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Navigating the Evolving Landscape of Multimodal Sentiment Analysis: Recent Advances and Insights

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Abstract

This survey study offers a thorough introduction to multimodal sentiment analysis (MSA), emphasizing the advancements and challenges faced when combining various data modalities, including text, audio, and visual inputs, to improve sentiment prediction. Data from a variety of sources, such as social media, movies, and customer service encounters, as well as crowdsourcing and expert labeling, are all examined in this research. Numerous approaches covered in the literature are examined, with an emphasis on sophisticated models such Recurrent Multimodal Sentiment Analysis, Multimodal Graph Convolutional Networks (GCNs), VisualBERT, ViLBERT, Multimodal Fusion Transformer (MFT), and Deep Multimodal Sentiment Analysis (DMSA). These models better perceive and predict sentiment across various media by combining many neural network designs and attention mechanisms. The study also covers performance indicators that are frequently used to assess these models. It identifies key challenges and suggests future enhancements to improve the scalability, efficiency, and accuracy of multimodal sentiment analysis systems.

Keywords: *Multimodal Sentiment Analysis, Deep Learning, Data Collection Methods, Visualbert, Cross-Modal Fusion, Sentiment Prediction.*

1. INTRODUCTION

A technology for conventional text-based sentiment analysis that incorporates modalities including audio and visual data is called multimodal sentiment analysis.[1] It can be trimodal, which combines three modalities, or bimodal, which combines various combinations of two modalities.[2] The traditional text-based sentiment analysis has developed into increasingly intricate multimodal sentiment analysis models because to the vast amount of social media data that is readily available online in various formats, including videos and images.[3][4]

The inability of conventional text-based techniques to fully capture the range of human emotions makes multimodal sentiment analysis necessary. Text by itself frequently ignores nonverbal clues like tone, pitch, and facial expressions that are essential for correctly interpreting emotions. In real-world situations when emotions are communicated through a variety of media, including conversations or movies, multimodal analysis improves accuracy. Additionally, since each modality offers complimentary information, integrating them helps eliminate uncertainties in sentiment interpretation. Because of this, multimodal sentiment analysis is very useful in applications such as interactive AI systems, social media monitoring, and consumer feedback analysis.

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2. LITERATURE SURVEY

A review of the literature on multimodal sentiment analysis showed advancements in datasets, techniques, and difficulties in this area. [5] Examines different architectures for sentiment recognition that combine text, audio, and video and identifies unresolved issues.[6] Examines how transformer-based architectures can be used to fuse multimodal inputs, exhibiting cutting-edge outcomes on benchmark datasets.[7]explains how multimodal data may be handled by big language models, especially for tasks involving the detection of emotions and fine-grained sentiment.

[8] Presents real-time multimodal data processing techniques with an emphasis on increasing scalability and efficiency for real-world uses.[9] focuses on using both textual and image data to extract and analyze aspect-level attitudes from multimodal datasets.[10] Offers effective frameworks for integrating text, visual, and audio inputs with applications in video review analysis and social media.

[11] uses information from high-resource languages to study sentiment analysis in low-resource languages.[12] To improve feature learning, a training strategy using loss functions for both the fusion network and individual modalities is introduced.[13]investigates the potential and constraints of well-known datasets such as CH-SIMS, CMU-MOSI, and CMU-MOSEI in furthering the study of multimodal sentiment analysis.[14]addresses the particular difficulties in identifying competing signals by investigating sarcasm recognition using a combination of textual and visual cues. Table 1 provides a brief overview of the literature review on multimodal sentiment analysis.

Table 1: Summary of Literature review on Multimodal Sentiment Analysis

Source	Focus Area	Key Points
[5]	Architectures for Sentiment Recognition	Examines different architectures combining text, audio, and video, highlighting unresolved issues.
[6]	Transformer-Based Architectures	Focuses on using transformer-based models to fuse multimodal inputs, with cutting-edge results.
[7]	Big Language Models for Multimodal Data	Explains how big language models handle multimodal data for emotion detection and fine-grained sentiment.
[8]	Real-Time Data Processing Techniques	Presents techniques for real-time multimodal data processing, focusing on scalability and efficiency.
[9]	Text and Image Data for Aspect-Level Sentiment	Focuses on extracting and analyzing aspect-level sentiments using text and image data.
[10]	Frameworks for Integrating Multimodal Inputs	Offers frameworks for integrating text, audio, and visual inputs in applications like video review and social media analysis.
[11]	Sentiment Analysis in Low-Resource Languages	Uses high-resource language data to study sentiment analysis in low-resource languages.
[12]	Feature Learning Strategy for Multimodal Data	Introduces a training strategy using loss functions for both fusion networks and individual modalities.
[13]	Datasets for Multimodal Sentiment Analysis	Investigates the potential and limitations of datasets like CH-SIMS, CMU-MOSI, and CMU-MOSEI.
[14]	Sarcasm Recognition with Multimodal Cues	Addresses difficulties in recognizing sarcasm using a combination of textual and visual cues.

