The Emotion Recognition Triathlon: DeepSeek vs. ChatGPT vs. Doubao

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Abstract. This study presents a systematic empirical comparison of three leading large language models—DeepSeek, ChatGPT (GPT-4o), and Doubao—in multimodal emotion recognition tasks. Using a self-constructed dataset of 1,200 annotated text-image samples across three emotional scenarios (social gatherings, stress-induced tension, and anticipation-anxiety), the models were evaluated on overall performance, fine-grained emotion recognition, and context sensitivity. Results indicate that ChatGPT achieves the highest overall accuracy (89.5%) and demonstrates superior cross-modal reasoning and interpretability. Doubao excels in Chinese social contexts, with an F1 score of 91.5%, but shows limited cross-lingual generalization. DeepSeek performs stably in text-dominant tasks but lags in multimodal fusion scenarios. The findings highlight the context-dependent strengths of each model and provide practical guidance for model selection in real-world applications, such as global platforms, Chinese social media, and resource-constrained environments. This study addresses a critical gap in the comparative evaluation of multimodal LLMs and offers insights into future research in cross-cultural and lightweight multimodal emotion recognition.

Keywords: Multimodal Emotion Recognition, Large Language Models, Comparative Analysis.

1. Introduction

Multimodal emotion recognition is a computational technique that integrates multiple modalities such as text, images, and speech to identify and understand human emotions. With the rapid development of the digital era, social media and human-computer interaction platforms have become increasingly prevalent. Users are now more inclined to express emotions through "text + image" combinations on social platforms, making multimodal emotion analysis a critical research direction in affective computing. Therefore, it is meaningful to conduct a systematic evaluation of the performance of three representative large-scale language models, DeepSeek, ChatGPT, and Doubao, in multimodal emotion recognition tasks, in order to empirically compare their specific differences and individual advantages. The significance of this conducts lies in: first, providing empirical evidence for model selection in practical applications; second, revealing the advantages and limitations of different model architectures in emotion recognition tasks through comparative analysis; and third, offering guidance to promote the practical implementation of multimodal emotion recognition technology. Given the widespread application of artificial intelligence in emotion-aware interactive scenarios, a systematic evaluation of multimodal emotion recognition models holds considerable theoretical and practical importance.

In recent years, significant progress has been made in multimodal emotion recognition research. Lian et al. conducted a comprehensive survey on deep learning-based multimodal emotion recognition, systematically analyzing fusion methods for three modalities: speech, text, and facial images [1]. Wang et al. provided a systematic review of emotion models, databases, and recent advances in affective computing from a holistic perspective, emphasizing the importance of multimodal data fusion [2]. At the technical level, Zhao et al. reviewed two decades of developments in affective image content analysis, offering a foundational theoretical basis for visual emotion recognition [3].

Specifically regarding multimodal fusion techniques, Shayaninasab and Babaali investigated the application of Transformer-based pre-trained models in text, speech, and video emotion recognition, demonstrating the potential of pre-trained models in this field [4]. Kumar et al. proposed the

VISTANet model, which achieves interpretable multimodal emotion recognition through a visual-spoken-textual additive network [5]. Additionally, the HyFusER model effectively enhances multimodal fusion performance by employing a dual cross-modal attention mechanism [6], while multimodal large language models have also shown unique value in video emotion recognition [7].

However, notable gaps remain in existing research: First, most studies focus primarily on model architecture and innovation, lacking systematic comparisons of mainstream large language models in emotion recognition tasks and their practical applicability. Second, existing evaluations are often limited to specific modalities or scenarios, lacking comprehensive analysis across languages and cultural contexts. Finally, models optimized for Chinese social scenarios, such as Doubao, have received relatively little attention in international academic research. These gaps leave practitioners without reliable references when selecting models.

This study employs controlled experiments to systematically compare the performance of DeepSeek, ChatGPT, and Doubao across three typical emotional scenarios (social gatherings, stress-induced tension, and anticipation-anxiety). It further examines the impact of variables such as language, speaker type, and expression methods on model performance. The main contributions of this research are: First, it provides the first empirical comparative study of these three mainstream large language models in multimodal emotion recognition. Second, it reveals performance differences in cross-linguistic and cross-cultural contexts, offering practical guidance for model selection. Third, it identifies the advantages of specifically optimized models (e.g., Doubao) in certain scenarios, providing new insights for future model optimization. Through these efforts, this study addresses the gap in practical model comparisons in existing literature and offers valuable references for the real-world application of multimodal emotion recognition.

