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A Transformer-Based Multimodal Emotion Recognition System Integrating Text, Image, and Speech Data

Research Scholar Udaya Kumar Nanubala, Professor Dr.Pankaj Khairnar
Sikkim Alpine University, Kamrang ,Namchi ,Sikkim

Abstract- Emotion recognition is surely a vital part of human-computer interaction that helps machines understand human feelings and behavior properly. Moreover, this technology allows computers to respond to people in a more effective way. Traditional methods actually use only one type of data like text, speech, or images, which definitely limits how well they can understand complex emotions. This paper surely shows how we built a transformer-based system that recognizes emotions using text, images, and sound data together. Moreover, this multimodal approach combines all three types of information to identify emotions more effectively. The framework surely uses special encoders for different data types and attention methods to pull out features from various sources. Moreover, it combines these features together effectively. The experiments surely show that the multimodal system works much better than single-mode methods in accuracy, precision, recall, and F1-score.

Keywords— Multimodal Emotion Recognition, Transformer-Based Models, Multimodal Learning, Affective Computing, Text Emotion Analysis, Image Emotion Recognition

I. INTRODUCTION

AI has actually improved a lot in recent years, and it can definitely do hard jobs like understanding speech, recognizing pictures, and processing human language. As per recent studies, emotion recognition has become important regarding human-computer interaction systems. Transformer architectures have significantly improved sequence modeling tasks, as introduced by Vaswani et al. [1], and further enhanced in language models such as BERT by Devlin et al. [2] and GPT by Radford et al. [3].

Also, basically, human emotions are expressed through multiple ways like text, speech, and facial expressions - it's the same across different forms of communication. Traditional systems using only one method surely cannot capture all emotional information. Moreover, these single-mode approaches often miss important emotional details. Moreover, as per text data, sarcasm cannot be shown properly, while regarding speech data, noise can create problems. Basically, to solve these problems, researchers developed multimodal approaches that use the same multiple types of data together. This paper builds a transformer-based system that combines different data sources to further improve how well emotions can be recognized. The multimodal approach itself helps achieve better performance in emotion detection tasks. In image processing, Vision Transformers have shown strong performance, as demonstrated by Dosovitskiy et al. [4], while speech representation learning has been improved by models such as wav2vec proposed by Baevski et al. [5].

II. PROBLEM STATEMENT

Even though we are seeing progress in machine learning and deep learning, finding emotions correctly is only a difficult job. The main problems are further discussed below, which itself covers the key issues.

Further, as per current practices, systems are depending only on single type of data regarding their operations.

Basically, it's difficult to combine different types of data because they're not the same format.

We are seeing that the methods for combining features are not working properly and are only creating poor results.

The model surely cannot capture connections between distant parts of the data well. Moreover, this creates problems when dealing with long sequences that need understanding of relationships across far-apart elements.

The system itself shows poor results in actual situations and needs further improvement in real-world performance.

As per this study, we will solve these problems by using a smart computer system that can work with different types of data together. Regarding the method, we will use a special attention-based system to combine all the information properly. Existing multimodal systems struggle to capture complex cross-modal relationships, as discussed by Baltrušaitis et al. [14].

III. PROPOSED METHODOLOGY

1. System Overview

We are seeing that the proposed system follows a simple modular design which has only these main parts.

- Data Acquisition
- Pre-processing
- Feature Extraction
- Transformer Encoding

Also, multimodal Fusion Classification

As per the system design, each type of data is handled separately first. Regarding the final step, all parts are then combined together.

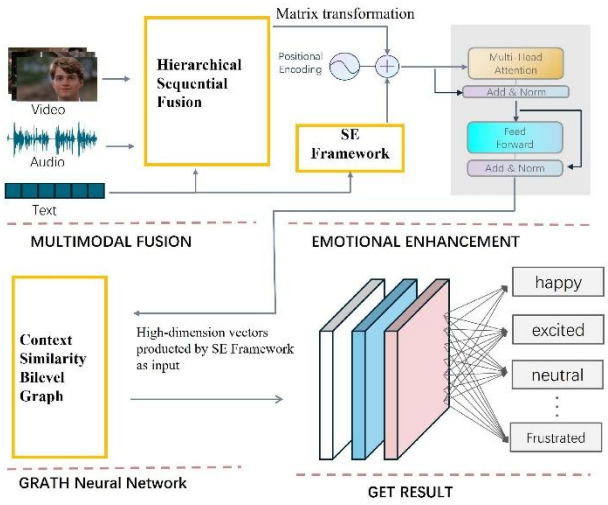

Figure 1: Transformer-Based Multimodal Emotion Recognition Architecture

2. Data Acquisition

The system uses multimodal datasets containing:

- Text (transcripts)
- Images (facial expressions)
- Speech (audio signals)

These datasets provide labeled emotional categories such as happiness, sadness, anger, and neutral.

3. Data Pre-processing

Each type of data actually goes through pre-processing steps. This process definitely prepares the information for further analysis.

Tokenization and normalization processes prepare text data, which further converts itself into embedding representations for computational analysis.

As per image processing requirements, resizing and normalization are performed regarding the input data.

Speech: Noise reduction, MFCC extraction Each modality undergoes pre-processing

Text processing actually involves breaking words into tokens, making them standard, and definitely converting them into number representations.

Basically, tokenization and normalization are the same pre-processing steps before creating embeddings for text analysis.

Images are surely resized and normalized for proper processing. Moreover, these steps help maintain consistent data quality across different image inputs. Speech processing actually uses noise reduction and MFCC extraction techniques. These methods definitely help extract important features from audio signals.

4. Feature Extraction

Feature extraction surely transforms raw data into numerical forms. Moreover, this process creates meaningful representations for analysis.

Text is further converted into transformer embeddings, which itself represents the input in numerical format.