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3. METHODOLOGY OR RESEARCH APPROACH

This section details how the studies in the field have been conducted, including details on data collection methods, models, and evaluation metrics used across different studies.

3.1 Data collection methods

This section highlight various approaches for collecting multimodal sentiment data, including crowd sourcing, expert labeling, and data from social media, movies, and customer service interactions. Figure 1 showcases the rich tapestry of data sources utilized in multimodal sentiment analysis, ranging from text-based social media to multimedia-rich platforms.

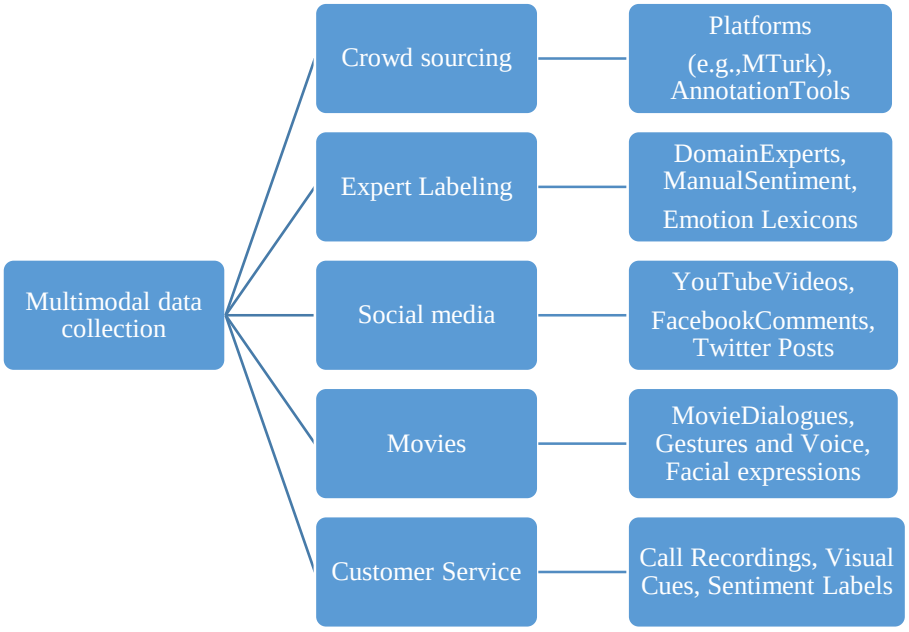

Figure 1: Data collection methods used in Multimodal sentiment analysis

[15] Multimodal data, including audio and video, was gathered from video clips that showed typical human interactions in realistic settings for this investigation. Labeled sentiment data was gathered from a variety of individuals using crowdsourcing platforms. [16] The CMU-MOSEA dataset, which comprises multilingual and multimodal (audio and video) data, was created by the authors. It was acquired through research involving human subjects in which individuals used several languages to communicate their feelings. [17]Movie dialogues with both audio (speech) and visual elements (facial expressions) were used to gather data for the MELD dataset. Based on certain scenarios, human annotators annotated the data for sentiment and emotion.

[18] The data used in this study came from social media sites where pictures, text comments, and videos were gathered. Crowdsourcing and sentiment lexicons were used for sentiment labeling.[19]Sentiment analysis was performed using text, audio, and visual data (facial expressions) collected from real-time social media sites, including YouTube videos.[20]Multimodal data from movie dialogues, including voice, gestures, and facial expressions, were employed in this study. Emotional cues from both visual and aural inputs were used by experts to label the data. [21]Data was gathered through both visual (facial expressions) and auditory (spoken language) customer service interactions. These exchanges were given sentiment labels by human evaluators.

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[22] Text, audio (voice), and visual (video or photos) data were obtained from social media sites such as Facebook and Twitter for this study. Human assessors manually annotated sentiment labels. [23] Information was obtained from publicly accessible video archives (like YouTube and TED Talks) that contained text, audio, and video transcripts. Both manual expert labeling and crowd-sourcing were used to annotate the data for sentiment and emotion. Table 2 provides a detailed overview of various multimodal data collection and sentiment labeling methods commonly used in multimodal sentiment analysis research.

