

Multimodal Speech Summarization using Audio-Text Fusion Transformers with Cross-Attention Alignment

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💡 MOTIVATION & PROBLEM

Human speech conveys meaning through **prosody** (pitch, pauses, emphasis) that text transcripts miss. Traditional "Pipeline" systems (ASR → Text) discard this signal.

Ex: "I suppose we can agree."
Tone implies **consensus** or **reluctance**.

PROPOSED SOLUTION

- Info Loss: Acoustic intent is ignored.
- Error Propagation: No backup for ASR errors.
- Modality Gap: 16kHz audio ≠ text tokens.

⚙️ METHODOLOGY

1. Dual Encoders

Audio: Wav2Vec 2.0 extracts latent speech representations (Z). We project these to model dimension ($d=768$).

Text: BART-Base encodes the transcript.

2. Cross-Attention Fusion

We align modalities by treating Text as Queries (Q) and Audio as Keys/Values (K, V).

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^\top / \sqrt{dk})V$$

3. Residual Connection

$$H_{\text{final}} = \text{LayerNorm}(H_{\text{Text}} + \text{Attention}(\dots))$$

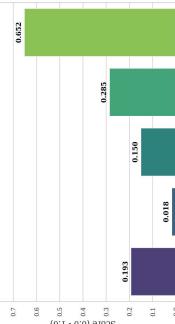
This prevents noisy audio from corrupting semantics.

DATA: MEETINGBANK (N=1000)

Avg Transcript Length	850 tokens
Avg Audio Duration	28.5 seconds
Avg Summary Length	55 tokens

☰ RESULTS

Multimodal Summarization Performance (N=1000)



Baseline R1: 0.536

Fusion R1: 0.193

Qualitative

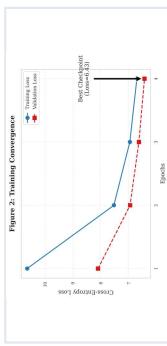


Figure 3: Qualitative Comparison of Summaries.

ID	Ground Truth Summary	Multimodal Model Prediction
S1	Recommends to eat more fruits and vegetables.	Recommends to eat more fruits and vegetables.
S2	Recommendations to reduce meat intake.	The multimodal fusion module detects the books reference to meat intake.
S3	Discusses importance of the benefits of fruits and vegetables for heart health.	The multimodal fusion module detects the books reference to heart health.

Fig 3: Model learns structure but struggles with alignment in low-resource settings.

▣ CONCLUSION

Multimodal fusion is theoretically robust but data-hungry. The frozen audio encoder limited adaptation in this low-resource setting. Future work will focus on unfreezing the encoder and scaling to the full 3000hr corpus.

Generated Summary

Fig 1: Dual-Encoder Fusion Architecture

We propose injecting acoustic embeddings into the text encoder via Cross-Attention to bridge the gap.