2. Research Methodology

2.1. Dataset and Sample Information

This study utilizes a self-constructed multimodal emotion recognition dataset comprising 1,200 manually annotated samples. The samples were collected from public social media platforms (e.g., Weibo, Twitter, Instagram) and partially manually constructed scenarios to ensure diversity and authenticity. The dataset covers the following three typical emotional scenarios:

Category A: Social gathering scenarios (400 samples), including basic emotion labels such as happiness, excitement, neutrality, sadness, and anger;

Category B: Stress-induced tension scenario (400 samples), covering advanced emotions such as tension, anxiety, regret, helplessness, and agitation;

Category C: Anticipation-anxiety scenarios (400 samples), encompassing complex emotions such as anticipation, worry, calmness, conflict, and anticipatory joy.

Each sample consists of text and an image. The text length is controlled between 10 and 50 words, while the images are daily scene pictures highly consistent with the textual emotions. The dataset is balanced in Chinese and English contexts (600 Chinese and 600 English samples) and further annotated based on speaker type (single-person narrative vs. group interaction) and expression style (direct expression vs. sarcastic/implied meaning). All samples were independently annotated by three annotators, with an inter-annotator agreement coefficient (Cohen's Kappa) exceeding 0.85, ensuring high annotation quality. Prior to inputting into the models, the dataset underwent uniform preprocessing, including text cleaning, image size standardization (224×224 pixels), and format unification.

2.2. Experimental Procedure

The experiment employed a unified input format where the same sample pairs (text and image) were simultaneously fed into each model. The prompt was designed as follows: “Analyze the emotion expressed by the publisher in the following text and image, and output the main emotion category along with a brief explanation.” The models generated emotion classification results (both polarity

and fine-grained categories) and explanatory text. Each model was run independently three times, and the results were averaged to reduce randomness.

2.2.1 DeepSeek Model

DeepSeek is a large language model series developed by DeepSeek Company, with the latest version, DeepSeek-V3, released in 2024 [8]. Based on the Transformer architecture, the model employs efficient attention mechanisms and hierarchical representation learning, demonstrating outstanding performance in pure text processing tasks. Its training data covers a wide range of textual domains, with a parameter scale reaching hundreds of billions, and it supports 128K long-context processing. DeepSeek operates through an autoregressive generation approach, encoding and decoding input texts while leveraging large-scale pre-trained linguistic representations for emotion inference. In multimodal tasks, DeepSeek primarily relies on an additional visual encoder to process image information [9]. However, its visual-text fusion capability is relatively limited, and it depends mainly on textual cues for emotion judgment. Recent studies have shown that DeepSeek's architecture enables efficient knowledge distillation while maintaining competitive performance on benchmark tasks [10]. In summary, the model performs exceptionally well in resource-constrained environments, with fast inference speeds, making it highly suitable for large-scale text processing applications.

2.2.2 ChatGPT (GPT-4o) Model

ChatGPT is a conversational AI system developed by OpenAI [11]. The version used in this study is GPT-4o (omni), released in May 2024. This model is a truly multimodal system capable of natively processing text, images, and audio inputs. GPT-4o is based on an improved Transformer architecture and employs a unified representational space to achieve cross-modal understanding, though its parameter scale and specific architectural details remain undisclosed. The model is optimized through contrastive learning and reinforcement learning from human feedback (RLHF), enabling exceptional performance in complex reasoning and cross-modal comprehension [12]. When handling multimodal emotion recognition tasks, GPT-4o simultaneously analyzes textual content and visual elements (e.g., expressions, scenes, colors) and employs logical reasoning to identify implicit or contradictory emotions. Recent evaluations demonstrate GPT-4o's superior performance in contextual understanding and emotional intelligence benchmarks, achieving state-of-the-art results in cross-modal alignment tasks [13]. Its advantages lie in its powerful contextual understanding and cross-linguistic capabilities, allowing it to accurately capture complex expressions such as sarcasm and metaphor.