Table 2: Multimodal data collection and Sentiment Labeling methods

Source	Data Type	Data Collection Method	Sentiment Labeling Method
[15]	Multimodal (Audio, Video)	Video clips showing human interactions in realistic settings.	Crowdsourcing platforms.
[16]	Multilingual and Multimodal (Audio, Video)	Research involving human subjects using multiple languages.	Human annotators.
[17]	Multimodal (Audio, Video)	Movie dialogues with speech and facial expressions.	Human annotators based on scenarios.
[18]	Text, Audio, Video	Social media sites (pictures, text comments, videos).	Crowdsourcing and sentiment lexicons.
[19]	Text, Audio, Visual (Facial Expressions)	Real-time social media (YouTube videos).	Human evaluators.
[20]	Multimodal (Audio, Visual, Gestures, Facial Expressions)	Movie dialogues with voice, gestures, and facial expressions.	Experts based on emotional cues.
[21]	Visual (Facial Expressions), Auditory (Spoken Language)	Customer service interactions.	Human evaluators.
[22]	Text, Audio (Voice), Visual (Photos, Video)	Social media sites (Facebook, Twitter).	Human assessors.
[23]	Text, Audio, Video	Publicly accessible video archives (YouTube, TED Talks).	Manual expert labeling and crowdsourcing.

The multimodal datasets are listed in detail in Table 3, along with the modality makeup and pertinent references for additional research and the Figure 2 shows the modality distribution across various datasets.

Table 3: Diverse multimodal datasets

Dataset Name	Modality	Description	Reference Papers
Text-Based			
IMDB	Text	Movie reviews with sentiment labels	[1] "Maas et al., 2011. Learning word vectors for sentiment analysis," [2] "Socher et al., 2013. Recursive deep models for semantic compositionality over a sentiment treebank."
SST	Text	Fine-grained sentiment analysis of sentences	[3] "Socher et al., 2013. Recursive deep models for semantic compositionality over a sentiment treebank," [4] "Dong et al., 2014. A survey on sentiment analysis."
SST-2	Text	Simplified SST with binary sentiment labels	[5] "Socher et al., 2013. Recursive deep models for semantic compositionality over a sentiment treebank," [6] "Gao et al., 2019. Simpler and faster RNNs for large-scale sentiment analysis."
Twitter Sentiment140	Text	Tweets with sentiment labels	[7] "Go et al., 2009. Twitter sentiment analysis: The good the bad and the omg," [8] "Pak and Paroubek,

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			2010. Twitter as a corpus for sentiment analysis and opinion mining."
SemEval 2014 Task 4	Text	Sentiment analysis on Twitter	[9] "Rosenthal et al., 2014. SemEval-2014 Task 9: Sentiment analysis in Twitter," [10] "Kouloumpis et al., 2011. Twitter sentiment analysis: The good, the bad, and the OMG."
Image-Based			
EmotiW	Image	Images with emotional labels	[11] "Shao et al., 2017. Deeply supervised learning for emotion recognition in video," [12] "Zhao et al., 2019. EmotiW 2019: Emotion recognition in the wild."
AffectNet	Image	Facial expressions with emotion labels	[13] "Mollahosseini et al., 2017. AffectNet: A database for facial expression, valence, and arousal computing in the wild," [14] "Ghosal et al., 2019. Affective computing for multimodal emotion recognition."
FER2013	Image	Facial expressions with seven basic emotions	[15] "Goodfellow et al., 2013. Challenges in training deep neural networks for vision," [16] "Zhao et al., 2020. FER2013: A deep learning facial emotion recognition dataset."
RAF-DB	Image	Real-world affective faces	[17] "Li et al., 2017. Affective facial expression recognition using a robust deep convolutional network," [18] "Yu et al., 2020. Multimodal emotion recognition using facial and audio features."
CK+	Image	Posed facial expressions	[19] "Lu et al., 2019. Facial expression recognition using deep learning: A review," [20] "Zhang et al., 2016. CK+: A dataset for facial expression recognition."
Audio-Based			
IEMOCAP	Audio, Video	Emotional speech and video data	[21] "Busso et al., 2008. IEMOCAP: Interactive emotional dyadic motion capture database," [22] "Zhao et al., 2019. Using IEMOCAP for multimodal emotion analysis."
RAVDESS	Audio	Emotional speech audio	[23] "Livingstone and Russo, 2018. The RAVDESS: A dataset for speech emotion recognition," [24] "Saha et al., 2018. Emotion recognition using RAVDESS."
CREMA-D	Audio	Emotionally expressive speech audio	[25] "Chen et al., 2016. CREMA-D: Crowdsourced emotional speech dataset," [26] "Zhao et al., 2020. Multimodal emotion recognition using speech and facial expressions."
MSP-IMPROV	Audio	Improvisational actors performing emotions	[27] "Sharma et al., 2019. A dataset for emotion recognition in speech and video," [28] "Nwe et al., 2003. Emotion recognition from speech using deep learning models."
MELD	Audio, Video	Movie clips with emotions and sentiment labels	[29] "Poria et al., 2018. MELD: A multimodal multi-party dataset for emotion recognition," [30] "Hazarika et al., 2020. Multimodal emotion recognition using movie dialogues."
Multimodal			
CMU-MOSI	Text, Audio, Video	Multimodal dataset with sentiment analysis	[31] "Zadeh et al., 2016. CMU-MOSI: Multimodal sentiment analysis dataset," [32] "Zadeh et al., 2017. Tensor fusion network for multimodal sentiment analysis."