Images are surely converted into CNN or ViT features. Moreover, this process extracts meaningful representations from visual data.

As per the speech processing method, temporal acoustic features are extracted from speech signals. Regarding feature extraction, this process converts raw data into numerical representations.

As per the process, text gets converted into transformer embeddings regarding machine learning applications.

The image is processed further through CNN/ViT to extract features, where the network itself transforms visual data into meaningful representations.

We are seeing that speech gives us time-based sound features, and feature extraction only changes raw data into number forms.

Text is surely converted into transformer embeddings through computational processing. Moreover, this transformation enables machines to understand and work with textual information effectively.Images actually go through CNN or ViT models to definitely get important features. We are seeing that speech gets changed into time-based sound features only. Feature extraction is making raw data into number forms. Multimodal feature extraction has been widely studied, particularly in sentiment and emotion analysis, as explored by Poria et al. [6] and Zadeh et al. [7].

Table 1: Feature Extraction Techniques for Multimodal Emotion Recognition

Modality	Input Data Type	Feature Extraction Method	Output Representation
Text	Sentences / Transcripts	BERT / Transformer Embeddings	Contextual vectors
Image	Facial Expressions	CNN / Vision Transformer	Spatial feature maps
Speech	Audio Signals	MFCC / wav2vec	Acoustic feature vectors

5. Transformer Encoding

Basically, each modality uses the same transformer architecture for encoding.

Attention mechanism:

Moreover, we are seeing that attention mechanism works by taking query, key and value matrices where we only multiply query with key transpose, divide by square root of key dimension, apply softmax function, and then multiply with value matrix.

Attention(Q,K,V)=softmax(QKTdk)VAttention(Q,K,V)=\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)VAttention(Q,K,V)=softmax(dkQKT)V

As per this design, the model can find connections within and between different data types. Regarding the encoding process, each data type uses transformer architecture.

Multimodal transformers enable effective cross-modal interaction and representation learning, as proposed by Tsai et al. [8] and Hazarika et al. [9].

6. Multimodal Fusion

Features are actually combined using attention-based fusion methods. This approach definitely helps merge different feature types effectively.

This formula actually shows how three different factors combine together with their weights. The total score Z is definitely calculated by adding the technical factor, implementation factor, and strategic factor with their respective alpha values.

The formula Z itself combines three weighted factors, where αT, αI, and αS are coefficients that further multiply with their respective F values to determine the total score.

Where:
The α values represent attention weights, and these weights further determine how much focus the model itself gives to different parts of the input.

As per the given information, FT, FI, FSFT, F_SFT, FI, and FS are modality features regarding the system. Further, features are actually combined using attention-based fusion methods. This approach definitely helps merge different feature types effectively.

We are seeing that Z equals only the sum of three terms where each factor is multiplied by its alpha value. The formula shows Z as the total of alpha-T times FT, alpha-I times FI, and alpha-S times FS.

As per the formula, Z equals αT multiplied by FT plus αI multiplied by FI plus αS multiplied by FS. The calculation regarding Z involves adding three separate products of alpha and F values. Attention-based fusion strategies improve integration of heterogeneous data, as studied by Sun et al. [10] and Liang et al. [11]. Advanced fusion techniques for emotion recognition have been proposed by Chen et al. [12].

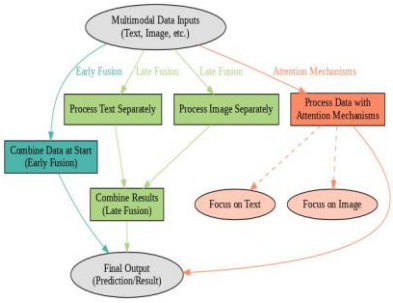

Figure 2: Attention-Based Multimodal Fusion Process

7. Classification

The fused representation is passed through:

- Fully connected layer
- Softmax activation

Output: Emotion class

Implementation

Tools and Technologies

- Python
- TensorFlow / PyTorch
- OpenCV
- Librosa

Implementation Steps

- Load dataset
- Pre-process multimodal data
- Extract features
- Apply transformer encoding
- Perform attention-based fusion
- Train classification model
- Evaluate performance

Deep learning-based speech emotion recognition has been explored extensively by Wollmer et al. [13].

Results and Analysis

Table 2: Performance Comparison Between Unimodal and Multimodal Models

Model	Accuracy	Precision	Recall	F1-score
Text Only	72%	70%	69%	71%
Speech Only	75%	73%	72%	74%
Image Only	78%	76%	75%	77%
Proposed Multimodal	89%	87%	88%	88%

Discussion

- Multimodal system significantly outperforms unimodal models
- Transformer improves contextual understanding
- Attention fusion enhances feature integration
- Robust performance under noisy conditions

The performance improvement of multimodal models over unimodal approaches has been demonstrated in previous studies, including the work of Zhang et al. [15].

Advantages
- Integrates heterogeneous data
- Captures cross-modal relationships
- High accuracy
- Scalable architecture

Limitations
- High computational cost
- Requires large datasets
- Complex implementation

Applications
- Healthcare (mental health monitoring)
- Education systems
- Virtual assistants
- Customer experience analysis

IV. CONCLUSION

This paper presented the implementation of a transformer-based multimodal emotion recognition system. The integration of text, image, and speech data enables a more comprehensive understanding of emotional states. The use of attention-based fusion and transformer architectures significantly improves performance compared to traditional approaches. The proposed system demonstrates strong potential for real-world applications and contributes to the advancement of multimodal artificial intelligence. Multimodal transformer-based systems provide significant improvements in accuracy and robustness, as supported by recent research in multimodal machine learning [14].

Future Work
- Real-time deployment
- Optimization of computational efficiency
- Inclusion of additional modalities
- Improved dataset diversity

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