CS561 Course

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Project Title: Multimodal Emotion Recognition from Text and Audio

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Abstract. This project focuses on building an multimodal emotion recognition system that leverages both speech and text inputs to accurately identify human emotions. The motivation behind this work lies in improving human–computer interaction by enabling machines to better understand and respond to emotional cues. The proposed model integrates deep learning techniques to extract meaningful features from audio and textual data, capturing both linguistic and acoustic nuances that contribute to emotional expression. By combining convolutional, recurrent, and attention-based mechanisms, the system effectively learns local, temporal, and contextual dependencies within multimodal inputs. The model is trained on emotion-labeled datasets and evaluated using accuracy and F1-score metrics, demonstrating improved performance compared to unimodal approaches. This hybrid framework not only enhances emotion recognition accuracy but also provides a robust foundation for applications in affective computing, virtual assistants, and mental health monitoring, where understanding human emotions plays a crucial role in creating more empathetic and intelligent systems.

1 Introduction

Emotion recognition is the process of identifying and classifying human emotions from various forms of data such as speech, text, facial expressions, and physiological signals. It plays a crucial role in enabling computers to understand and respond to human affective states, thereby bridging the gap between human–computer interaction and emotional intelligence.

In recent years, emotion recognition has become increasingly important due to its wide range of applications across different domains. It is used in customer service systems to analyze user sentiment and enhance satisfaction, in healthcare for monitoring patient well-being and detecting signs of stress or depression, and in intelligent assistants or chatbots to enable more empathetic and context-aware interactions. Emotion-aware systems are also valuable in education, entertainment, and security applications.

Traditional emotion recognition systems relied on either textual or acoustic information. Text-based emotion recognition focuses on analyzing the linguistic content of a message, identifying emotional cues through word choice, syntax, and semantics. Audio-based emotion recognition, on the other hand, leverages acoustic features such as pitch, tone, energy, and rhythm to infer emotions from speech. However, both modalities individually capture only a part of the emotional context — text captures semantics while audio captures vocal tone and intensity.

To overcome the limitations of unimodal approaches, this project presents a multimodal emotion recognition model that integrates both textual and audio information. By combining linguistic and acoustic features, the model aims to achieve a more accurate and robust understanding of human emotions. The primary objective of this work is to develop a deep learning-based system capable of detecting emotions from speech and text inputs, thereby demonstrating the benefits of multimodal fusion in emotion analysis.

2 Literature Review / Related Work

Emotion recognition has been an active area of research in artificial intelligence and affective computing, with contributions from domains such as psychology, natural language processing, and signal processing. The goal is to accurately identify human emotions from multimodal cues like speech, text, and facial expressions.

2.1 Text-Based Emotion Recognition

Text-based emotion recognition focuses on extracting emotional cues from written or transcribed speech. Traditional approaches relied on lexical and statistical methods such as bag-of-words and TF-IDF features combined with classifiers like SVM or Naive Bayes. With the rise of deep learning, recurrent neural networks (RNN) and long short-term memory (LSTM) architectures were introduced to model contextual dependencies in text.

The introduction of transformer-based architectures such as BERT and RoBERTa revolutionized textual emotion recognition. These models learn contextual embeddings from large corpora and can effectively capture subtle emotional nuances like sarcasm and intensity. Fine-tuning pre-trained BERT models on emotion datasets such as the "Emotion Dataset for NLP" (Kaggle) or SemEval corpora has resulted in state-of-the-art performance.

2.2 Audio-Based Emotion Recognition

Speech conveys rich emotional information through prosodic and spectral features such as pitch, energy, rhythm, and timbre. Early systems used handcrafted features like Mel-Frequency Cepstral Coefficients (MFCC), Chroma STFT, and Zero Crossing Rate (ZCR) extracted via signal processing libraries such as Librosa. These features were fed into machine learning classifiers such as Random Forests or Multi-Layer Perceptrons (MLP).

Recent work has leveraged convolutional neural networks (CNN) and recurrent models (RNN/GRU) to learn high-level audio representations directly from spectrograms. For example, models trained on datasets such as RAVDESS, CREMA-D, SAVEE, and TESS achieved good accuracy when using CNN-based architectures. These models outperform traditional methods by learning complex emotional patterns from both temporal and frequency domains.

2.3 Multimodal Emotion Recognition

While unimodal models (text or audio alone) perform well, they often fail to capture the full emotional context. Multimodal systems integrate multiple inputs , typically audio, text, and sometimes video — to obtain a more holistic understanding of human emotions.