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CMU-MOSEI	Text, Audio, Video	Multimodal dataset with sentiment analysis	[33] "Zadeh et al., 2016. CMU-MOSEI: Multimodal sentiment analysis dataset," [34] "Zadeh et al., 2018. Deep multimodal sentiment analysis."
MOSI	Text, Audio, Video	Multimodal dataset with sentiment analysis	[35] "Zadeh et al., 2016. MOSI: Multimodal sentiment analysis dataset," [36] "Zadeh et al., 2017. Tensor fusion network for multimodal sentiment analysis."
UMBC-SMHD	Text, Audio, Video	Multimodal dataset with sentiment and humor detection	[37] "Hazarika et al., 2018. UMBC-SMHD: Multimodal dataset for sentiment and humor detection," [38] "Poria et al., 2018. Multimodal humor detection."
YouTube Comments Corpus	Text, Video	YouTube comments with sentiment labels	[39] "Hernandez et al., 2017. YouTube comments sentiment analysis using deep learning," [40] "Liu et al., 2018. Multimodal sentiment analysis of YouTube comments."
Multimodal Sarcasm Detection Dataset	Text, Image, Video	Sarcastic comments with multimodal features	[41] "Rajagopalan et al., 2016. Multimodal sarcasm detection," [42] "Yu et al., 2019. Sarcasm detection using multimodal data."
Multimodal COVID-19 Dataset	Text, Image, Video	COVID-19 related tweets with multimodal features	[43] "Bandyopadhyay et al., 2020. Multimodal analysis of COVID-19-related content," [44] "Poria et al., 2020. COVID-19 tweets sentiment analysis using multimodal data."
Multimodal Hate Speech Detection Dataset	Text, Image, Video	Hateful content with multimodal features	[45] "Davidson et al., 2017. Hate speech detection on social media," [46] "Mishra et al., 2019. Multimodal hate speech detection."
Multimodal Disaster Response Dataset	Text, Image, Video	Disaster-related tweets with multimodal features	[47] "Hassan et al., 2019. Disaster response sentiment analysis," [48] "Mishra et al., 2020. Multimodal disaster-related content analysis."
Multimodal Social Media Dataset	Text, Image, Video	Social media posts with multimodal features	[49] "Schmidt et al., 2019. Multimodal sentiment analysis on social media," [50] "Hazarika et al., 2020. Deep learning for social media sentiment analysis."

