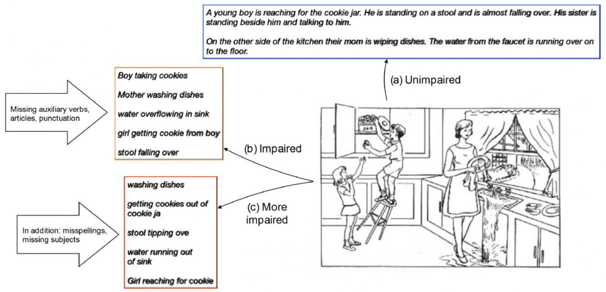
4.2 Methodology – Data Understanding



Source: [6], Abbreviations: MCI = Mild Cognitive Impairment, HC = Healthy Control

Delaware

- Standardized dataset
- Picture descriptions; Story-, Procedural-, Personal-Narratives
- Participants: older adults (61-91)
- Audio recordings and manually transcribed and annotated speech data (CHAT format, 95 Participants).
- Includes data from a control group and individuals diagnosed with MCI (61 MCI, 34 HC).
- Number of .mp3 files: 111
- Total Length: 18 h
- Data Collection Ongoing



Source: Figure 1

4.2 Methodology – Data Understanding

Report
- Project Outcomes
- Answers to Research Questions & Implications

Context Understanding
- Literature Review
- Expert Interview

Evaluation
- RQ1: Differentiation HC vs. MCI/DM
- RQ2: Combine features

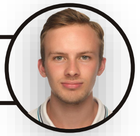
Data

Data Understanding
- Dementia TalkBank
- Delaware & VAS

Modeling
- RQ1: Unimodal
- RQ2: Multimodal

Data Preparation
- Data Cleaning
- Audio Editing

VAS

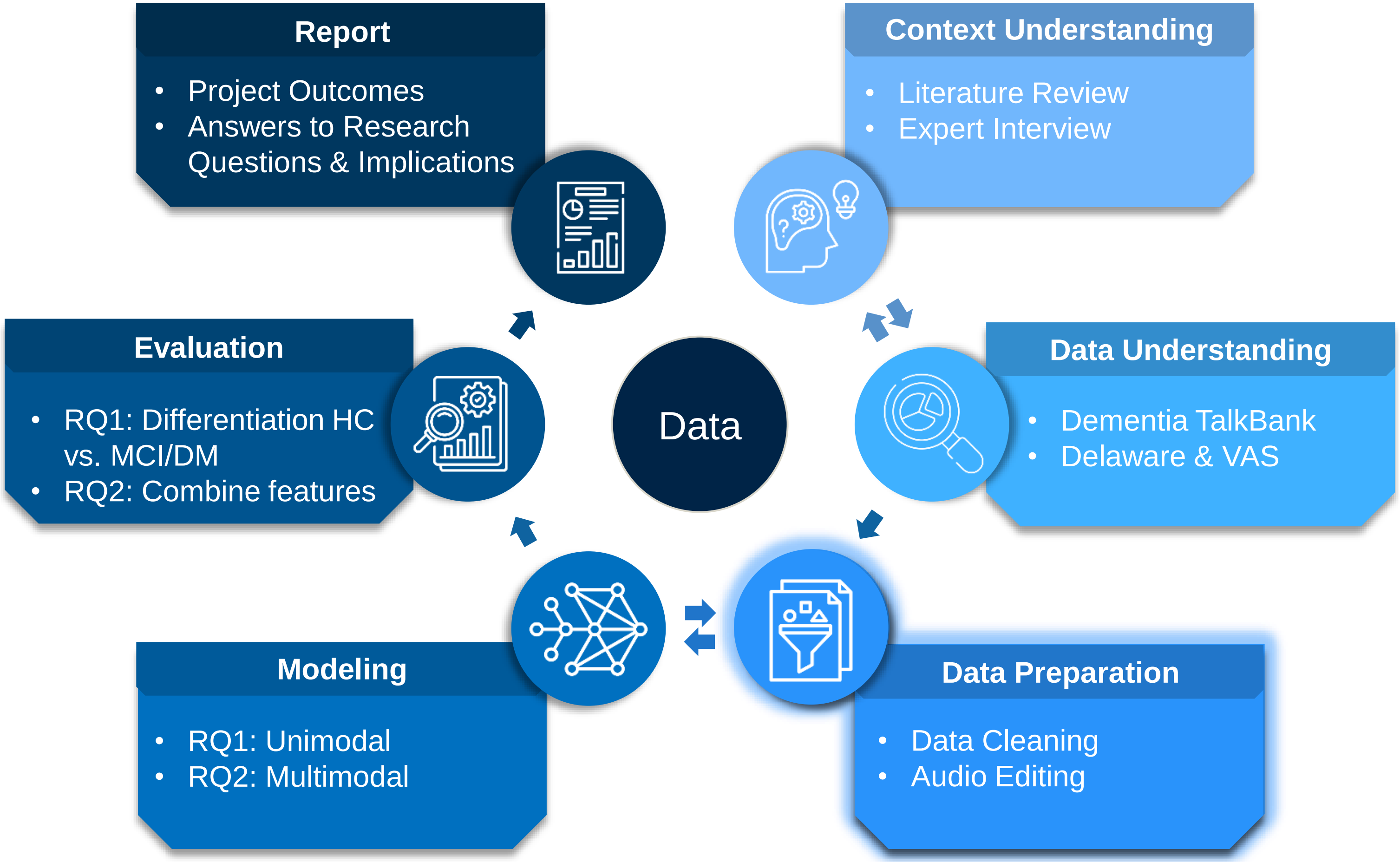


- Dataset of voice interactions from older adults (64-94).
- Audio recordings and text transcripts from Amazon Alexa (CHAT format, 101 Participants).
- Includes data from a control group and individuals diagnosed with dementia (DM:30, HC: 36, MCI: 35).
- Number of .mp3 files: 101
- Total Length: 3.5h

Source: Figure 2

Source: [6]; Abbreviations: MCI = Mild Cognitive Impairment, DM = Dementia, HC = Healthy Control

