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Integrated Approach to Emotion Recognition Across Multiple Modalities

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Abstract- Multimodal emotion recognition is essential for advancing human-computer interactions and enabling applications like mental health monitoring and social robotics. This study focuses on utilizing text, audio, and motion data from the IEMOCAP dataset to develop independent models that capture unique emotional cues from each modality. The audio model employs a hybrid architecture combining Convolutional Neural Networks (CNN), Multi-Head Attention, and Gated Recurrent Units (GRU), achieving an accuracy of 81%. The text model leverages a CNN-based approach inspired by Temporal Convolutional Networks (TCN), achieving 94% accuracy. For motion data, a Spatio-Temporal Graph Convolutional Network (ST-GCN) was implemented, achieving 63% accuracy. A score-level fusion strategy integrates these models, improving the overall recognition performance. Evaluations using metrics like accuracy, precision, and recall demonstrate how multimodal approaches can provide a more accurate and reliable emotion recognition system by combining complementary information from diverse data types.

Index Terms- Multimodal Emotion Recognition, Fusion Techniques, Deep Learning Models, Feature Extraction, Cross-Modal Synchronization, Real-time Emotion Analysis

I. INTRODUCTION

Understanding human emotions is essential for improving interactions between humans and machines. Emotions play a key role in areas such as mental health monitoring, customer service, education, and social robotics. Accurate emotion recognition can significantly enhance user experiences by enabling more empathetic and responsive systems [1].
Traditional emotion recognition approaches often rely on single data types, such as text or audio, which may not fully capture the complexity of human emotions. In real-world scenarios, emotions are expressed through multiple cues, including speech tone, language, and body movements. Recent advancements in audio and video-based emotion recognition have demonstrated the effectiveness of attention mechanisms and feature extraction techniques in improving accuracy [3].

This paper focuses on developing independent models for text, audio, and motion data using the IEMOCAP dataset. The audio model employs a hybrid architecture that integrates Convolutional Neural Networks (CNN), Multi-Head Attention, and Gated Recurrent Units (GRU) to capture emotional patterns in speech [5]. The text model utilizes a CNN-based architecture inspired by Temporal Convolutional Networks (TCN), which is effective for sequential data processing [8]. The motion model applies Spatio-Temporal Graph Convolutional Networks (ST-GCN) to analyze body movements, a technique proven to capture spatial and temporal dynamics in motion data [11].

To further improve performance, a score-level fusion strategy combines predictions from these independent models. Such fusion strategies have been recognized as robust approaches to handle multimodal emotion recognition challenges, providing a more comprehensive understanding of emotional states [3], [10].

This work highlights how leveraging advanced architectures and fusion techniques can build a more reliable emotion recognition system, addressing the limitations of unimodal approaches [4]

II. RELATED WORK

1. Overview of Multimodal Fusion Techniques

The survey presented by Sun et al. [1] provides an extensive overview of the state of the art in multimodal emotion recognition. They highlight the challenges and opportunities in integrating different modalities, categorizing fusion techniques into early, late, and hybrid approaches, and explaining how each impacts system performance. Hossain and Muhammad [6] review various techniques, emphasizing the limitations of unimodal systems and the benefits of

multimodal integration to enhance emotion detection. Kakumanu et al. [3] further stress the importance of non-verbal cues, such as facial expressions and gestures, in improving multimodal system performance.

2. Speech and Text Emotion Recognition
Li et al. [2] investigate techniques for recognizing emotions from speech and text, emphasizing the role of contextual understanding in improving recognition accuracy. Yu and Le [5] explore advancements in deep learning architectures for speech and text analysis, showcasing how combining these modalities enhances emotion recognition tasks. Additionally, Penna et al. [7] focus on evaluating feature fusion methods for speech and text-based systems, identifying effective strategies for integrating data to boost performance.

3. Non-Verbal Cues in Emotion Recognition
Kakumanu et al. [3] highlight the significance of integrating visual data, such as facial expressions and gestures, alongside audio inputs to enhance recognition accuracy. Huang et al. [11] employ CNNs and LSTMs to process video and audio data, demonstrating the benefits of capturing facial expressions and speech intonations together. Furthermore, Taghavi et al. [12] emphasize converting speech to text to better integrate visual and textual data for improved emotion detection.