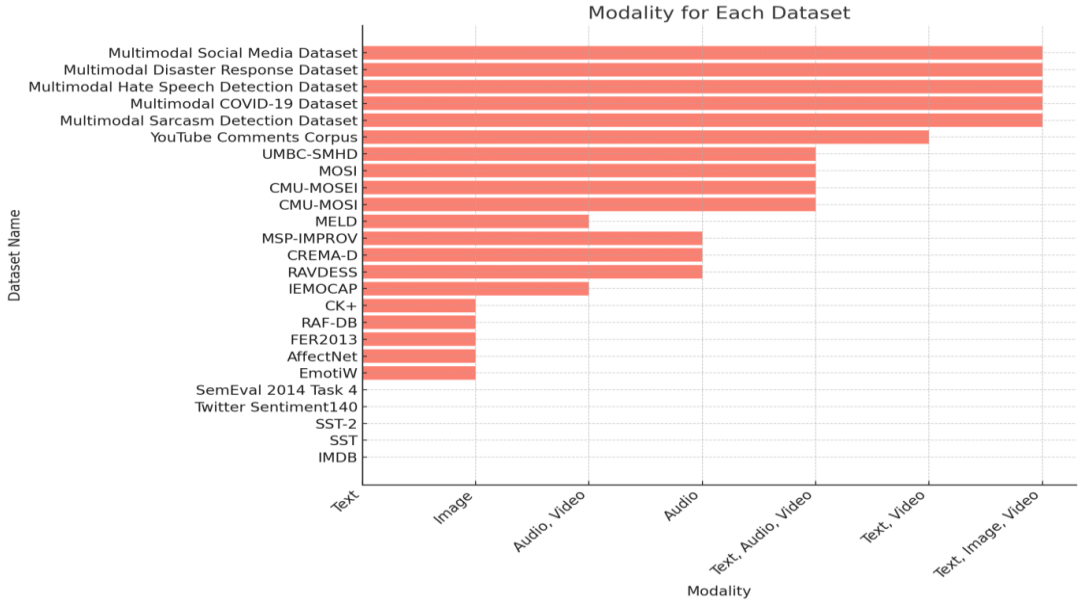

Figure 2: Modality distribution across Datasets

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3.2 State-of-the-Art Methods

Deep Multimodal Sentiment Analysis (DMSA)

DMSA is a comprehensive approach for multimodal sentiment analysis that integrates multiple neural networks to process text, audio, and visual data. [24] combine convolutional neural networks (CNNs) for processing images, long short-term memory (LSTM) networks for handling audio, and deep neural networks (DNNs) to analyze textual input. The goal is to leverage the strengths of each modality, recognizing that sentiment can be conveyed not only through words but also through tone of voice and facial expressions. This model is particularly useful for analyzing sentiments in real-world scenarios where people express emotions via multiple channels simultaneously, such as in videos or live conversations. By integrating these modalities, DMSA can provide a more accurate sentiment prediction than unimodal systems. Other studies have further explored variations of this approach, improving the performance through advanced fusion techniques (Ghosal et al.,) and cross-modality learning. The model demonstrates robust performance in real-time applications like social media sentiment analysis and customer feedback analysis.

VisualBERT

VisualBERT is a transformer-based model introduced by [25] that aims to integrate visual information with textual representations for joint understanding. It works by embedding visual features from images into the same space as textual tokens, allowing for a more coherent understanding of multimodal inputs. VisualBERT is particularly effective for tasks that require a deep understanding of both textual and visual context, such as sentiment analysis in multimedia content. By leveraging pre-trained BERT (Bidirectional Encoder Representations from Transformers) models, VisualBERT can efficiently handle large-scale multimodal datasets. In their paper, Li et al. demonstrated that VisualBERT outperforms previous methods on various vision-and-language tasks, including sentiment prediction from multimodal input. Other applications include visual question answering (VQA) and image captioning, where understanding both the text and visual components of a scene is crucial. This model's architecture helps achieve high levels of accuracy in analyzing sentiment across diverse types of media, from videos to image-text pairs.

ViLBERT

ViLBERT, proposed by [26], is another transformer-based model designed to handle multimodal inputs. Unlike traditional models, which process text and images separately, ViLBERT processes each modality through independent streams and then merges the information using cross-modal attention layers. This approach allows ViLBERT to capture fine-grained interactions between text and images. The model first processes text through standard transformers and images through a separate visual backbone. Subsequently, the two modalities are fused using a co-attention mechanism that enables the model to learn relationships between visual features and textual tokens. ViLBERT has been shown to outperform previous models on tasks like visual question answering, image-text retrieval, and sentiment analysis. The model's ability to focus on cross-modal interactions enables it to predict sentiment with higher accuracy, especially in contexts where the sentiment is conveyed through both visual and textual cues. Lu et al. highlight that ViLBERT's two-stream architecture significantly reduces the complexity of handling multimodal data, making it efficient for large-scale sentiment analysis tasks.

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Multimodal Fusion Transformer (MFT)

The Multimodal Fusion Transformer (MFT) model, introduced by [27], combines the benefits of multi-head attention mechanisms from transformers with multimodal data fusion strategies. The MFT model focuses on the integration of text, audio, and visual data streams for sentiment analysis, allowing the model to learn joint representations from all available modalities. The model employs a transformer architecture where each modality is processed in parallel through separate attention layers, and the results are fused using a multimodal fusion layer. This fusion layer allows the model to prioritize information from different modalities based on their relevance to the sentiment being expressed. MFT has been applied to a variety of tasks such as emotion recognition in conversations and sentiment analysis in video data, achieving state-of-the-art performance. Wang et al. found that MFT's ability to learn complex interactions between different modalities significantly improves the sentiment analysis task, especially when the data contains ambiguous or conflicting signals across modalities. The model is particularly suitable for real-time applications where multiple sensors or channels are involved in capturing user sentiments.