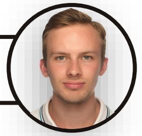
4.3 Methodology – Data Preparation



Delaware

- Clean Dataset
- Isolate participant speech
- Reduce to CTP descriptions
- Estimated Total Length: 3h

VAS



- Clean Dataset
- Split Audios
  - Separate audios for each Alexa request

Abbreviations: CTP = Cookie Theft Picture

4.4 Methodology – Modeling

Report
- Project Outcomes
- Answers to Research Questions & Implications

Context Understanding
- Literature Review
- Expert Interview

Evaluation
- RQ1: Differentiation HC vs. MCI/DM
- RQ2: Combine features

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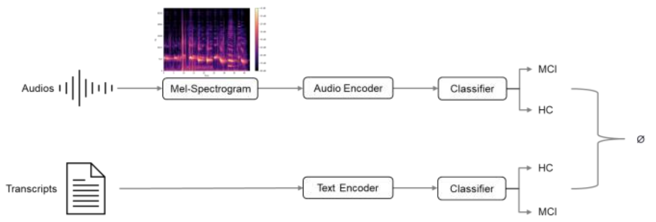
Data Understanding
- Dementia TalkBank
- Delaware & VAS

Modeling
- RQ1: Unimodal
- RQ2: Multimodal

Data Preparation
- Data Cleaning
- Audio Editing

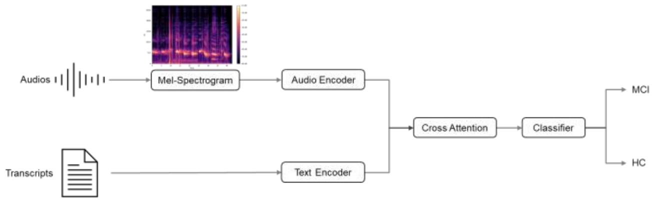
RQ1 - Unimodal

- Late Fusion
- Simplified Model:



RQ2 - Multimodal

- Early Fusion with Cross Attention
- Simplified Model:



Source: [Figure 3]

4.5 Methodology – Evaluation

Report
- Project Outcomes
- Answers to Research Questions & Implications

Context Understanding
- Literature Review
- Expert Interview

Data Understanding
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Data Preparation
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- RQ2: Multimodal

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Data

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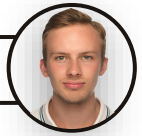
Delaware