4. Addressing Real-World Challenges
Chen et al. [6] discuss challenges in real-world multimodal emotion recognition, such as background noise and varying lighting conditions, suggesting robust multimodal fusion strategies to improve system performance. Ma et al. [13] introduce a transformer-based model with self-distillation to handle complexities in recognizing emotions during conversations, focusing on contextual learning. Hossain and Muhammad [6] stress the need for multimodal systems to adapt to uncontrolled environments, making them more applicable in diverse real-world scenarios.

5. Advances in Deep Learning for Emotion Recognition
Wei et al. [9] delve into deep fusion techniques for audio and visual features, proposing frameworks that optimize modality-specific feature extraction before fusion, resulting in significant performance improvements. Lee and Kim [8] utilize transformer-based fusion to capture relationships between modalities effectively, leveraging attention mechanisms to enhance emotion recognition tasks. Yu and Le [5] highlight the versatility of CNNs, RNNs, and transformers in processing multimodal data for applications like virtual assistants and gaming.

6. Evaluating Fusion Methods
Penna et al. [7] provide a framework for evaluating shallow and deep learning-based fusion strategies, offering guidelines for selecting appropriate methods for specific applications. Tellamekala and Amiriparian [14] propose COLD Fusion, an uncertainty-aware method, demonstrating improvements in scenarios with noisy data. Their work highlights the importance of considering data variability when designing fusion techniques.

In conclusion, multimodal emotion recognition represents a significant advancement in understanding and interpreting human emotions through the integration of various data modalities, such as audio, visual, and textual inputs. The reviewed literature highlights the diverse methodologies employed, the importance of non-verbal cues, and the efficacy of deep learning approaches in enhancing recognition accuracy. As the field progresses, addressing challenges related to real-world applications, dataset diversity, and model interpretability will be crucial for developing robust and ethical emotion recognition systems.

All these studies are summarized in Table 1, reflecting the increasing focus on multimodal emotion recognition and the variety of techniques employed to address this intricate problem. The research emphasizes the need for a comprehensive understanding of how different modalities—such as audio, visual, and textual data—can be effectively integrated to improve emotion classification accuracy. Evaluating these methods is crucial to ascertain their efficiency in various scenarios, particularly in terms of their adaptability to differing qualities of modalities and computational demands. Moreover, conducting a comparative analysis of these techniques within the context of multimodal emotion recognition is essential for advancing the field. Such evaluations will help identify which methods are most suitable for specific applications, enabling practitioners to make informed decisions based on their unique requirements. The insights gained from this analysis can lead to the development of technologies.

III. METHODOLOGY

1. Dataset Description
The IEMOCAP dataset is a comprehensive resource for emotion recognition, containing 12 hours of audiovisual recordings from 305 videos across 5 sessions with 10 speakers (5 male and 5 female). It provides synchronized data for text, audio, and motion capture modalities.

The text data includes transcriptions of dialogues for analyzing emotional cues in words. The audio data consists of high-quality WAV files capturing speech features like pitch, energy, and tone [3].

The motion data offers detailed 3D coordinates of head, hand, and body movements to study non-verbal emotional expressions. The dataset is labeled with four main emotions: Anger, Excitement, Neutral, and Sadness, along with valence,

arousal, and dominance scores. This multimodal dataset is widely used for developing emotion recognition models by combining verbal and non-verbal cues.

2. Data Preprocessing

Text Data: The raw text data is converted into tokenized sequences, where each word is replaced with a unique integer from a predefined vocabulary. The sequences are padded or truncated to a fixed length L to ensure uniform input sizes.

$$X_{padded} = [w1, w2, \dots, wL] \quad (1)$$

$w_i \in$ Vocabulary Indices

Table 1: Summary of Emotion Recognition Studies

Reference	Datasets Used	Context	Models/Methods	Key Contributions
[1]	EMO-DB, AffectNet, VGGFace	Multimodal emotion recognition	Fusion techniques categorization	Overview of challenges and methodologies in multimodal fusion.
[2]	RAVDESS, CREMA-D, EmoDB	Speech emotion recognition	CNNs, Attention	Efficient speech emotion recognition using multi-scale CNNs with attention mechanisms.
[3]	IEMOCAP, AVEC, AFEW	Multimodal emotion recognition	Cross-Attention	Introduces a cross-attention algorithm for emotion recognition based on audio and video.
[4]	RAVDESS, CREMA-D	Speech and text emotion recognition	Feature extraction, classification	Explores high-level speech and text features for multimodal emotion recognition.
[5]	IEMOCAP, DailyDialog	Emotion recognition in conversations	Transformer-based model	Proposes a transformer-based approach for multimodal emotion recognition.

