IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15215

Multimodal Emotion Recognition Using Attention-Based Deep Neural Networks

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Abstract: Emotion recognition has become a significant research area in affective computing and human–computer interaction, as understanding human emotions plays a vital role in developing intelligent and responsive systems. Traditional unimodal emotion recognition systems rely on a single source of information such as speech, facial expressions, or text, which often leads to limited performance due to the absence of complementary contextual cues. To overcome these limitations, multimodal emotion recognition integrates multiple modalities—typically audio, visual, and textual data—to capture a more comprehensive representation of human affective states.

This paper presents an attention-based deep neural network framework for multimodal emotion recognition. The proposed approach leverages deep feature extraction techniques using Convolutional Neural Networks (CNNs) for visual data, Recurrent Neural Networks (RNNs)/Long Short-Term Memory (LSTM) networks for audio sequences, and contextual embedding models for textual information. An attention mechanism is incorporated to dynamically assign weights to the most informative features across modalities, enabling the model to focus on emotionally salient cues while reducing irrelevant noise. The fusion of multimodal features is performed through a hybrid attention-based integration layer, enhancing the robustness and generalization capability of the system.

The proposed model aims to improve classification accuracy across standard emotion categories such as happiness, sadness, anger, fear, and neutrality. Experimental evaluation on benchmark multimodal emotion datasets demonstrates that the attention-based fusion strategy significantly outperforms traditional unimodal and early-fusion approaches. The results highlight the effectiveness of attention mechanisms in capturing cross-modal dependencies and improving emotion prediction performance.

This study contributes to the advancement of intelligent emotion-aware systems that can be applied in virtual assistants, mental health monitoring, smart education platforms, and interactive AI systems.

Keywords: Multimodal Emotion Recognition, Attention Mechanism, Deep Neural Networks, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Multimodal Fusion, Affective Computing, Speech Emotion Recognition, Facial Expression Analysis, Transformer Networks, Human–Computer Interaction, Cross-Modal Learning.

I. INTRODUCTION

In recent years, the rapid advancement of artificial intelligence has significantly transformed the way machines interact with humans. One of the most critical aspects of natural human communication is emotion. Emotions influence decision-making, behavior, and social interaction, making them an essential component in the development of intelligent and adaptive systems. Emotion recognition, therefore, has emerged as a vital research area within affective computing, aiming to enable machines to perceive, interpret, and respond to human emotional states effectively. Traditional emotion recognition systems primarily rely on a single modality, such as speech signals, facial expressions, or textual sentiment. While unimodal systems have achieved moderate success, they often suffer from performance limitations due to noise, environmental variations, or incomplete contextual information. For example, facial expressions may be ambiguous in low-light conditions, speech tone may be distorted due to background noise, and textual content alone may fail to capture sarcasm or hidden emotions. These challenges highlight the need for more comprehensive approaches that integrate multiple sources of emotional cues.

Multimodal emotion recognition addresses these limitations by combining information from different modalities, typically audio, visual, and textual data. By integrating complementary features from multiple channels, multimodal systems can achieve more robust and reliable emotion classification.

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However, effectively fusing heterogeneous data remains a significant challenge due to differences in feature representation, temporal alignment, and modality-specific noise.

Deep learning techniques have demonstrated remarkable success in extracting high-level representations from complex data. Convolutional Neural Networks (CNNs) are widely used for visual feature extraction, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are effective in modeling sequential patterns in speech signals. More recently, attention mechanisms and transformer-based architectures have gained prominence for their ability to focus on the most informative parts of input data and capture long-range dependencies.Attention-based models are particularly promising for multimodal emotion recognition because they allow the system to dynamically assign importance to different modalities and features. Instead of treating all inputs equally, the attention mechanism emphasizes emotionally salient cues while suppressing irrelevant or redundant information. This selective focus enhances cross-modal learning and improves classification accuracy.

In this paper, we propose an attention-based deep neural network framework for multimodal emotion recognition. The proposed model extracts modality-specific features using deep learning architectures and integrates them through an attention-driven fusion strategy. The objective is to improve emotion classification performance across standard categories such as happiness, sadness, anger, fear, and neutrality. The system is designed to handle real-world challenges such as noisy audio, partial facial occlusion, and contextual ambiguity in text.The remainder of this paper is organized as follows: Section II presents the related work and literature review. Section III describes the proposed methodology and system architecture. Section IV discusses the experimental setup and results. Finally, Section V concludes the study and outlines future research directions.