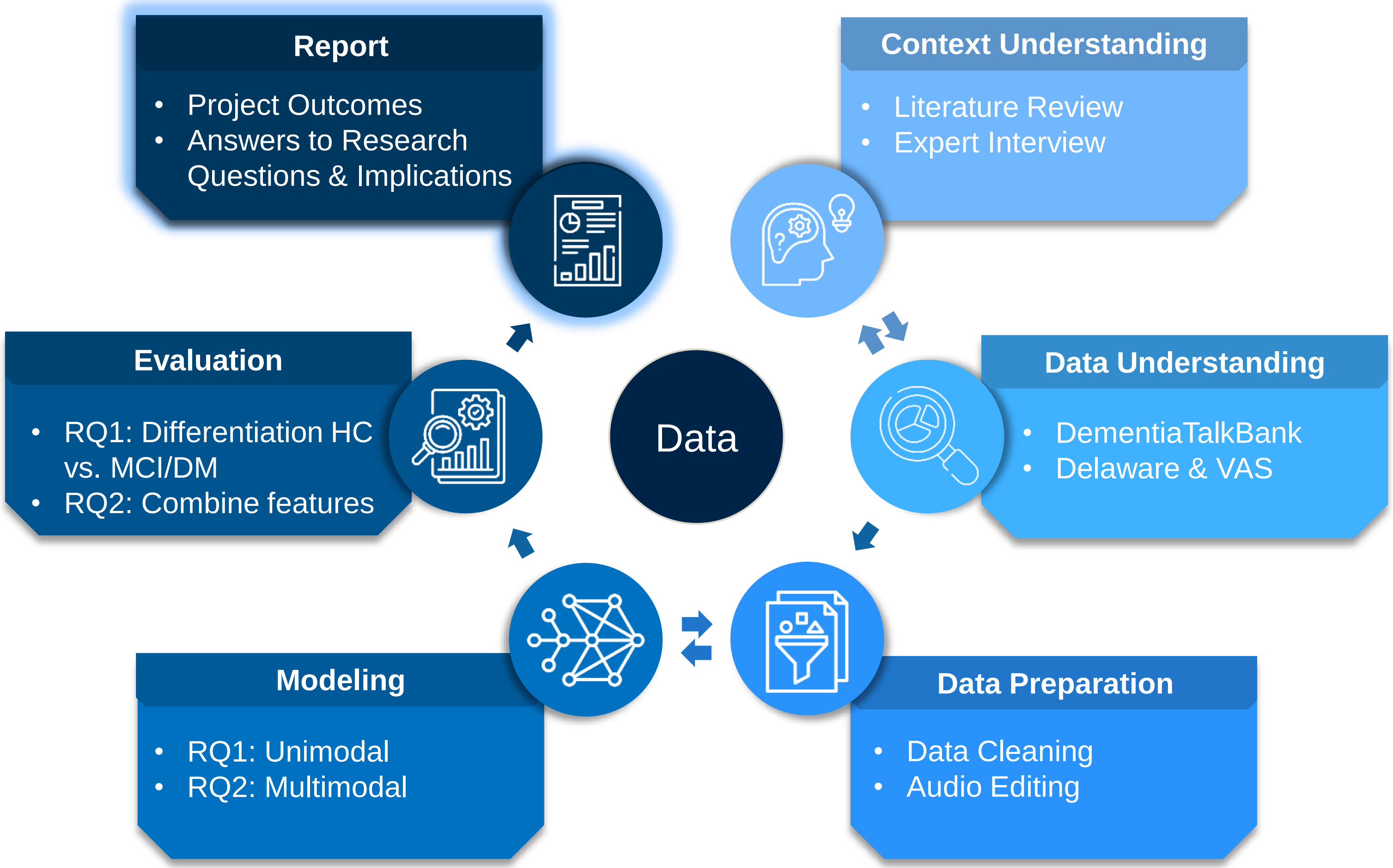
- How accurately can ML models based on acoustic and linguistic features from Cookie Theft Picture descriptions **distinguish** between HC and MCI patients?
- Does combining audio and text features from Cookie Theft descriptions enhance early dementia classification compared to single-modality models?