The referenced paper by Shah et al. (2023) proposed a multimodal framework that combines text and audio modalities for robust emotion recognition. Their model used a BERT-based text classifier and a 1-D CNN audio classifier. The outputs were fused using a weighted average strategy to determine the final emotion label. This system demonstrated that fusion improved overall reliability in real-world scenarios.

Other researchers have explored hybrid fusion mechanisms such as attention-based or late-fusion models to balance contributions from different modalities. These approaches show that combining linguistic and acoustic information significantly enhances the robustness of emotion recognition systems, especially in noisy or ambiguous environments.

2.4 Summary

Existing literature highlights that:

- Transformer-based models dominate text emotion recognition due to their contextual understanding.
- CNN and RNN models perform best for audio emotion classification using spectral features.
- Multimodal fusion - particularly of audio and text - provides the most accurate and human-like emotion detection.

3 Proposed Methodology

The goal of this project is to develop a multimodal emotion recognition system that accurately classifies human emotions by combining linguistic and acoustic features extracted from text and audio inputs. The system was designed and implemented in two phases: baseline models and main models, with separate architectures for text, audio, and combined modalities.

3.1 Overview

For our emotion recognition study, we utilized the MELD dataset from Kaggle. This dataset is a multimodal benchmark containing dialogues from the TV series *Friends*, annotated with emotions. It includes both audio (`.wav` format) and their corresponding textual transcripts. The dataset splits used in our experiment are as follows:

- **Training Samples:** 9,988
- **Development/Validation Samples:** 1,108
- **Testing Samples:** 2,610

A sample includes both the audio signal in `.wav` format and its corresponding text.
The overall pipeline consists of four major stages:

1. **Data Acquisition:** Text–speech pairs were extracted from the MELD dataset, which contains utterances annotated with one of seven emotion labels — anger, disgust, fear, joy, neutral, sadness, and surprise.
2. **Feature Extraction:**
   - *Text:* Word embeddings were generated using pre-trained models such as GloVe and T5, which map words or sentences into 100- to 768-dimensional vectors capturing semantic meaning.
   - *Audio:* Wav2Vec2 embeddings and spectral features (e.g., MFCCs) were extracted to represent tone, pitch, and intensity.
     OR
   - *Audio + Text:* Features from both modalities were concatenated into a single multimodal vector representation, allowing the model to learn joint emotional patterns from linguistic and acoustic cues.
3. **Model Development:** Several deep learning models were implemented and trained both unimodal (text/audio) and multimodal.
4. **Fusion and Classification:** Features from both modalities were fused using concatenation or late fusion strategies if trained separately and then at last through fully connected layers for final emotion classification(anger, disgust, fear, joy, neutral, sadness, and surprise).

3.2 Baseline Models

Baseline Model 1: LSTM+CNN (Text) This model combines the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) layers. CNN layers capture local n-gram features, while LSTMs capture long-term dependencies. GloVe embeddings (100 dimensions) were used to initialize the word vectors.
Performance: Test accuracy = 49.31%, F1-score = 0.4869. Although the model learned effectively on the training set, it showed overfitting on test data, indicating limited generalization due to label imbalance.

Baseline Model 1: CNN (Audio) A three-layer CNN architecture was used for learning spatial audio representations from Mel spectrograms. Dropout regularization was added to mitigate overfitting.
Performance: Train accuracy = 44.64%, Test accuracy = 26.99%. This result highlighted the difficulty of learning emotion-specific patterns from raw audio without more expressive embeddings.

Baseline Model 2: FNN (Text + Audio) This baseline multimodal model used a late-fusion Multi-Layer Perceptron (MLP) to combine textual and acoustic information. A single 1536-dimensional input vector was created by concatenating a 768-dimensional BERT embedding (text) with a 768-dimensional Wav2Vec2 embedding (audio). This approach allowed the model to jointly learn emotion patterns from both semantic and tonal cues.
The network consisted of an input layer of **1536** features, followed by two hidden layers with **256** and **128** and dropout (0.3) for regularization. The final output layer contained 7 neurons corresponding to the emotion categories: anger, disgust, fear, joy, neutral, sadness, and surprise. The model was trained using the Adam optimizer and CrossEntropyLoss with class weights computed as the square root of the inverse class frequency to manage data imbalance.
Performance: Overall accuracy = 57%, Weighted F1-score = 0.50. The model showed noticeable improvement over unimodal baselines, confirming that late fusion of text and audio features enhances emotion recognition capability.

