Two-Stage Emotion Detection from Multimodal Data

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Outline

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Introduction

- **Emotion detection** is crucial for human-computer interaction
- Enables machines to recognize and respond to human emotional states
- Applications:
  - Mental health monitoring
  - Customer service
  - Human-computer interaction
  - Sentiment analysis
- **Challenge**: Emotions are complex, multidimensional phenomena

Research Questions

1. How does a **two-stage approach** (dimensional prediction $\rightarrow$ category mapping) compare to **direct classification** for emotion recognition?
2. What is the relative contribution of **text vs. audio modalities** for emotion detection?
3. Which **fusion strategies** best integrate multimodal information?
4. How do different **transformer architectures** perform for emotion detection tasks?

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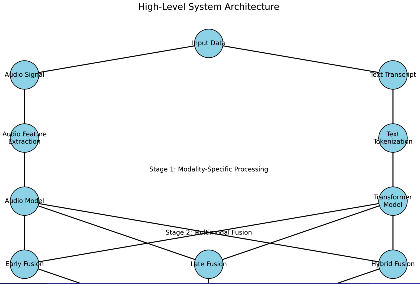
Dimensional vs. Categorical Emotion Models

Dimensional Model

- Represents emotions as points in continuous space
- **AVD dimensions**:
  - **A**rousal: energy/intensity
  - **V**alence: positive/negative
  - **D**ominance: control/power
- Captures nuanced emotional states

Categorical Model

- Discrete emotion labels (anger, joy, sadness, etc.)
- Easier to classify
- More intuitive for humans
- Less granular representation



Evolution of Emotion Recognition

- **Pre-2012**: Mostly rule-based systems and traditional ML
  - SVM, Decision Trees, Bayesian methods
  - Handcrafted features like lexicons and acoustic parameters
- **Deep Learning Era (2013-2017)**:
  - CNNs, RNNs for feature extraction
  - Word embeddings (Word2Vec, GloVe)
- **Transformer Era (2018-Present)**:
  - BERT, RoBERTa, XLNet, DeBERTa
  - Attention-based architectures enable better context modeling

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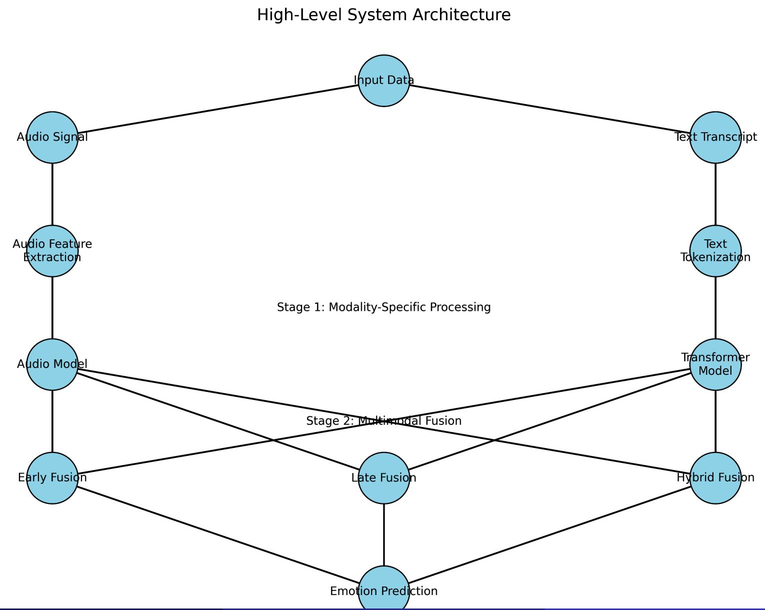
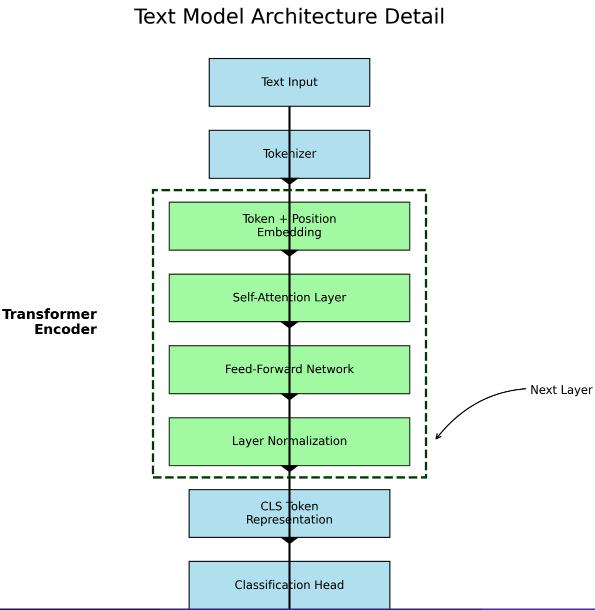
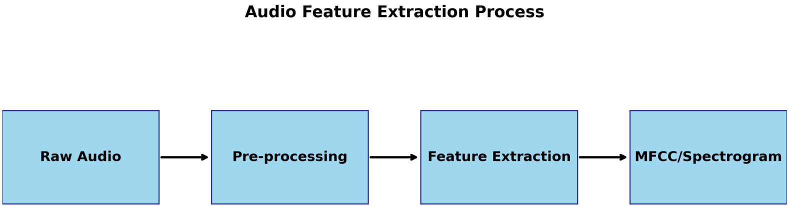
System Architecture