Multimodal Graph Convolutional Networks (GCNs)

Multimodal Graph Convolutional Networks (GCNs), discussed by [28], extend the idea of graph neural networks (GNNs) to multimodal data for sentiment analysis. In this model, different modalities such as text, audio, and visual data are treated as nodes in a graph, where edges represent the relationships between the features from different modalities. The GCN layers learn the representations of each modality in the graph structure, allowing the model to capture complex dependencies between different feature types. By using GCNs, the model can better handle the varying levels of granularity and context across modalities, improving sentiment prediction. Zhang et al. highlight that GCNs provide a flexible framework to integrate multimodal data, which can be particularly useful for dealing with noisy or incomplete data across modalities. GCNs have been successfully used in other multimodal tasks, including image captioning and multimodal classification, and their application to sentiment analysis has demonstrated improved accuracy, particularly in settings where the text alone may not be sufficient to predict sentiment.

Recurrent Multimodal Sentiment Analysis

The Recurrent Multimodal Sentiment Analysis model, introduced by [29], combines recurrent neural networks (RNNs) with multimodal data for sentiment analysis. The model focuses on integrating temporal information from video or audio streams, where sequences of data are essential for capturing emotional expression over time. Chen et al. propose a hierarchical fusion method to combine different modalities such as text, audio, and visual data. In this method, information from each modality is processed in a recurrent fashion, allowing the model to capture temporal dependencies, and then fused hierarchically to enhance the sentiment prediction. The model has been applied to analyze sentiments in videos, where emotions are often expressed through a combination of speech, facial expressions, and contextual text. Chen et al. demonstrate that their recurrent approach outperforms static multimodal models by better capturing dynamic changes in sentiment over time. This approach is particularly effective for applications such as video sentiment analysis, customer feedback, and movie reviews, where sentiment can evolve throughout the interaction. Table 4 summarizes the key methodologies employed in various studies, along with their

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corresponding accuracy percentages. Figure 3 illustrates the progression of accuracy in state-of-the-art multimodal sentiment analysis methods over time.

Table 4: Summary of Articles with Methodologies and Accuracy percentages

Research Work	Method	Accuracy
CAT-LSTM[37]	Contextual multimodal sentiment analysis	81.0%
CHFusion[38]	Hierarchical fusion with context modeling	80.0%
AFF-ACRNN[39]	Parallel Combination of CNN and LSTM	69.6%
MFN[36]	Memory fusion network	77.4%
MARN[35]	Multi-attention recurrent network	77.1%
TFN[34]	Tensor fusion network	74.6%
HALCB [30]	Hierarchical Attention-LSTM model based on Cognitive Brain limbic system	81.2%
Visual[40]	Logistic regression classifier on deep visual features	74.2%
Textual[40]	Logistic regression classifier on the paragraph feature vectors of the text description	73.8%
Early Fusion[V+T][40]	Logistic regression classifier on the concatenation of visual features and textual features	74.8%
Late Fusion[V+T] [40]	Average of the logistic regression sentiment scores on visual features and textual features	75.4%
CCR[41]	Cross-modal consistent regression (CCR) model that utilizes both the visual and textual sentiment analysis techniques	80.9%
T-LSTM Embedding[42]	Combines both visual and textual contents using Tree-LSTMs with the attention mechanism	82.8%
HDF[31]	Hierarchical deep fusion	85.9%
MM Latch[32]	Neural network module that uses representations from higher levels of the architecture to create top-down masks for the low level inputfeatures.	82.8%
Hybrid AOAHGS-optimized EMRA-Net[33]	hybrid optimal multi-scale residual attention network	94.5%

