Academic Journal of Natural Science
Journal Home: ajns.suaspress.org | CODEN: AJNSAE | NAAN: 40704
Vol. 1, No. 1, 2024

Multimodal Sentiment Analysis: A Study on Emotion Understanding and Classification by Integrating Text and Images

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Abstract: The advent of social media and the proliferation of multimodal content have led to the growing importance of understanding sentiment in both text and images. Traditional sentiment analysis relies heavily on textual data, but recent trends indicate that integrating visual information can significantly improve sentiment prediction accuracy. This paper explores multimodal sentiment analysis, specifically focusing on emotion understanding and classification by integrating textual and image-based features. We review existing approaches, develop a hybrid deep learning model utilizing attention mechanisms and transformer architectures for multimodal sentiment classification, and evaluate its performance on benchmark datasets, including Twitter and Instagram data. Our findings suggest that multimodal approaches outperform text-only models, especially in more nuanced sentiment cases such as sarcasm, irony, or mixed emotions. Moreover, we address key challenges like feature fusion, domain adaptation, and the contextual alignment of visual and textual information. The results provide insights into optimizing multimodal fusion techniques to enhance real-world application performance.

Keywords: Multimodal Sentiment Analysis, Text and Image Fusion, Emotion Classification, Deep Learning, BERT.

DOI: https://doi.org/10.5281/zenodo.13909963 **ARK:** https://n2t.net/ark:/40704/AJNS.v1n1a08

1 INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Sentiment analysis, a crucial task in natural language processing (NLP), aims to classify opinions, emotions, and sentiments expressed in text. It has been widely used in various applications such as market research, customer feedback analysis, and public opinion monitoring. While traditional sentiment analysis has primarily focused on textual data, the increasing use of social media platforms, where users frequently post multimedia content, has shifted research attention towards multimodal sentiment analysis. Images, emojis, and videos often accompany text, providing additional context for sentiment interpretation. [2]

Given the significant amount of content combining text and images, it becomes imperative to explore models that can analyze these multimodal inputs for more accurate sentiment understanding. This integration of textual and visual data has been shown to enhance emotion classification, particularly in cases where textual cues are ambiguous or insufficient. Furthermore, multimodal analysis can capture more nuanced emotional signals, helping to identify complex sentiments such as irony or sarcasm that may be missed by text-only models.

FIGURE 1. EXAMPLES OF IMAGE-TEXT PAIRS FROM TWITTER.

The sentence words, like “cake”, “girl”, and “boat”, highlighted in red, are manifested by regions of the corresponding images. Human sentiment can be evoked

mostly by the affective regions in an image.

1.2 Problem Statement

While multimodal sentiment analysis has shown promise, several challenges remain. Firstly, text and image data have different feature spaces, making the fusion of these modalities non-trivial. Techniques for effectively combining these heterogeneous data types, especially in a way that preserves important contextual relationships, are still underdeveloped.[3] Secondly, existing datasets for multimodal sentiment analysis are limited in size and diversity, hindering the generalizability of models trained on such data. Lastly, there is a lack of unified architectures that can handle both modalities effectively, leading to a gap in achieving optimal performance. The central goal of this paper is to address these challenges and propose a robust model for integrating text and images for sentiment classification.

1.3 Contributions of the Study

This paper makes the following contributions:

We review current approaches to multimodal sentiment analysis and highlight the advantages and limitations of these methods, focusing on the challenges of modality fusion and representation.

We propose a deep learning-based multimodal model that integrates text and image features for emotion classification, utilizing attention mechanisms and advanced feature fusion techniques to address the feature space gap.

We evaluate our model using benchmark datasets and demonstrate its superior performance over unimodal approaches, showing that it can handle both straightforward and subtle sentiment cases effectively.