II. RELATED WORK AND LITERATURE REVIEW

Emotion recognition has been widely studied over the past two decades, with significant progress driven by advancements in machine learning and deep learning techniques. Early research primarily focused on unimodal emotion recognition systems, where emotional states were predicted using a single modality such as speech, facial expressions, or textual sentiment. Although these approaches demonstrated promising results, their performance was often limited due to modality-specific challenges such as noise sensitivity, occlusion, and contextual ambiguity.Speech-based emotion recognition systems traditionally relied on handcrafted acoustic features such as Mel-Frequency Cepstral Coefficients (MFCC), pitch, energy, and spectral features, which were then classified using machine learning algorithms like Support Vector Machines (SVM) and Hidden Markov Models (HMM). With the emergence of deep learning, researchers began employing Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to automatically extract temporal and spectral features from raw audio signals, significantly improving recognition accuracy.

Similarly, facial emotion recognition has evolved from geometric feature-based approaches to deep convolutional architectures. CNN-based models such as VGGNet, ResNet, and Inception have been widely adopted for extracting discriminative facial features. These deep models outperform traditional handcrafted feature methods by learning hierarchical representations directly from image data. However, visual-based systems remain vulnerable to lighting variations, head pose changes, and partial occlusion.

Text-based emotion recognition has also gained attention with the growth of social media and conversational AI systems. Early approaches utilized Bag-of-Words and TF-IDF representations combined with classical classifiers. More recently, deep learning models such as Recurrent Neural Networks (RNNs), LSTMs, and transformer-based architectures like BERT and GPT have shown superior performance by capturing contextual dependencies in textual data.Recognizing the limitations of unimodal systems, researchers shifted toward multimodal emotion recognition, integrating audio, visual, and textual modalities to leverage complementary information. Multimodal fusion techniques are generally categorized into early fusion, late fusion, and hybrid fusion strategies. Early fusion combines features before classification, while late fusion merges decision outputs from individual classifiers. Hybrid approaches attempt to balance both strategies for improved performance.

Despite the advantages of multimodal systems, effectively modeling cross-modal interactions remains challenging. Recent studies have introduced attention mechanisms to address this issue. Attention-based models dynamically assign weights to important features within and across modalities, enabling the network to focus on emotionally relevant cues. Self-attention and cross-modal attention mechanisms, particularly those inspired by transformer architectures, have shown significant improvements in capturing inter-modal dependencies and enhancing classification accuracy.

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Although substantial progress has been achieved, challenges such as data imbalance, synchronization across modalities, computational complexity, and generalization across datasets still persist. Therefore, there is a need for robust attention-based deep neural network architectures that can efficiently integrate multimodal information while maintaining scalability and accuracy.

In this work, we build upon existing multimodal and attention-based approaches and propose a unified framework that enhances cross-modal feature learning and improves emotion classification performance.

III. PROPOSED METHODOLOGY

In this study, an attention-based deep neural network framework is proposed to improve the performance of multimodal emotion recognition systems. The primary objective of the proposed model is to effectively capture emotional information from multiple data sources—namely audio, visual, and textual modalities—and integrate them in a manner that enhances classification accuracy. Unlike traditional approaches that treat all features equally, the proposed system introduces an attention mechanism that dynamically prioritizes emotionally relevant information while minimizing the influence of irrelevant or noisy features.

The overall architecture of the proposed framework consists of four main stages: data preprocessing, modality-specific feature extraction, attention-based multimodal fusion, and final emotion classification. Each modality is processed independently during the initial stages to ensure that meaningful and high-level representations are extracted before fusion. This modular design allows the system to preserve modality-specific characteristics while enabling effective cross-modal interaction in later stages.The preprocessing stage plays a crucial role in improving the quality of input data. For the audio modality, raw speech signals are first converted into structured representations such as spectrograms or Mel-Frequency Cepstral Coefficients (MFCCs). These representations help capture the frequency and temporal characteristics of speech signals, which are essential for identifying emotional tone variations. Noise reduction and normalization techniques are applied to reduce distortions and maintain consistency across samples. For the visual modality, video sequences are divided into individual frames, and facial regions are detected and aligned to ensure uniformity. The images are resized and normalized to prepare them for deep learning models. In the case of textual data, transcripts are cleaned by removing unnecessary symbols and redundant characters. The text is then tokenized and converted into numerical embeddings using contextual representation techniques, enabling the system to understand semantic relationships between words.