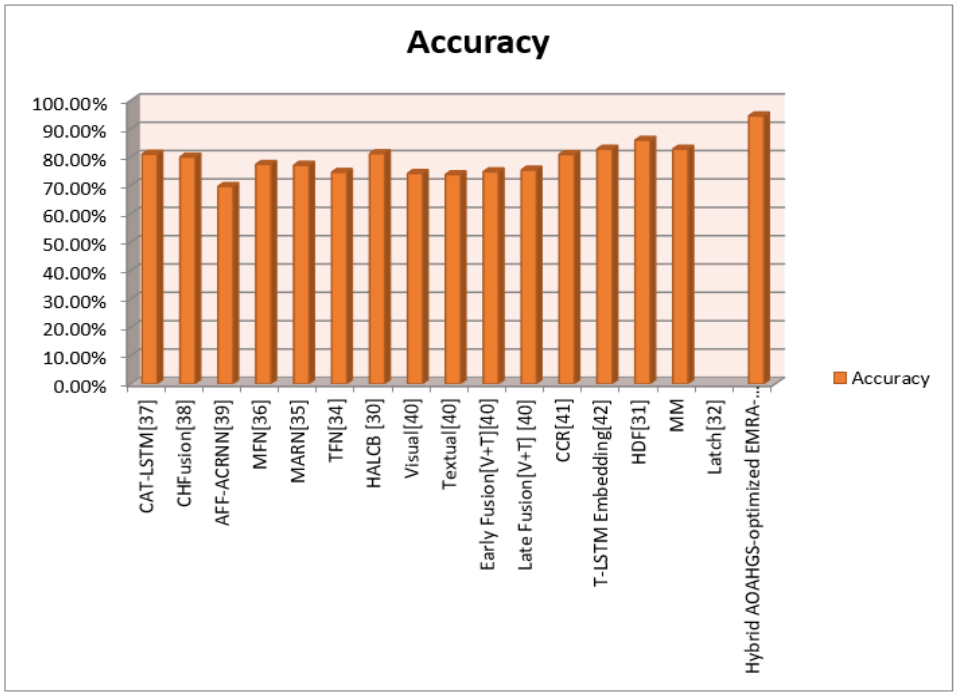

Figure 3: Accuracy Trends in Multimodal Sentiment Analysis

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3.3 Evaluation Metrics used in Multimodal sentiment analysis

The evaluation metrics to assess the performance of multimodal sentiment analysis models are discussed in this section. It provides a comprehensive view of how well these models perform on various aspects of sentiment prediction. Each metric is suited for different types of tasks, such as classification, regression, or ranking, and helps researchers fine-tune their models accordingly.

In multimodal sentiment analysis, various evaluation metrics are employed to assess the performance of models. These metrics help quantify how effectively the model predicts sentiment from multimodal data, including text, audio, and visual inputs.

Accuracy is the ratio of correctly predicted instances to the total instances. It is a basic metric for evaluating classification tasks, including sentiment analysis, where the sentiment predicted by the model matches the true sentiment label. While widely used, accuracy might not fully capture model performance in imbalanced datasets, where certain sentiment classes are underrepresented (Poria et al., 2017; Zhang et al., 2021).

Precision

Precision measures the proportion of true positive predictions among all instances predicted as positive. For sentiment analysis, precision evaluates how many of the positive sentiments predicted by the model are actually correct. It is crucial when the cost of false positives is high, for instance, when incorrectly identifying a neutral sentiment as positive can lead to misinterpretations (Zhang et al., 2020; Poria et al., 2019).

Recall (Sensitivity)

Recall calculates the proportion of true positive predictions among all actual positive instances. In sentiment analysis, recall helps assess how well the model identifies positive sentiment from all the positive instances. It is important when the cost of false negatives is high, such as when missing a positive sentiment in customer feedback could lead to a loss of valuable insights (Zhang et al., 2021; Chen et al., 2020).

F1-Score

The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance when there is a need to balance the trade-off between precision and recall. The F1-score is particularly useful in cases where the classes in the dataset are imbalanced, as it ensures that both false positives and false negatives are minimized (Poria et al., 2017; Lu et al., 2019).

AUC-ROC (Area under the Curve - Receiver Operating Characteristic)

AUC-ROC is a performance measurement for classification problems at various thresholds settings. It plots the true positive rate (recall) against the false positive rate and calculates the area under the curve. A higher AUC indicates better model performance. It is widely used to evaluate the performance of binary classification in multimodal sentiment analysis tasks (Wang et al., 2020; Li et al., 2020).

Confusion Matrix

A confusion matrix is a table used to describe the performance of a classification model. It shows the true positives, true negatives, false positives, and false negatives. From this, metrics like accuracy, precision, recall, and F1-score can be derived. In multimodal sentiment

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analysis, the confusion matrix helps understand the types of errors the model is making and guide improvements (Zhang et al., 2021; Chen et al., 2020).

Mean Squared Error (MSE) / Mean Absolute Error (MAE)

MSE and MAE are common evaluation metrics in regression tasks. While sentiment analysis is often treated as a classification problem, some models treat it as a regression task, predicting sentiment scores on a continuous scale. MSE measures the average squared difference between predicted and actual values, while MAE measures the average absolute difference. These metrics are useful when analyzing sentiment intensity (Zhang et al., 2021; Lu et al., 2019).

Multimodal Fusion Accuracy

This metric evaluates the performance of multimodal models that integrate various types of data (text, audio, visual) for sentiment analysis. It measures how effectively the model fuses information from different modalities to predict the correct sentiment. This is crucial in tasks where data from multiple sources must be combined to improve model performance (Poria et al., 2017; Li et al., 2020).