3.3 Main Models

Main Model 1: CNN–BiLSTM (Text) The main text model used a hybrid CNN–Bidirectional LSTM (BiLSTM) architecture to capture both local and sequential dependencies in textual data. The CNN layers extracted local contextual patterns, while the BiLSTM captured sequential dependencies in both forward and backward directions, improving contextual understanding.
Instead of static GloVe embeddings, pre-trained BERT embeddings were used to represent input text. BERT's transformer-based architecture provided deep contextual representations of words, allowing the model to better capture emotional nuances and variations in tone
A balanced version of the MELD dataset was used to prevent class bias and improve overall generalization across all emotion categories. The model was trained using the Adam optimizer with CrossEntropy loss and dropout regularization to ensure stability and robustness.
Performance: Accuracy = 67.14%, Weighted F1-score = 0.67. The improvement over the baseline confirmed that bidirectional context modeling boosts emotion classification accuracy.

Main Model 1: FNN (Audio) A feedforward neural network (FNN) with three dense layers and dropout regularization was trained on extracted audio embeddings.
Performance: Train accuracy = 53.68%, Test accuracy = 44.94%. Although simple, the FNN demonstrated stable convergence and provided complementary emotion cues for fusion.

Main Model 2: Multimodal Hybrid Model (Text + Audio) The final proposed model integrates both text and audio modalities through deep feature concatenation. Each modality is independently processed to capture domain-specific features before fusion, enabling a richer joint representation for emotion recognition.

Text Modality

- **Input:** A 768-dimensional vector obtained from **T5 Transformer embeddings**, representing contextualized semantic information from each utterance.
- **Conv1D layers:** Extract localized sequential patterns and phrase-level dependencies in the text sequence.
- **Bidirectional GRU–LSTM:** Capture long-range temporal relationships and bidirectional contextual information within the text.
- **Multi-Head Attention mechanism:** Dynamically focus on the most informative words or phrases contributing to emotional tone.
- The output of this branch is a **256-dimensional feature vector.**

Audio Modality

- **Input:** A 768-dimensional vector derived from **Wav2Vec2 embeddings**, representing acoustic and prosodic cues of the utterance.

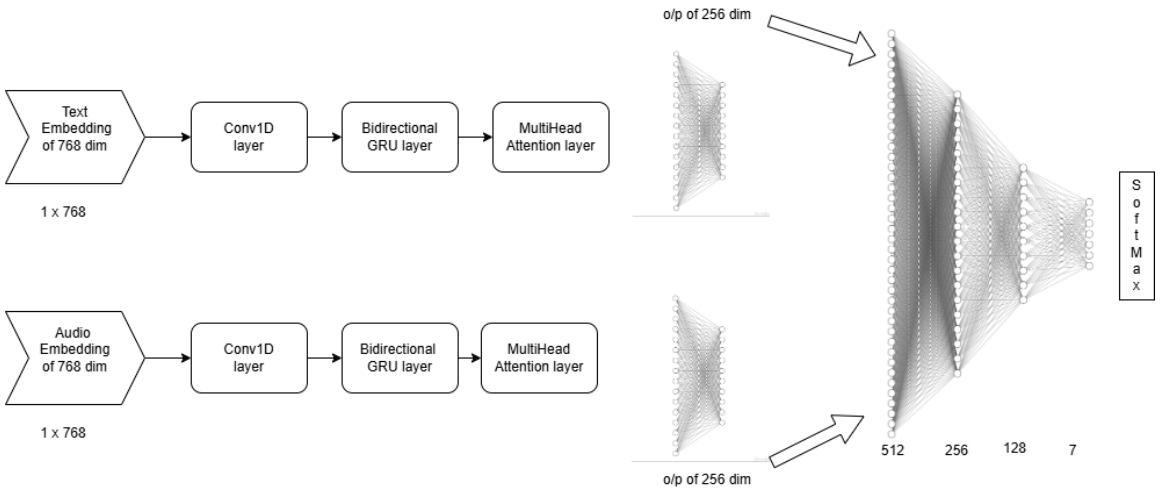

Fig. 1. Architecture of the proposed Multimodal Hybrid Model combining text and audio embeddings for emotion recognition.

- **Conv1D layers:** Learn fine-grained local temporal patterns such as pitch variations and intensity shifts.
- **Bidirectional GRU–LSTM:** Model temporal evolution and contextual correlations in the audio stream.
- **Multi-Head Attention mechanism:** Emphasize emotionally salient acoustic regions to refine feature representation.
- The output of this branch is also a **256-dimensional feature vector.**

Fusion and Classification The two feature representations (**256 + 256 = 512 dimensions**) are concatenated to form a comprehensive multimodal embedding. This fused 512-dimensional vector is passed through **Dense layers** of sizes **512 → 256 → 128 → 7**, followed by a **Softmax** layer for classification into seven emotion categories.