VAS

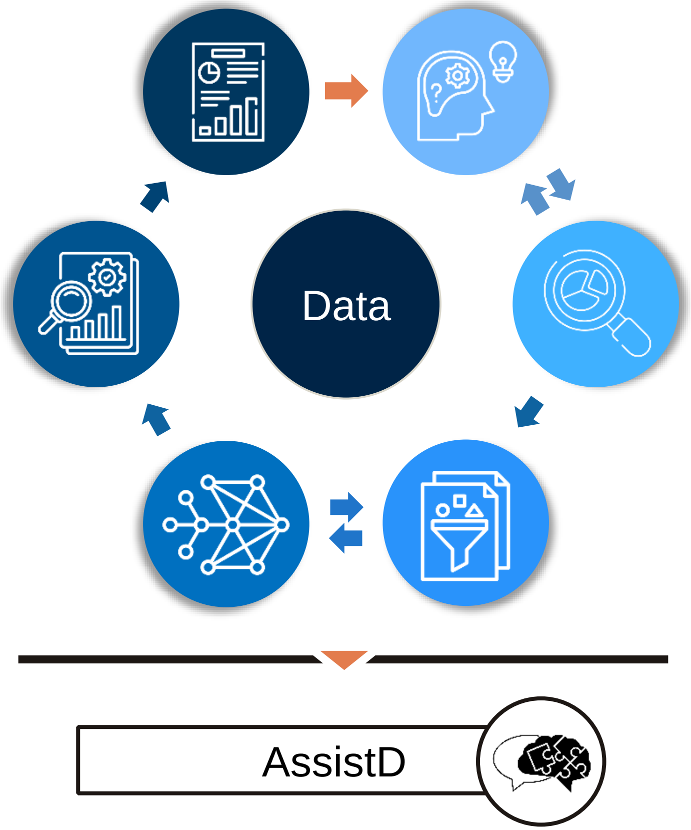


- How well can ML models using acoustic and linguistic features from Alexa conversations **differentiate** HC and DM/MCI patients?
- Does integrating audio and linguistic features from Alexa-based free speech responses improve early dementia classification compared to unimodal approaches?

4.6 Methodology – Report



4.7 Methodology – Future Work



Source: [4]

5. Outlook

Expected Contribution

Academic Insights

- **Deeper insights** into MCI vs. HC, addressing the prior focus on AD/DM vs. HC in most studies
- **Comparison** of multimodal vs. unimodal model performance
- **Comparative analysis** of spontaneous speech versus standardized speech in terms of classification accuracy

Practical Guidance

- **Test both standardized** (CTP) and **free/spontaneous** (Alexa) improves clearness in regard to future projects (e.g. Smartwatch)
- **Offer guidance** on (standardized) data collection and task setup for consistent dataset quality and better accuracy