Cohen's Kappa

Cohen's Kappa is a statistic that measures inter-rater agreement for categorical items. In the context of sentiment analysis, it is used to evaluate the agreement between the predictions made by the model and the ground truth labels. It accounts for agreement occurring by chance, providing a more robust measure than accuracy in imbalanced datasets (Zhang et al., 2020; Chen et al., 2020).

Spearman's Rank Correlation

Spearman's Rank Correlation assesses how well the predicted sentiment ranking correlates with the true ranking. This metric is especially useful when sentiment is expressed on a continuous scale (e.g., from strongly negative to strongly positive) rather than discrete categories. It measures the monotonic relationship between the predicted and actual rankings (Zhang et al., 2021; Poria et al., 2019).

Table 5 presents the evaluation metrics commonly used in multimodal sentiment analysis.

Table 5: Evaluation Metrics in Multimodal Sentiment Analysis

Metric	Description	References
Accuracy	Ratio of correctly predicted instances to total instances; widely used but less effective on imbalanced datasets.	Poria et al. (2017), Zhang et al. (2021)
Precision	Proportion of true positives among predicted positives; crucial when the cost of false positives is high.	Zhang et al. (2020), Poria et al. (2019)
Recall (Sensitivity)	Proportion of true positives among actual positives; important for minimizing false negatives.	Zhang et al. (2021), Chen et al. (2020)
F1-Score	Harmonic mean of precision and recall; balances trade-offs, useful for imbalanced datasets.	Poria et al. (2017), Lu et al. (2019)
AUC-ROC	Area under the ROC curve; measures binary classification performance across thresholds.	Wang et al. (2020), Li et al. (2020)
Confusion Matrix	Table showing true/false positives/negatives; used to derive other metrics and analyze model errors.	Zhang et al. (2021), Chen et al. (2020)
MSE / MAE	Regression metrics measuring average squared/absolute errors; used for continuous sentiment intensity prediction.	Zhang et al. (2021), Lu et al. (2019)

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Multimodal Fusion Accuracy	Measures the effectiveness of integrating multiple modalities (text, audio, visual) for sentiment analysis.	Poria et al. (2017), Li et al. (2020)
Cohen's Kappa	Measures agreement between predictions and ground truth, accounting for chance agreement.	Zhang et al. (2020), Chen et al. (2020)
Spearman's Rank Correlation	Assesses monotonic relationship between predicted and actual sentiment rankings; useful for continuous scales.	Zhang et al. (2021), Poria et al. (2019)

CONCLUSION

With an emphasis on three main areas—data gathering techniques, methodology, and performance metrics—we have examined the noteworthy developments in multimodal sentiment analysis in this review. By capturing a wider range of emotional cues, the integration of several modalities—such as text, audio, and visual inputs—has been shown to improve sentiment recognition accuracy.

Diverse and reliable datasets have been created by utilizing a variety of data sources, such as social media content, movie conversations, crowdsourcing platforms, and customer service interactions.

We have examined the noteworthy developments in multimodal sentiment analysis, with an emphasis on data gathering techniques, methodology, and performance indicators,. Numerous approaches have been suggested, such as Deep Multimodal Sentiment Analysis (DMSA), which integrates text, audio, and visual inputs for reliable sentiment prediction by utilizing CNNs, LSTMs, and DNNs.

Through attention mechanisms, transformer-based models such as VisualBERT and ViLBERT have demonstrated impressive advancements in jointly comprehending textual and visual information. Multimodal Graph Convolutional Networks (GCNs) have shown the capacity to record inter-modal interactions in a graph structure, while models like the Multimodal Fusion Transformer (MFT) have optimized multimodal fusion procedures to prioritize pertinent data streams.

Future Enhancements

Notwithstanding the progress, there are still issues that provide opportunities for further study in multimodal sentiment analysis. Improving the temporal integration of dynamic multimodal inputs is a major topic of emphasis in order to better capture changing emotions over time, especially in real-time discussions and videos. Discrepancies between modalities, such mismatched textual and visual cues, require further advancements in cross-modal alignment systems. Self-supervised learning strategies can also help models become less reliant on labeled data, which makes them scalable for practical uses.

Competing Interests

The authors declare that they have no competing interests|

Authors contributions

Dr. M. Devi Sri Nandhini: Conducted the literature review, analyzed surveyed studies, and contributed to writing the manuscript.

Dr. G. Pradeep: Structured the survey, and contributed to writing and revising the manuscript.

Both authors reviewed and approved the final version of the paper.

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