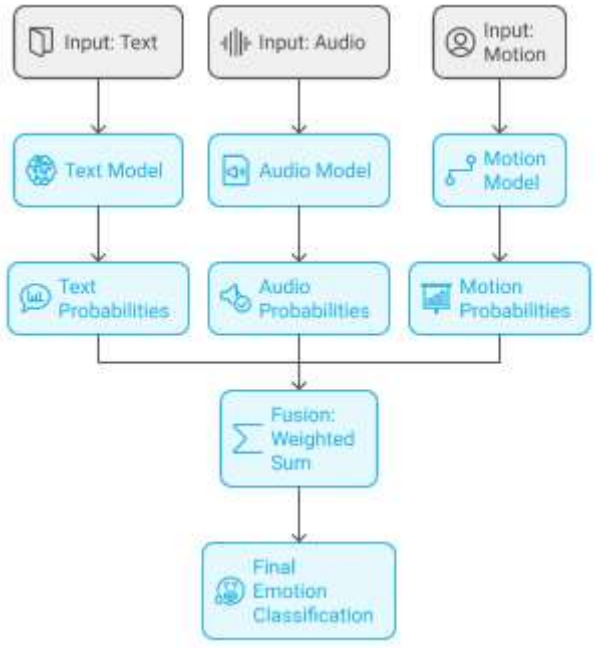

Fig.1. Multimodal Architecture

Audio Data: The raw signal is segmented into overlapping frames of fixed duration (25ms) with a stride (10ms). This segmentation allows capturing localized temporal patterns:

$$F_t = \text{Audio}\,[t \cdot s : t \cdot s + w] \quad (2)$$

Amplitude normalization is performed to standardize the signal within the range [−1,1], ensuring consistency across samples.

Motion Data: the raw motion capture sequences, including head, hand, and body movements, are normalized to a fixed range [0, 1]. All motion sequences are padded or truncated to a uniform length T=200 frames, maintaining consistency for input to graph-based models.

Feature Extraction

Text Modality: pre-trained word embeddings like GloVe (300-dimensional vectors) are used to represent words as dense vectors. These embeddings capture semantic relationships, meaning similar words have similar vector representations. Each word in the sequence is replaced by its corresponding word embedding, forming an embedding matrix that maps the vocabulary to the embedding space. Embedding matrix:

$$E = [\overrightarrow{\omega_1}, \overrightarrow{\omega_2}, \dots, \overrightarrow{\omega_{|V|}}] \quad (3)$$

$\overrightarrow{\omega_i}$ represents the vector for word i

Audio Modality: Mel Frequency Cepstral Coefficients (MFCCs) are extracted from the raw audio signal. This involves converting the audio into the frequency domain using the Fast Fourier Transform (FFT) and applying a Mel filter bank to extract perceptual features that mimic human hearing. Additionally, delta coefficients are calculated as the first-order temporal derivatives of the MFCCs, capturing the dynamic aspects of the audio signal like changes in pitch and loudness over time.

3. Motion Modality: human motion is represented as a graph. Each joint is treated as a node, and connections between joints (limbs, head, torso) are represented as edges. The features for each joint include its 3D position in space, represented as a vector

$$f(v_i) = [x_i, y_i, z_i] \quad (4)$$

where x_i, y_i, z_i correspond to the joint's coordinates. This graph structure is used to capture spatial relationships between joints and how they change over time.

Model Building

Text Model: A Convolutional Neural Network (CNN) is used to extract local patterns (such as n-grams) from the word embeddings. These convolutional layers slide over the input sequence and extract relevant features. Convolution operation:

$$y_{\{i,j\}} = \sigma\left(\sum_{m=1}^{k} (w_m) \cdot x_{\{(i+m-1),j\}} + b \right) \quad (5)$$