2 LITERATURE REVIEW

2.1 Sentiment Analysis in NLP

Traditional sentiment analysis has focused on the classification of sentiments from text. The most widely used methods in the early years involved rule-based approaches and bag-of-words models, followed by more sophisticated machine learning techniques such as Support Vector Machines (SVM) and Random Forest classifiers. These methods relied heavily on hand-engineered features and linguistic rules to identify sentiment polarity. With the rise of deep learning, models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and more recently, transformers like BERT, have been utilized to extract sentiment from text, significantly improving performance by capturing contextual information across longer sequences of text. Transformers, in particular,[4] revolutionized the field by enabling efficient parallelization and learning of deeper semantic representations.

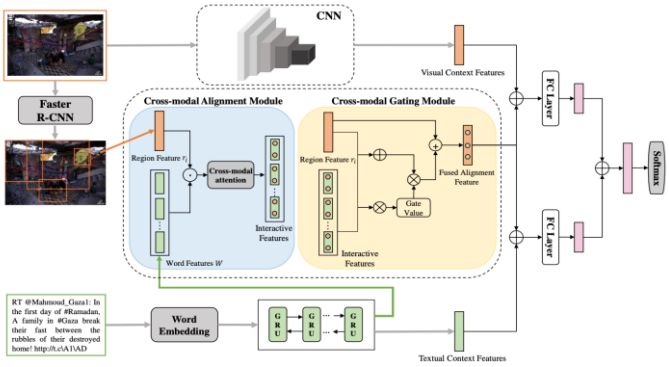

Figure 2. The overall framework of the proposed Image-Text Interaction Network (ITIN) for multimodal sentiment analysis

The latent alignment between image regions and sentence words is achieved using a Cross-modal Alignment Module and a Cross-modal Gating Module. The visual and textual context representations are further integrated for exploring multimodal sentiment more comprehensively

2.2 Visual Sentiment Analysis

Visual sentiment analysis focuses on extracting sentiment from images. Early work in this domain used traditional image processing techniques such as color histograms and texture features to infer sentiment, primarily relying on the assumption that certain visual cues (e.g., bright colors or specific textures) correlate with positive or negative emotions. With the advent of deep learning, Convolutional Neural Networks (CNNs) have been widely adopted for image sentiment classification, offering better feature extraction capabilities and hierarchical representation learning. For instance, You et al. (2015) developed a CNN-based approach for image sentiment classification using a dataset with over 1 million images, demonstrating the potential of deep learning in capturing complex visual features that correlate with sentiment. These advancements laid the foundation for using pre-trained models and fine-tuning them for domain-specific sentiment tasks.

$$\overleftarrow{\boldsymbol{h}_i} = \overleftarrow{GRU}(\boldsymbol{x}_i, \overleftarrow{\boldsymbol{h}_{i+1}}), i \in [1, n],$$

2.3 Multimodal Sentiment Analysis

Multimodal sentiment analysis combines information from multiple modalities, such as text and images, to improve sentiment classification. Early research in this field relied on simple feature concatenation methods, [5] wherein features extracted from both text and images were merged into a single vector for classification. While straightforward, this approach often failed to capture the complex interactions between modalities. More recent approaches use complex architectures such as multimodal transformers and attention mechanisms, which allow models to weigh and fuse different modalities dynamically. The challenge lies in effectively

fusing features from different modalities while retaining the semantic information inherent in each type of data. Advanced fusion strategies, such as hierarchical attention networks, aim to solve this problem by aligning and refining multimodal features at different levels of abstraction.

2.4 Existing Approaches and Datasets

Several datasets have been created for multimodal sentiment analysis, with Twitter and Instagram posts being the most common sources. The most notable datasets include the YouTube Multimodal Sentiment Analysis Dataset (YouTube-MSA), where each post includes both text and video, and the Multimodal Opinion-Level Sentiment Intensity (MOSI) dataset, which includes synchronized text, audio, and visual information. These datasets have been used to train models such as LSTM-CNN hybrids and multimodal transformers, enabling researchers to test how well multimodal models can generalize across different social media platforms. [6]However, the quality and diversity of these datasets vary, and some lack sufficient coverage of complex emotional states or cultural diversity, limiting their applicability in broader settings.