Next Steps

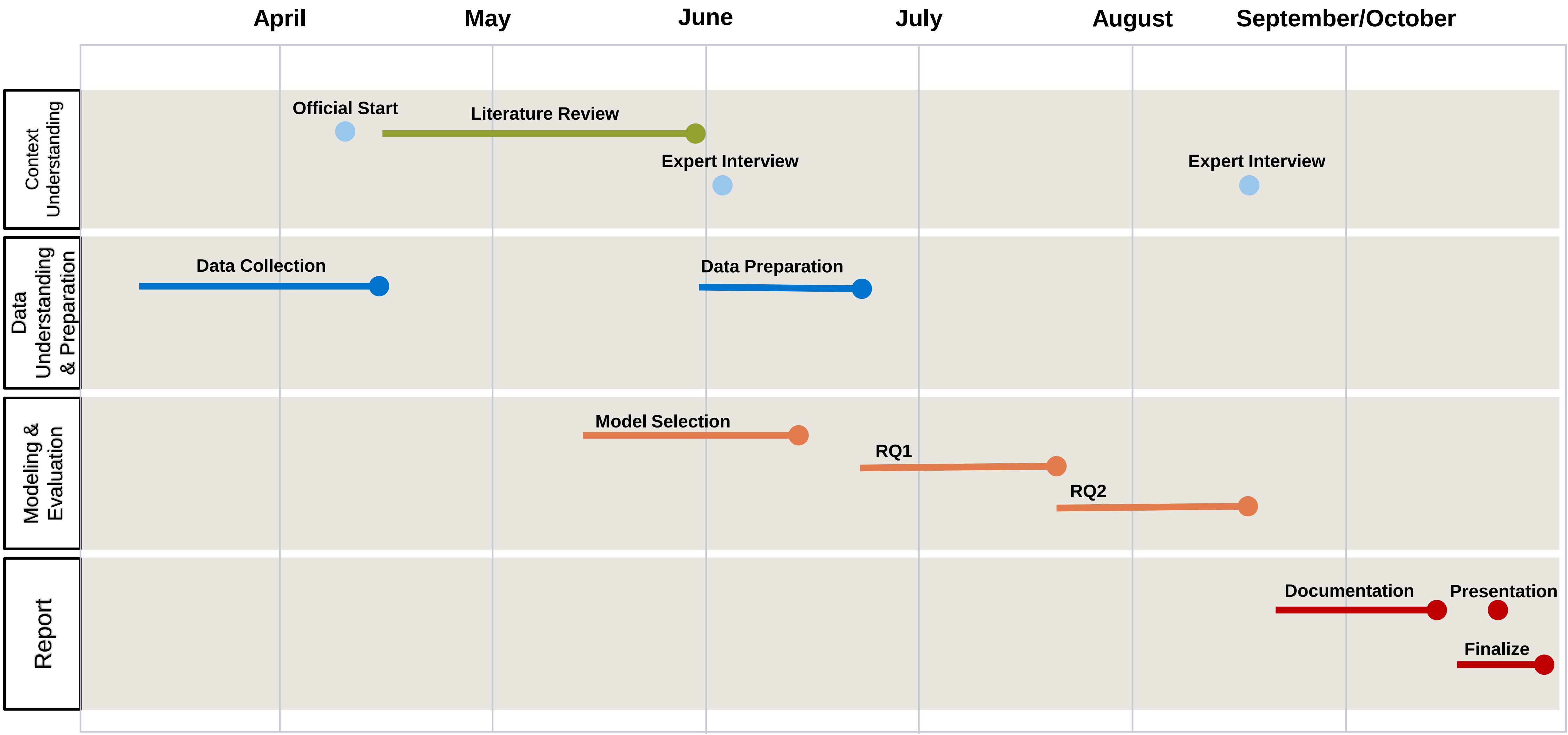
Preprocess Data

Modeling

Evaluation

Abbreviations: MCI = Mild Cognitive Impairment, DM = Dementia, HC = Healthy Control, CTP = Cookie Theft Picture

6. Timeline


April
May
June
July
August
September/October
Context Understanding
Official Start
Literature Review
Expert Interview
Expert Interview
Data Understanding & Preparation
Data Collection
Data Preparation
Modeling & Evaluation
Model Selection
RQ1
RQ2
Report
Documentation
Presentation
Finalize