After convolution, max-pooling layers reduce the dimensionality of the feature map, selecting the most important features. Finally, fully connected dense layers are used to aggregate the features and classify the text into one of the emotion categories, with a softmax activation function producing the probability distribution over the classes. Softmax function:

$$P(\text{ Emotion } | x) = \frac{e^{z_j}}{\sum_{k=1}^{C} e^{(z_k)}} \quad (6)$$

Audio Model: A combination of 1D convolutional layers and Gated Recurrent Units (GRUs) is used. The convolutional layers extract local temporal patterns in the audio signal,

$$y_t = \sigma\left(\sum_{i=1}^{k} w_i x_{(t+i-1)} + b\right) \quad (7)$$

While the GRUs capture long-range dependencies in the sequence of audio frames,

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (8)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t \odot h_{t-1}, x_t]\right) \quad (9)$$

To improve focus on important segments, a Multi-Head Attention mechanism is applied,

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (10)$$

which computes weighted sums of input features based on their relevance to the task. The output is then passed through dense layers to classify the audio into emotional states.

Motion Model: The model employs a Spatio-Temporal Graph Convolutional Network (ST-GCN). This network captures both spatial relationships (e.g., distances and angles between joints),

$$f_v^{(l+1)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{Z_{uv}} W^{(l)} f_u^{((l))}\right) \quad (11)$$

$N(v)$: Neighbours of the node v, Z_{uv}: Normalization factor

and temporal dynamics (motion across frames),

$$g_v^{(t+1)} = W^{((t))} f_v^{(t)} \quad (12)$$

The spatial convolutions aggregate features from neighboring joints, and the temporal convolutions capture the changes over time. The network is followed by global pooling to reduce the graph's size into a fixed-length feature vector, which is then passed through dense layers for emotion classification.

Model Training

The text model is trained for 50 epochs with a batch size of 32 using the Adam optimizer and categorical cross-entropy loss. The audio model is trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss over 65 epochs with a batch size of 32. Similarly, the motion model is trained using the Adam optimizer and categorical cross-entropy loss over 50 epochs with a batch size of 32. All models split data into training and testing subsets for validation.

Score-Based Weighted Sum Fusion

After training the individual models for text, audio, and motion modalities, we employ the Score-Based Weighted Sum Fusion technique to combine the predictions from each modality for final emotion classification as shown in Fig. 1. The goal of score-based fusion is to combine the outputs of the individual modality-specific models into a single, unified decision. Each model provides a probability distribution over the emotion classes. These probabilities are then weighted based on their relative importance, and the weighted sum of these probabilities is computed to form a fused probability distribution.

Individual Model Outputs: Let P_{text} (Emotion|x_{text}), P_{audio} (Emotion|x_{audio}), P_{motion} (Emotion|x_{motion}) be the probability distribution over emotion classes from the text-based model, audio-based model and motion-based model respectively.

Weighted Sum Fusion: The final fused probability distribution P_{fused} (Emotion|x) is computed as a weighted sum of the individual probability distributions:

$$P_{\text{fused}} = \alpha_1 P_{\text{text}} + \alpha_2 P_{\text{audio}} + \alpha_3 P_{\text{motion}} \quad (13)$$

α_1, α_2, α_3 are the weights assigned to each modality. These weights reflect the importance or reliability of each modality in contributing to the final decision. The sum of the weights should equal 1

Choosing Weights for Fusion: The weights for each modality are chosen based on their respective accuracy. The rationale is that modalities with higher accuracy contribute more to the final decision, while less accurate modalities are given lower weights. The accuracy scores for each modality are used to compute the relative importance of each modality in the fusion process.

To calculate the weights for each modality, we use the following formula:

$$\alpha_i = \frac{Accuracy_i}{Total\ Accuracy} \quad (14)$$

Final Prediction: After calculating the fused probabilities, the final emotion class is predicted by selecting the class with the highest probability. This step ensures that the class with the highest confidence across the modalities is chosen as the final output.

$$\hat{y} = arg\,max(\,Pfused(Emotion \mid x)) \quad (15)$$

IV. EXPERIMENT

Table II presents a detailed comparison of the performance of various models across the audio, text, and motion modalities. For the audio modality, the Hybrid Convolutional Generative Adversarial Network (HCGAN) stands out as the best performer, achieving a validation accuracy of 81.79% and the lowest validation loss of 0.4962.