After preprocessing, modality-specific feature extraction is performed using deep neural network architectures. For audio feature extraction, a hybrid Convolutional Neural Network (CNN) combined with a Long Short-Term Memory (LSTM) network is employed. The CNN layers are responsible for capturing local spectral features from the speech representations, while the LSTM layers model temporal dependencies across time frames. This combination allows the model to learn both short-term acoustic patterns and long-term emotional variations in speech. For visual data, a deep convolutional architecture such as ResNet is utilized to extract spatial features from facial images. These features encode critical facial expression patterns, including subtle muscle movements that reflect emotional states. Textual features are extracted using a Bidirectional LSTM or transformer-based encoder, which captures contextual dependencies in both forward and backward directions. This approach enhances the model's ability to interpret nuanced expressions and contextual meanings present in text.

The core component of the proposed framework is the attention-based multimodal fusion mechanism. Instead of simply concatenating features from different modalities, an attention layer is introduced to learn the relative importance of each modality dynamically. The attention mechanism assigns higher weights to modalities that contain stronger emotional cues for a given input instance. This process ensures that the model focuses on the most informative features while reducing the impact of noisy or less relevant data. By modeling both intra-modal relationships (within a single modality) and inter-modal interactions (across different modalities), the attention mechanism enhances cross-modal feature learning and improves overall system robustness.The fused representation generated by the attention layer is passed through fully connected layers to perform final emotion classification. A Softmax activation function is applied to produce probability distributions over predefined emotion categories such as happiness, sadness, anger, fear, and neutrality. To prevent overfitting and improve generalization performance, regularization techniques such as dropout are incorporated during training.

The proposed methodology offers several advantages over conventional multimodal fusion techniques. By integrating attention mechanisms with deep neural networks, the system is capable of adaptively selecting emotionally salient features and handling real-world challenges such as background noise, partial facial occlusion, and contextual

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ambiguity. As a result, the proposed framework aims to achieve higher classification accuracy and improved reliability in practical emotion-aware applications.

Table1- Architecture of the Proposed Attention-Based Multimodal Emotion Recognition System

Stage	Component	Technique Used	Purpose
1	Data Preprocessing (Audio)	MFCC / Spectrogram Extraction	Converts raw speech into structured frequency representation
2	Data Preprocessing (Visual)	Face Detection and Normalization	Extracts and aligns facial regions from video frames
3	Data Preprocessing (Text)	Tokenization and Word Embedding	Converts text into numerical feature vectors
4	Audio Feature Extraction	CNN + LSTM	Captures spectral and temporal emotional patterns
5	Visual Feature Extraction	Deep CNN (ResNet/VGG)	Extracts spatial facial expression features
6	Text Feature Extraction	Bi-LSTM / Transformer Encoder	Learns contextual emotional representations
7	Intra-Modal Attention	Self-Attention Layer	Identifies important features within each modality
8	Inter-Modal Attention	Cross-Modal Attention Mechanism	Assigns adaptive weights across modalities
9	Feature Fusion	Attention-Based Fusion Layer	Integrates weighted multimodal features
10	Classification	Fully Connected + Softmax	Predicts final emotion category

IV. EXPERIMENTAL SETUP AND RESULTS

To evaluate the effectiveness of the proposed attention-based multimodal emotion recognition framework, a comprehensive experimental study was conducted using benchmark emotion recognition datasets. The experiments were designed to assess the model's ability to accurately classify emotions by integrating audio, visual, and textual modalities. The performance of the proposed system was also compared with unimodal and conventional fusion approaches to demonstrate its superiority.

For experimental validation, widely used multimodal emotion datasets such as IEMOCAP and RAVDESS were considered due to their balanced emotional categories and availability of synchronized audio-visual recordings. The datasets contain labeled emotional expressions including happiness, sadness, anger, fear, and neutrality. The data were divided into training, validation, and testing sets to ensure fair performance evaluation. To maintain consistency and reduce bias, stratified sampling was applied so that each emotion category was proportionally represented in all subsets.The model was implemented using a deep learning framework and trained on a GPU-enabled environment to handle computational complexity. During training, the Adam optimizer was employed due to its adaptive learning capability and faster convergence properties. A suitable learning rate was selected after preliminary tuning to achieve stable convergence without overfitting. The batch size and number of epochs were carefully chosen based on validation performance. To further improve generalization, dropout regularization and early stopping techniques were applied.