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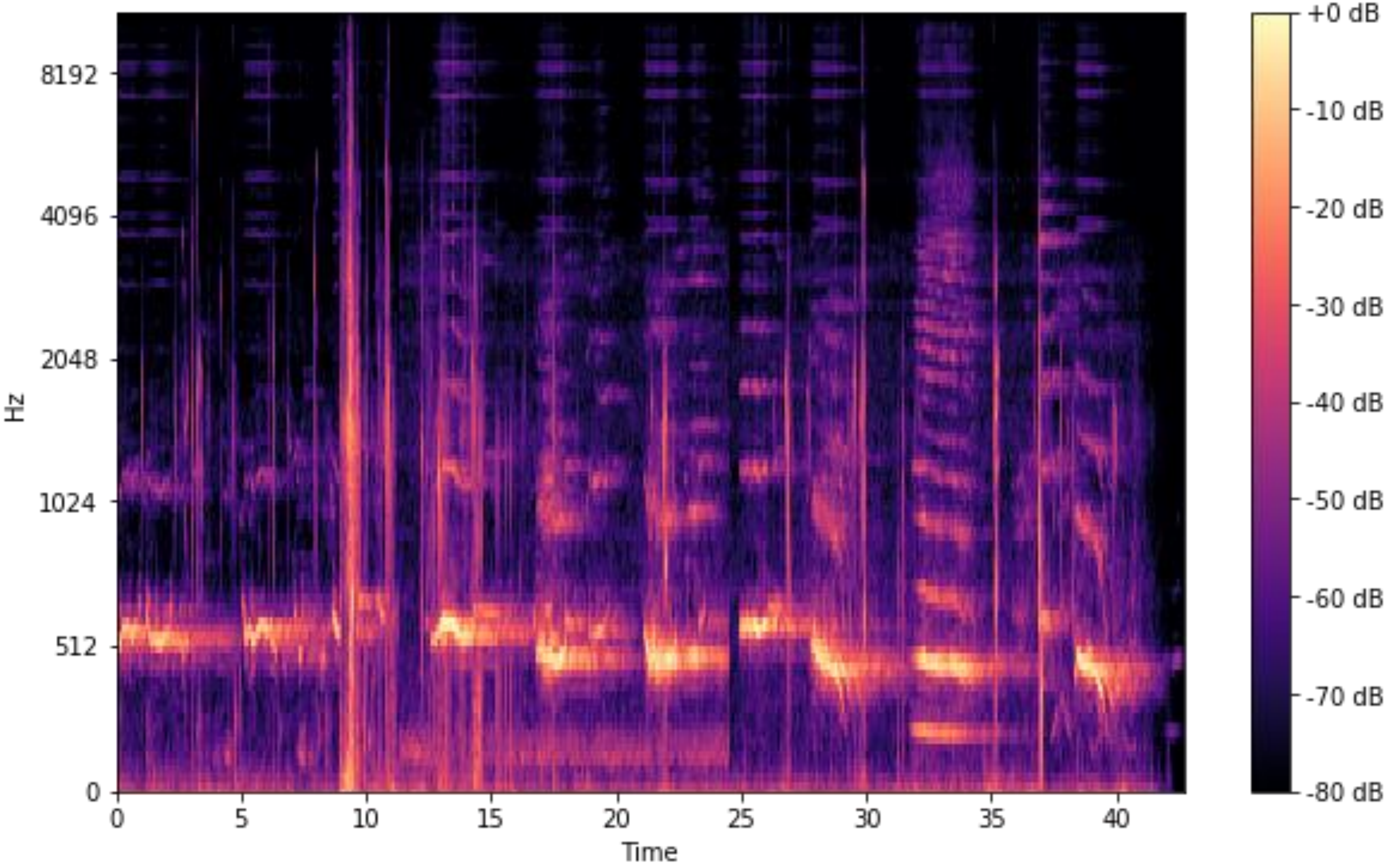
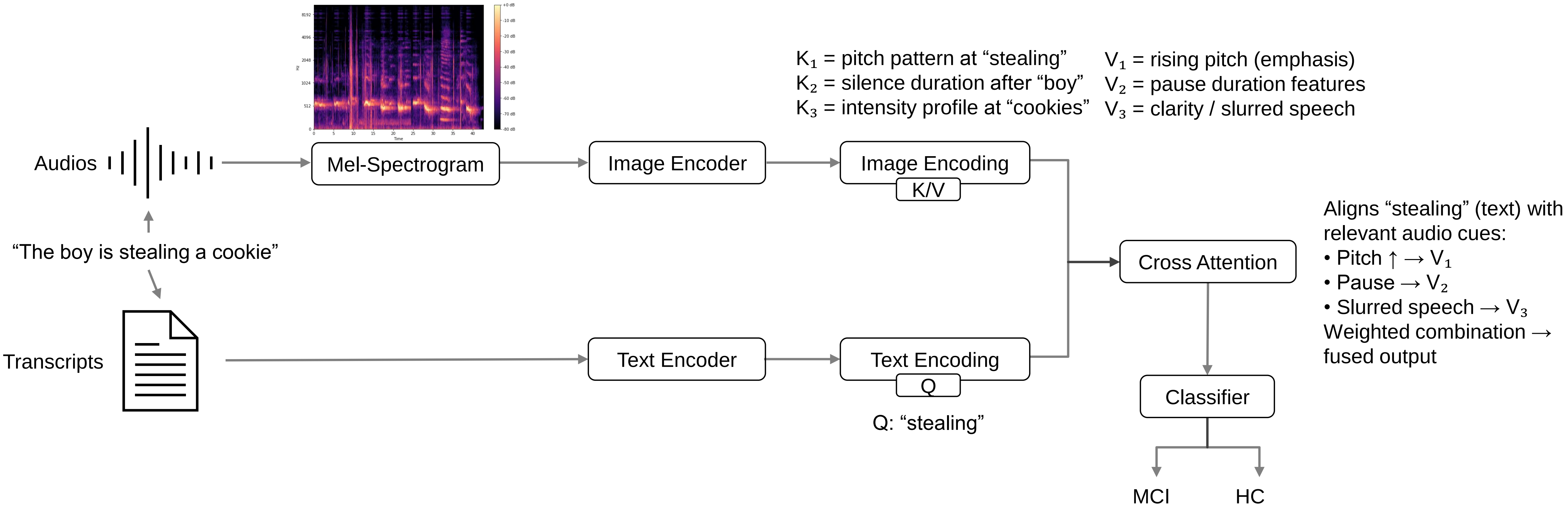
wwwmatthes.in.tum.de

Mel Spectrogram



Source: Figure 3

Cross Attention – Example



Source: Mel-Spectrogram: Figure 3