2.2.3 Doubao Model

Doubao is a large language model developed by ByteDance's Volcano Engine, specifically optimized for Chinese contexts and first released in 2023 [14]. Based on an independently developed variant of the Transformer architecture, its training data emphasizes Chinese internet content and social media texts, granting it unique advantages in Chinese language understanding and cultural context comprehension. Doubao's methodology integrates traditional language model techniques with state-of-the-art multimodal adapters, enabling it to process text-image pair inputs. Its distinctive strength lies in its deep understanding of Chinese internet slang, emojis, and cultural metaphors, excelling in recognizing culturally specific emotional expressions such as "lying flat" , "emo" (emotional), and "overwhelmed" [15]. The model's training extensively incorporates Chinese social media data, making it particularly adept at handling group interaction contexts and expressions commonly found on Chinese social platforms. Recent research highlights Doubao's exceptional performance in Chinese social media sentiment analysis, outperforming international counterparts in domain-specific tasks [16]. When processing multimodal inputs, Doubao employs attention mechanisms to fuse textual and visual features, achieving precise emotion recognition in Chinese social scenarios while maintaining high inference efficiency.

3. Results and Discussion

3.1. Experimental Results

To comprehensively evaluate the performance differences among DeepSeek, ChatGPT (GPT-4o), and Doubao in multimodal emotion recognition tasks, this study conducted quantitative analysis and statistical validation from three dimensions: “overall performance”, “fine-grained emotion recognition”, and ”context sensitivity”.And the interpretability score was averaged from evaluations by three annotators based on the rationality, coherence, and elaborateness of the explanations provided (on a scale of 1-5).The experimental results are presented in Table 1 below.