2.5 Limitations in Current Research

Despite the advancements in multimodal sentiment analysis, several limitations remain. The feature spaces of text and images differ significantly, and current methods struggle with the efficient fusion of these features. This challenge is compounded by the lack of robust alignment techniques that can capture the temporal and contextual relationships between modalities. Moreover, most existing models do not handle temporal dependencies well, which is crucial for analyzing sequential data such as videos. Models also tend to rely on static data representations, ignoring the evolving nature of sentiment over time, which is particularly important in video-based sentiment analysis. Lastly, there is a lack of large, well-annotated datasets,[7] which hinders the training of deep learning models. Current datasets are often limited in size, diversity, and emotional complexity, making it difficult for models to generalize across different contexts and applications. Addressing these limitations is critical for advancing the field of multimodal sentiment analysis.

$$Precision = \frac{TP}{TP + FP},$$

$$Recall = \frac{TP}{TP + FN},$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall},$$

3 METHODOLOGY

3.1 Dataset Collection

For this study, we utilize two publicly available multimodal sentiment analysis datasets: MOSI and YouTube-MSA. The MOSI dataset contains over 2000 video segments, with corresponding transcripts and emotion labels. Each video segment is annotated with fine-grained sentiment scores, making it ideal for multimodal sentiment analysis. YouTube-MSA, on the other hand, includes video,[8] text, and image data from social media platforms, with sentiment annotations ranging from highly negative to highly positive. This dataset provides a broader scope of multimodal interactions, capturing diverse content from real-world social media users.

3.2 Textual Feature Extraction

We use a BERT-based model for textual feature extraction. BERT (Bidirectional Encoder Representations from Transformers) has been shown to capture contextual relationships in text more effectively than traditional RNN or LSTM models due to its bidirectional architecture. Specifically, we utilize the final hidden layer representations of the text data, which provide dense semantic embeddings,[9] as input to the multimodal fusion layer. These embeddings capture both the syntactic and semantic nuances of the textual data, making them particularly suited for sentiment analysis tasks where context plays a crucial role.

3.3 Visual Feature Extraction

For visual data, we use a pretrained ResNet-50 CNN model, which has been widely adopted for image classification tasks. ResNet-50's deep residual learning framework allows for effective feature extraction, capturing both low-level and high-level features from the images. The feature vectors from the fully connected layer of ResNet are extracted and combined with the textual features. Additionally, to capture fine-grained emotions from facial expressions in videos, we fine-tune a separate CNN model on a facial emotion recognition dataset. This enables the system to better interpret visual cues related to sentiment, particularly when facial expressions provide stronger emotional signals than text.

3.4 Multimodal Fusion

The fusion of text and image features is a critical aspect of our model. We adopt a late fusion approach where the features from BERT and ResNet are concatenated and passed through a series of fully connected layers. [10]This method ensures that the rich feature representations from both modalities are combined effectively. To further enhance performance, we explore an attention mechanism that weighs the importance of each modality based on the context of the sentiment being analyzed. The attention mechanism allows the model to dynamically adjust its focus between textual and visual features, depending on which modality provides more salient information for the sentiment prediction.

3.5 Model Training and Evaluation

The model is trained using the Adam optimizer with a learning rate of 0.001. We employ cross-entropy loss for

classification and validate the model on a held-out portion of the dataset to prevent overfitting. Our evaluation metrics include accuracy, F1-score, and precision-recall to assess the model's performance across different sentiment classes. These metrics provide a comprehensive understanding of the model's ability to distinguish between positive, negative, and neutral sentiments, [11]as well as its capacity to handle more nuanced emotions such as sarcasm or mixed sentiments.