Text Processing Models



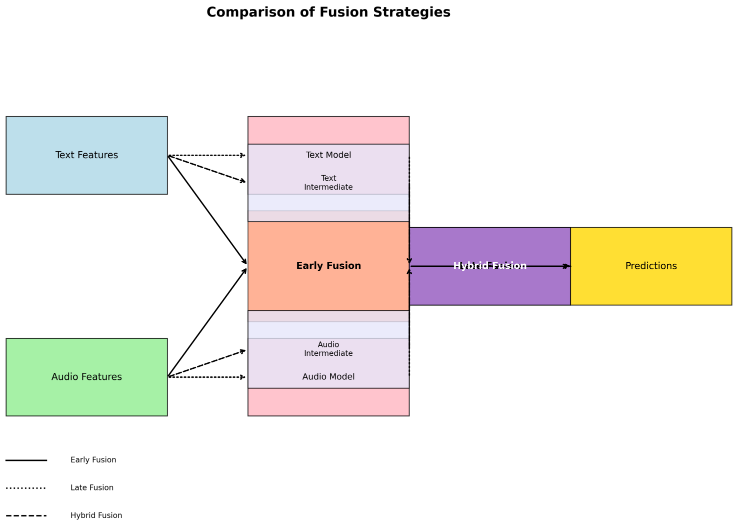
Audio Feature Extraction



Audio feature extraction pipeline

- **MFCCs**: Mel-Frequency Cepstral Coefficients (vocal tract characteristics)

Fusion Strategies



Multimodal fusion approaches

Experimental Setup

- **Dataset**: IEMOCAP (Interactive Emotional Dyadic Motion Capture)
  - 12 hours of audio-visual data
  - 10 speakers (5 male, 5 female)
  - Both categorical and dimensional annotations
- **Implementation**: PyTorch, Hugging Face Transformers
- **Training Protocol**:
  - AdamW optimizer with linear learning rate schedule
  - Early stopping based on validation loss
  - 5-fold cross-validation
- **Evaluation Metrics**: Accuracy, F1 (Macro/Micro), RMSE, MAE

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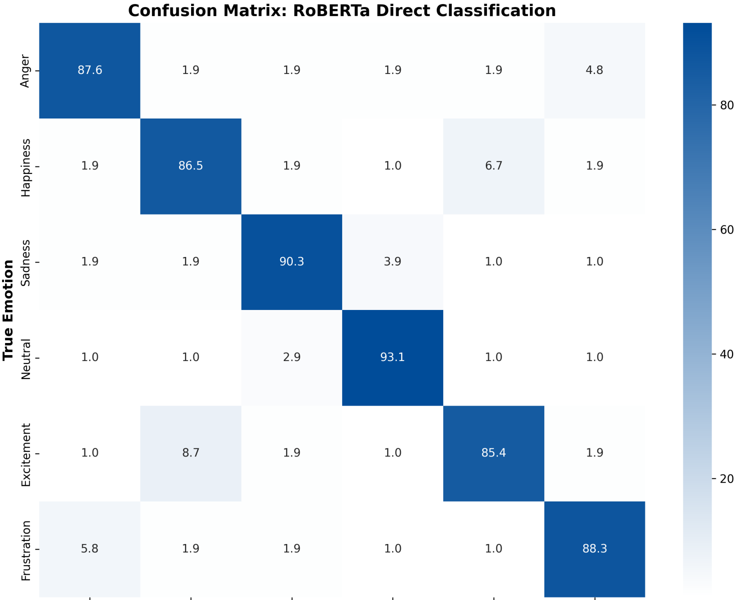
Dimensional Emotion Prediction (Stage 1)