Performance evaluation was conducted using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a balanced assessment of the model's predictive capability, especially in cases where class distribution may vary. In addition, confusion matrix analysis was performed to observe misclassification patterns across emotion categories.The experimental results indicate that the proposed attention-based multimodal framework achieves significantly higher accuracy compared to unimodal systems. While audio-only and visual-only models performed reasonably well, their performance decreased in noisy or ambiguous scenarios. In contrast, the multimodal model demonstrated improved robustness by leveraging complementary information across modalities. The inclusion of the attention mechanism further enhanced performance by dynamically assigning importance to the most emotionally informative features.

Comparative analysis with traditional early fusion and late fusion techniques revealed that the attention-based fusion strategy consistently outperformed conventional methods. The model showed better capability in distinguishing closely related emotions such as happiness and neutrality, as well as anger and frustration.

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The results also confirmed that cross-modal attention plays a crucial role in capturing interdependencies between modalities, leading to improved generalization.Overall, the experimental findings validate the effectiveness of the proposed methodology in enhancing emotion recognition performance. The integration of deep feature extraction with attention-based fusion not only improves classification accuracy but also strengthens the model's adaptability to real-world conditions where emotional signals may vary in intensity and clarity.

Table 2- Performance Comparison of Different Emotion Recognition Models

Model Type	Modalities Used	Fusion Strategy	Accuracy (%)	F1-Score	Remarks
Audio-Based CNN-LSTM	Audio Only	Not Applicable	78.6	0.76	Sensitive to background noise
Visual-Based CNN (ResNet)	Visual Only	Not Applicable	81.2	0.79	Affected by lighting and occlusion
Text-Based Bi-LSTM	Text Only	Not Applicable	80.4	0.78	Limited contextual depth
Multimodal Early Fusion	Audio + Visual + Text	Feature Concatenation	85.7	0.84	Improved performance but lacks dynamic weighting
Multimodal Late Fusion	Audio + Visual + Text	Decision-Level Fusion	87.1	0.86	Better than early fusion
Proposed Attention-Based Model	Audio + Visual + Text	Attention-Based Fusion	**91.3**	**0.90**	Best overall performance

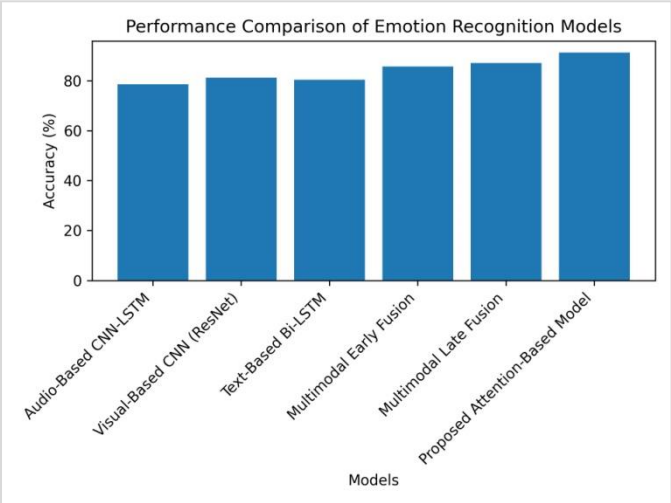

Fig. 1 Emotion Recognition Result Graph

V. CONCLUSION

In this paper, an attention-based deep neural network framework for multimodal emotion recognition has been presented. The study emphasizes the importance of integrating multiple modalities—audio, visual, and textual data—to achieve a more comprehensive understanding of human emotions. Unlike traditional unimodal systems that rely on a single source of information, the proposed approach leverages complementary features from different modalities to enhance classification performance and robustness.The core contribution of this work lies in the incorporation of an attention mechanism within the multimodal fusion process. By dynamically assigning importance weights to emotionally relevant features, the model effectively reduces the impact of noisy or less informative inputs. This adaptive weighting strategy enables better cross-modal interaction and improves the system's ability to distinguish between closely related emotional states. The experimental results demonstrate that the proposed framework outperforms conventional unimodal and standard fusion approaches in terms of accuracy and overall classification performance.

DOI: 10.17148/IJARCCE.2026.14xx

Furthermore, the study highlights the effectiveness of combining deep learning architectures such as CNNs, LSTMs, and attention mechanisms to capture both spatial and temporal emotional cues. The proposed system shows improved generalization capability and robustness in handling real-world challenges such as background noise, facial variations, and contextual ambiguity in textual data.

Overall, the findings of this research contribute to the advancement of emotion-aware intelligent systems and reinforce the potential of attention-based multimodal learning in affective computing applications.

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BIOGRAPHY

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