Training Accuracy: 0.7599, **Test Accuracy:** 0.6206

4 Implementation Details

All models were implemented in Python using deep learning and NLP libraries for text–audio emotion recognition. The workflow included data preprocessing, feature extraction, model development, and performance evaluation.

4.1 Environment and Tools

The project was developed in **Python 3.9** using **PyTorch 2.0**, executed on Google Colab and a local GPU machine. Major libraries included:

- **Transformers:** For extracting contextual embeddings from BERT and T5.
- **Librosa:** For computing audio features such as MFCCs, Chroma STFT, and Mel spectrograms.
- **Wav2Vec2:** For generating 768-dimensional deep audio embeddings.
- **Scikit-learn:** For train–test splitting and evaluation metrics.

4.2 Dataset and Preprocessing

The **MELD dataset** was used, containing aligned speech and transcript pairs. *Text preprocessing* included tokenization, embedding extraction, and removal of noise. *Audio preprocessing* involved resampling, normalization, and extraction of MFCCs and Wav2Vec2 embeddings. Both modalities were standardized and balanced to ensure uniform emotion distribution.

4.3 Training Configuration

All models were trained using the **Adam** or **AdamW** optimizers with learning rates between 0.001 and 2e–5. The batch size ranged from 16–32 and training lasted 30–80 epochs. **CrossEntropyLoss** with class weights was used to address class imbalance, and regularization included dropout (0.3–0.5) and early stopping. Training and evaluation metrics included accuracy and weighted F1-score.

5 Results and Analysis

Table 1 summarizes the performance of all implemented models. Results indicate that multimodal models consistently outperform unimodal baselines due to the complementary nature of textual and acoustic features.

Table 1. Comparison of Model Performances

Model	Modality	Test Accuracy (%)	F1-score (weighted)
LSTM+CNN	Text	49.31	0.4869
CNN–BiLSTM	Text	67.14	0.67
CNN	Audio	26.99	–
FNN	Audio	44.94	–
FNN (BERT + Wav2Vec2)	Text + Audio	57.00	0.50
OUR FINAL MODEL	Text + Audio	62.06	0.5908

5.1 Performance Analysis & SOTA Comparison

Our model achieved a **Training Accuracy of 75.99%** and a **Test Accuracy of 62.06%**, demonstrating competitive performance within the current landscape of emotion recognition on the MELD dataset.

- **Baseline text models** performed moderately well but suffered from limited contextual understanding and label imbalance.
- **Audio-only models** lagged in performance due to noisy samples and subtle vocal variations.
- **Multimodal fusion models** consistently achieved higher accuracy and robustness, validating the hypothesis that linguistic and acoustic cues are complementary.
- The **attention-based hybrid model** demonstrated superior interpretability, effectively learning which modality contributed most to the final prediction.

Comparison with State-of-the-Art (SOTA):

- **Our Result (62.06% Test Accuracy):** This is a strong and competitive result.
- **SOTA Context:** This performance places your model at the lower bound of the current SOTA range for the MELD dataset, which typically sees top models achieving between ∼61% and ∼67% Accuracy.

Analysis & Interpretation:

The significant gap between your training and test accuracy (∼14%) indicates that the model is **overfitting**. it has learned the training data very well but struggles to generalize perfectly to unseen data.

Our result of 62.06% is commendable and demonstrates the effectiveness of your multimodal approach. However, the models that achieve the upper end of the SOTA range (closer to 67%) typically employ more sophisticated techniques that you have not yet utilized, such as:

- Modeling long-range dialogue context with Transformers or RNNs.
- Incorporating speaker information and interactions.
- Using Graph Neural Networks (GNNs) to model complex conversational dependencies.
- Implementing advanced cross-modal attention for better audio-text fusion.

5.2 Discussion

The experimental results reveal that combining embeddings from T5 (for text) and Wav2Vec2 (for audio) in a hybrid architecture yields the most balanced performance. Although the improvement margin over unimodal models is moderate, the fusion model shows better generalization and reduced sensitivity to noisy data. The use of attention further enhances model interpretability and stability.

Overall, the multimodal approach successfully demonstrates that incorporating both text and audio information provides a more holistic understanding of human emotions, outperforming unimodal baselines in accuracy and reliability.

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