Model	Modality	Dimension	Test RMSE	MAE
RoBERTa	Text	Valence	0.630	0.500
		Arousal	0.730	0.560
		Dominance	0.680	0.530
CNN+MFCC	Audio	Valence	0.720	0.590
		Arousal	0.650	0.510
		Dominance	0.700	0.560
RoBERTa+MFCC	Multimodal	Valence	0.610	0.490
		Arousal	0.640	0.500
		Dominance	0.660	0.520

- Text models perform better for **Valence** (positive/negative sentiment)
- Audio models perform better for **Arousal** (intensity/energy)
- Multimodal approaches show balanced performance across dimensions

Categorical Emotion Classification

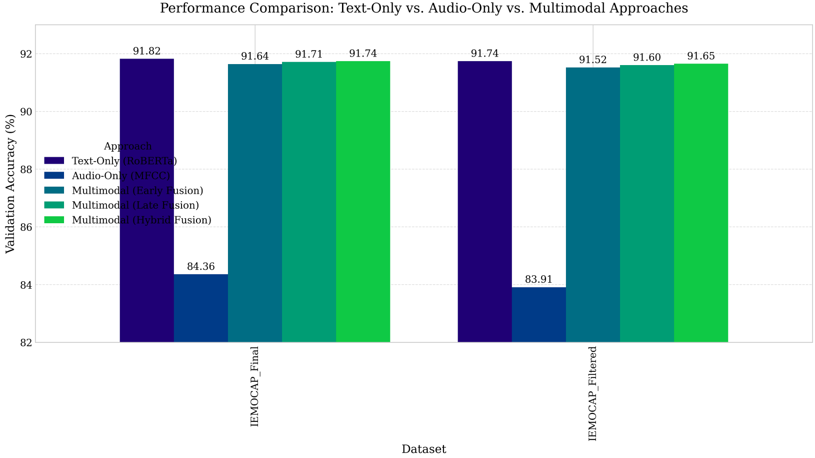


Two-Stage vs. Direct Classification

Approach	**Modality**	**Test Acc.**	**Macro F1**	**M**
Direct (RoBERTa)	Text	0.95	0.94	
Two-Stage (RoBERTa)	Text	0.92	0.91	
Direct (CNN+MFCC)	Audio	0.89	0.87	
Two-Stage (CNN+MFCC)	Audio	0.87	0.85	
Direct (RoBERTa+MFCC)	Multimodal	0.94	0.93	
Two-Stage (RoBERTa+MFCC)	Multimodal	0.90	0.89	

- Direct classification consistently outperforms two-stage approach
- But two-stage approach provides richer emotional representation
- Performance gap consistent across modalities (1.5-2.5%)

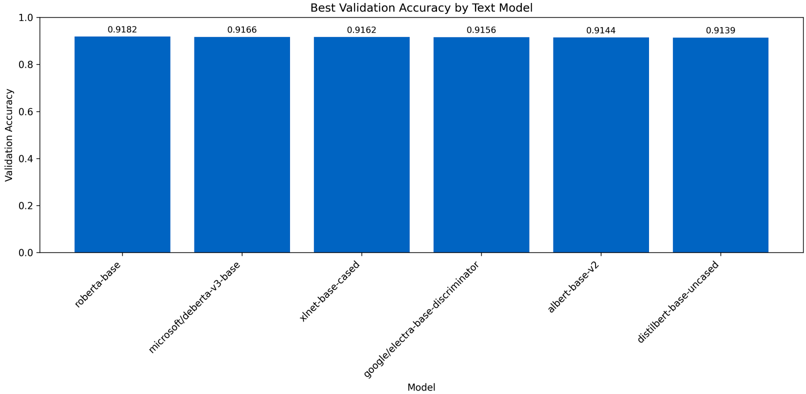
Modality Importance



Performance comparison across modalities

- Text-only approaches slightly outperform multimodal approaches
- But gap narrows with optimal fusion strategies
- Audio-only models lag but provide complementary information

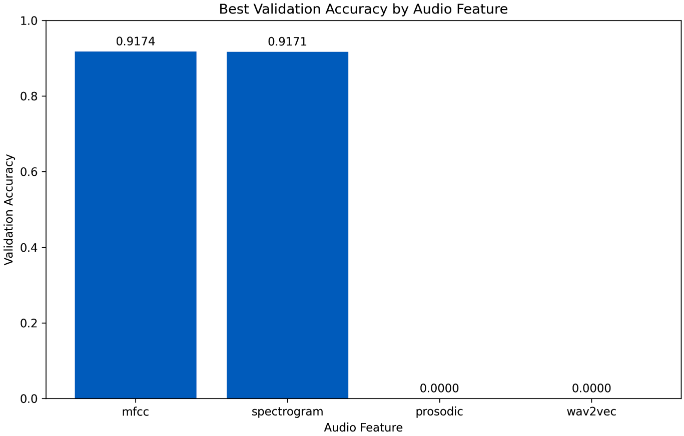
Transformer Model Comparison



Performance comparison of transformer models

- RoBERTa consistently outperforms other models
- DeBERTa shows strong performance, particularly for valence
- ALBERT shows lowest performance despite parameter efficiency