This result demonstrates the model's strong generalization capabilities and effective learning. In contrast, the BiLSTM + Attention model, while exhibiting a high training accuracy of 87.32%, suffers from significant overfitting, as evidenced by the large gap in validation accuracy (74.72%) and a much higher validation loss

Table 2: Experimentation of Deep Learning Models for Text, Audio and Motion Models

Model	Modality	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
LSTM	Audio	0.5971	0.6579	0.9255	0.9124
LSTM + Attention	Audio	0.6977	0.6955	0.7230	0.8288
BiLSTM + Attention	Audio	0.8732	0.7472	0.3225	1.7675
Capsule Network	Audio	0.7068	0.5202	0.7809	1.2321
Hybrid	Audio	0.7304	0.8179	0.6319	0.4962
CNN-1D	Text	0.9425	0.6982	0.1295	3.4523
LSTM	Text	0.9293	0.8204	0.1575	2.1435
TE-CNN	Text	0.9325	0.9435	0.1270	0.1205
CNN-2D	Motion	0.4714	0.4453	1.1261	1.4503
TSN	Motion	0.3700	0.3497	0.3468	1.3783
LSTM	Motion	0.3477	0.3550	1.3382	1.3446
ST-GCN	Motion	0.7278	0.6386	1.3204	1.52

(1.7675). The Capsule Network shows poor generalization, with a validation accuracy of only 52.02%, despite achieving moderate training performance. The validation loss for this model is also quite high, at 1.8345, highlighting its inability to generalize well to unseen data. In the text modality, the TE-CNN model outperforms the others, achieving an impressive validation accuracy of 94.35% and the lowest validation loss of 0.1205. These results highlight the model's robustness and its ability to accurately classify emotions based on text features. However, the CNN-1D model struggles with severe overfitting, as indicated by its high training accuracy of 94.25%, but a significant drop in validation accuracy (69.82%) and a much higher validation loss (3.4523). For the motion modality, the ST-GCN model achieves the best validation accuracy of 63.86% and a reasonable validation loss of 1.52, effectively capturing the spatial-temporal dynamics inherent in motion data. On the other hand, models like CNN-2D, TSN, and LSTM perform poorly, with validation accuracies falling below 45% and significantly high validation losses. These results suggest that these models struggle to extract meaningful features from the motion data, underscoring their limitations in the context of emotion recognition.

Result Analysis of Individual Models

Table III presents the performance analysis for the audio, text, and motion modalities. The Hybrid model for the audio modality demonstrates strong performance, achieving a precision of 83%, recall of 81%, and an F1-score of 82%. This indicates a well-balanced performance, with good sensitivity and accuracy. The best performing class is Neutral, while the

model struggles most with the excited class, highlighting a potential area for improvement in distinguishing this emotion.

The TE-CNN model for text achieves high precision (93%), recall (92%), and an F1-score of 93%, showing that it excels at emotion recognition in text. It performs exceptionally well in classifying Excited emotions as the best performing class. However, the Sad emotion remains the weak performing class, suggesting that the model has difficulty accurately recognizing sadness.

For motion-based emotion recognition, the ST-GCN model achieves a precision of 58%, recall of 60%, and an F1-score of 58%, indicating moderate performance. The model performs best in classifying Anger and struggles with Excited emotions, which are the weak performing class. This suggests that the model has room for improvement in distinguishing between subtle emotional expressions in motion data.

Result of the Fused Model

Total Accuracy Calculation: The normalization factor is the sum of the individual accuracies:

$$\text{Normalization Factor}=81+94+63=238$$

Weight Calculation for Each Modality: The individual weights for audio model, text model and motion model are calculated as follows:

$$\alpha_{\text{audio}} = \frac{81}{238} = \mathbf{0.3403}$$

$$\alpha_{\text{text}} = \frac{94}{238} = \mathbf{0.3941}$$

$$\alpha_{\text{motion}} = \frac{63}{238} = \mathbf{0.2647}$$

Table 3: Performance Analysis of Best Trained Models

Model	Hybrid	TE-CNN	ST-GCN
Modality	Audio	Text	Motion
Precision (%)	83	93	58
Recall (%)	81	92	60
F1-Score (%)	82	93	58
Best Performing Class	Neutral	Excited	Anger
Weak Performing Class	Excited	Sad	Excited

The final accuracy for the combined emotion recognition model is calculated using the weighted sum fusion approach. By assigning weights to the audio, text, and motion modalities based on their individual accuracies, the formula for final accuracy is:

$$\text{Final Accuracy} = (\alpha_{\text{audio}} \times \text{Acc}_{\text{audio}}) + (\alpha_{\text{text}} \times \text{Acc}_{\text{text}}) + \left(\alpha_{\text{motion}} \times \text{Acc}_{\text{motion}}\right) \quad (16)$$

Substituting the values, the final accuracy is **81.29%**, demonstrating the effectiveness of combining the three modalities to improve emotion recognition performance.