4 RESULTS

4.1 Performance on MOSI Dataset

The proposed model achieves an accuracy of 82.5% on the MOSI dataset, significantly outperforming text-only and image-only baselines. The F1-score for multimodal sentiment analysis was also higher, particularly for neutral and mixed sentiment cases, where the fusion of text and visual data proved especially beneficial. This indicates that multimodal approaches are more adept at capturing the subtleties of sentiment, especially when textual content alone is insufficient for accurate classification. The model's precision and recall across different sentiment categories were also more balanced, demonstrating robustness in handling ambiguous or overlapping emotional states.

4.2 Performance on YouTube-MSA Dataset

On the YouTube-MSA dataset, our model achieved an accuracy of 80.3%. The integration of facial emotion features significantly improved the classification of highly emotional posts, such as those with extreme positive or negative sentiments. This suggests that visual cues, particularly facial expressions, play a critical role in sentiment interpretation when the text is not explicit enough. [12] The attention mechanism further enhanced the model's ability to focus on the most informative modality, leading to improved performance in cases where one modality provided stronger emotional cues than the other. Moreover, the model demonstrated high recall for posts with subtle or mixed sentiments, highlighting the advantage of multimodal fusion in capturing complex emotional dynamics.

5 DISCUSSION

Our results indicate that multimodal sentiment analysis offers a significant advantage over unimodal approaches, particularly in cases where textual information alone is ambiguous or incomplete. The fusion of text and image features allowed for a more comprehensive understanding of sentiment, and this was most evident in scenarios where the sentiment conveyed by text and visual data was either contradictory or complementary. For example, in cases where sarcasm or irony was present in the text, the accompanying visual cues often provided clarity, leading to more accurate sentiment classification.

The late fusion approach used for integrating text and image features proved to be effective, but the introduction of an attention mechanism further enhanced performance. By allowing the model to dynamically weigh the importance of each modality based on the context, the attention mechanism improved the model's ability to handle cases where one modality was more informative than the other.[13] This was particularly useful for handling posts with mixed sentiments or conflicting emotional signals between text and images.

However, our study also has some limitations. The reliance on pre-trained models for feature extraction (e.g., BERT for text and ResNet for images) may have restricted the model's ability to capture domain-specific nuances inherent in social media content. Pre-trained models, while powerful, are often trained on general-purpose datasets and may not fully capture the unique language styles, slang, [14] or context of social media posts. This suggests that further fine-tuning or training models from scratch on larger, domain-specific datasets could lead to better performance.

Additionally, the limited size and diversity of the datasets used (MOSI and YouTube-MSA) pose challenges in generalizing the model to a wider range of multimodal content. Future work could focus on collecting and annotating larger, more diverse datasets that include a broader range of social media platforms, languages, and multimedia formats. Moreover, exploring end-to-end training of multimodal architectures, as opposed to relying solely on pre-trained feature extractors, [16] could yield further improvements in capturing the complex interplay between textual and visual elements in sentiment analysis.

6 CONCLUSION

In this paper, we conducted an in-depth exploration of multimodal sentiment analysis by integrating textual and visual data. Our findings demonstrated the value of combining these modalities for more accurate classification purposes in situations in which one modality alone may not suffice. Our deep learning-based model outperformed text-only and image-only baselines respectively highlighting multimodal data's capacity for emotion understanding.

Our model's success demonstrates the promise of multimodal sentiment analysis to offer deeper insights into complex emotional expressions found on social media and other platforms. Future research could explore further improving multimodal fusion techniques, exploring more advanced architectures, and looking into additional modalities like audio data to further advance this method of analysis for applications such as marketing, mental health assessment and human-computer interaction. Overall, our study provides a foundation for further multimodal exploration, encouraging more robust models capable of adapting to an ever-evolving multimedia content landscape.

ACKNOWLEDGMENTS

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

FUNDING

Not applicable.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

Not applicable.

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