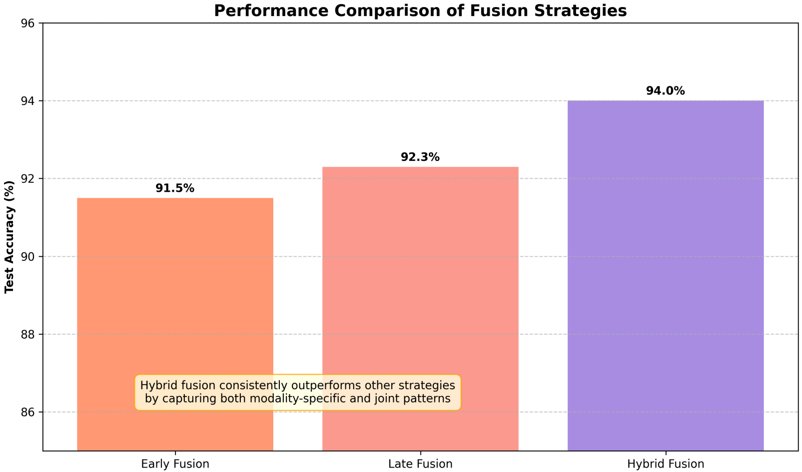
Audio Feature Effectiveness



Comparison of audio feature extraction methods

- MFCCs provide the best performance for emotion detection
- Spectrograms capture more temporal information but are noisier

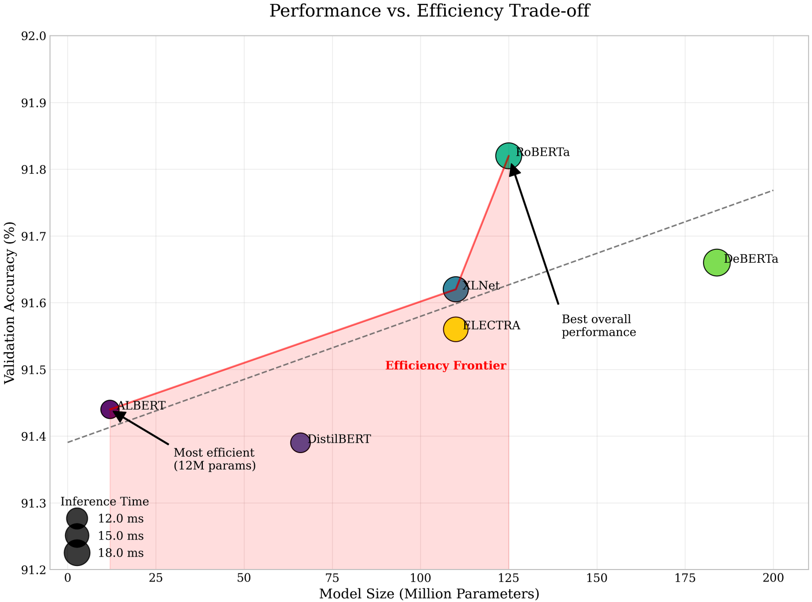
Fusion Strategy Considerations



Performance comparison of fusion strategies

- Attention-based fusion provides best overall performance
- Late fusion performs well for categorical classification

Performance-Efficiency Tradeoffs



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Key Findings

- Direct classification slightly outperforms two-stage approach for categorical emotion recognition
- Text-only approaches slightly outperform multimodal ones, though the gap narrows with optimal fusion
- Textual features better capture valence, while audio features more effectively represent arousal
- RoBERTa consistently outperforms other transformer models
- Attention-based fusion provides the best integration of multimodal information

Practical Implications

- **Application-Specific Approach Selection**:
  - Direct classification: When accuracy is critical
  - Two-stage approach: When continuous emotional representation is valuable
- **Resource Considerations**:
  - Text-only approaches offer better efficiency
  - ALBERT provides good performance-efficiency tradeoff
- **Modality Selection**:
  - Valence-focused applications: Prioritize text
  - Arousal-focused applications: Incorporate audio

Future Work

- Incorporate visual modality (facial expressions, gestures)
- Explore more sophisticated fusion techniques (cross-modal attention)
- Investigate culture-specific emotional expressions
- Develop personalized emotion recognition models
- Explore few-shot and zero-shot learning for emotion recognition
- Evaluate on more diverse datasets across languages and contexts

Thank You

Questions?

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