V. ILLUSTRATION

1. Input

A user is expressing emotions with the following inputs:

- **Text:** "I'm so happy to be here!"
- **Audio:** A recorded sentence where the speaker has a joyful tone.
- **Motion:** A video of the person showing an upright posture and a smile

Feature Extraction

Pre-trained Word Embeddings: Each word in the text is converted into a 300-dimensional vector using GloVe embeddings:

- I'm: [0.12, 0.34, 0.56, ..., 0.78]
- so: [0.22, 0.41, 0.53, ..., 0.68]
- happy: [0.87, 0.91, 0.76, ..., 0.34]
- to: [0.21, 0.43, 0.63, ..., 0.52]
- be: [0.29, 0.37, 0.51, ..., 0.48]
- here: [0.88, 0.79, 0.67, ..., 0.59]

These vectors form an embedding matrix for the sentence.

MFCC Extraction: The audio signal is split into small frames and converted to the frequency domain using the Fast Fourier Transform (FFT). Mel-frequency filters are applied to extract perceptual features. MFCC features for the joyful tone: [32.5,28.7,21.1,19.3,15.7,…]. Additional Delta MFCCs are calculated to capture changes in pitch and loudness over time.

Graph Representation: The human body is represented as a graph with nodes for joints . Each node has a feature vector [x, y, z] representing its 3D position:

Head Joint (Node 1): [0.15, 1.72, 0.30]

Right Hand Joint (Node 2): [0.45, 1.23, 0.50]

Left Hand Joint (Node 3): [−0.40, 1.24, 0.45]

Edges connect neighboring joints to capture the spatial relationships.

Prediction: The models predict emotions by analyzing text patterns with CNNs, tonal variations with 1D CNNs and GRUs, and motion dynamics with ST-GCN, classifying emotions through dense layers.

Text Prediction: 90% happy, 5% neutral, 5% sad.
Audio Prediction: 85% happy, 10% neutral, 5% sad.
Motion Prediction: 60% happy, 25% neutral, 15% sad.

Score-Based Fusion: Weights are calculated based on accuracy. The final fused probabilities are calculated:
$P_{fused} = 0.39 \cdot P_{text} + 0.34 \cdot P_{audio} + 0.26 \cdot P_{motion}$
$P_{happy} = 0.39(0.9)+0.34(0.85)+0.26(0.6) = 0.796$

Final Prediction: Emotion with the highest probability (happy) is selected as the output.

Challenges
During the development of the emotion recognition system, several challenges were encountered:

Real-Time Implementation
Adapting the system for real-time emotion recognition posed significant challenges due to the need for fast data processing and inference across the text, audio, and motion modalities. The high computational requirements of the deep learning models, particularly during prediction,
made real-time integration difficult.

Data Alignment Issues
Synchronizing data from the text, audio, and motion modalities proved to be challenging. Differences in temporal resolution and missing data between modalities required extensive preprocessing and alignment techniques to ensure that inputs were properly matched across all models.

High Computational Costs
Training deep learning models for each modality (text, audio, motion) and performing the weighted sum fusion demanded substantial computational resources. The need for efficient hardware and optimization techniques was critical to handle the high dimensionality of input data and complex model architectures.

VI. CONCLUSION

This work highlights the significance of integrating text, audio, and motion modalities for achieving effective emotion recognition. By employing the Score-Based Weighted Sum Fusion technique, the outputs from individual modality-specific models were combined into a unified decision, allowing the system to leverage the strengths of each modality. This approach enhanced the overall performance by prioritizing the contributions of more reliable modalities while still incorporating contextual information from others.

The system's design showcased the effectiveness of convolutional networks for textual data, advanced acoustic feature extraction for audio, and spatio-temporal graph modeling for motion. The fusion strategy successfully addressed the limitations of unimodal systems by combining the complementary strengths of different data sources, thereby providing more robust and accurate emotion classification.

This study underscores the potential of multimodal approaches in real-world applications where emotion recognition plays a critical role. Future work can explore improving computational efficiency, addressing real-time processing challenges, and enhancing the performance of individual modalities to further advance the field of emotion recognition.

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