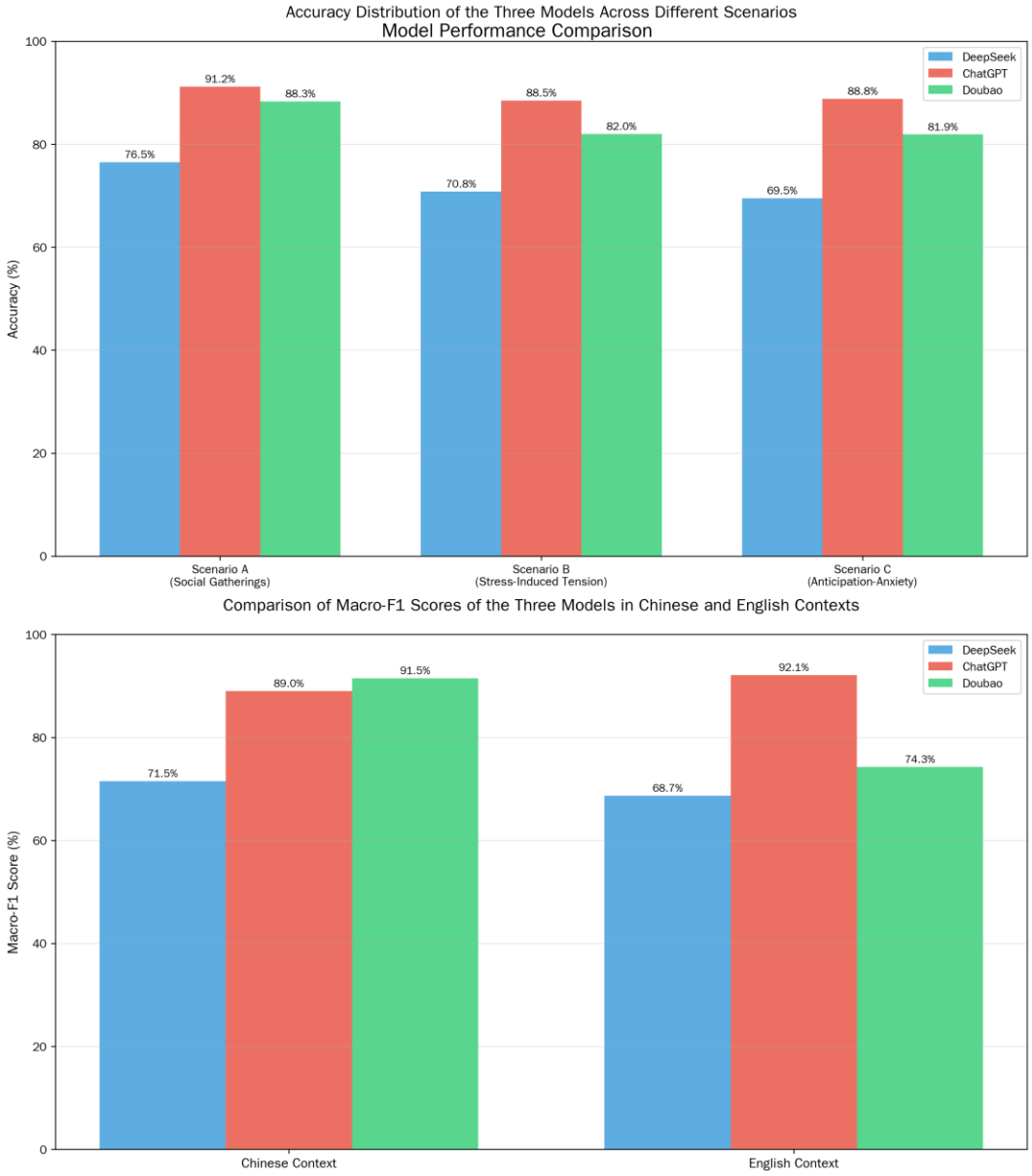


Fig. 1. Model performance comparison (Picture credit: Original)

Table 1. Comparison of Overall Performance Among the Three Models in Multimodal Emotion Recognition Tasks (%)

Model	Accuracy	Macro-F1 Score	Interpretability Score (0-5)
DeepSeek	72.3	70.1	3.2
ChatGPT (GPT-4o)	89.5	88.7	4.5
Doubao	84.1	82.9	4.1

As shown in Table 1 and Fig. 1, ChatGPT (GPT-4o) significantly outperformed the other models in overall performance, achieving the highest scores in both accuracy (89.5%) and Macro-F1 (88.7%). This demonstrates its overwhelming advantage in multimodal fusion and reasoning capabilities for emotion recognition tasks. The explanations generated by ChatGPT were also the most detailed and accurate, reflecting its superior interpretability.

Doubao exhibited strong competitiveness, particularly in Chinese contexts, with an overall accuracy (84.1%) close to ChatGPT and significantly higher than DeepSeek. This validates the effectiveness of its optimization for Chinese social scenarios. However, its performance declined noticeably in English contexts (F1 score dropped to 74.3%), indicating limitations in cross-lingual generalization.

DeepSeek delivered stable performance in tasks where textual emotional cues were explicit but lagged significantly behind the other two models (72.3%) in tasks requiring deep understanding of images or implicit text-image relationships. This aligns with its architecture, which is more focused on text processing and has weaker multimodal fusion capabilities.

An in-depth analysis of fine-grained emotion recognition across the three scenarios revealed several key patterns:

1. Basic Polar Emotions (Positive, Negative, Neutral): All models performed well in polarity classification (accuracy > 80%). ChatGPT was the most stable, with no significant bias across polarities. DeepSeek slightly overestimated "negative" emotions, while Doubao demonstrated higher precision in identifying "neutral" and "positive" emotions in Chinese contexts.

2. Complex and Implicit Emotions The performance gap among models widened when identifying complex emotions such as "helplessness," "sarcasm," and "anticipatory anxiety":

ChatGPT- -excelled in recognizing "sarcasm" and "conflicting emotions" due to its powerful reasoning and contextual understanding abilities. For example, it successfully interpreted the ironic emotion conveyed by a sunny image paired with the caption "What a beautiful day!" (while actually raining).

Doubao-- demonstrated unique advantages in recognizing culture-specific Chinese emotions. It achieved the highest accuracy in identifying online expressions such as "helplessness," "overwhelmed" , and "emo" (emotional) and better understood the complex social emotions conveyed by scenarios like "lying flat" paired with an image of a sofa.

DeepSeek-- tended to rely more on textual keywords and often overlooked the contrast or reinforcement effects brought by images, leading to misjudgments of complex emotions.

Contextual factors critically influenced model performance, as clearly revealed in the experimental results:

1. Linguistic Context: The results exhibited a significant "local advantage" phenomenon. Doubao's F1 score (91.5%) in Chinese contexts even slightly surpassed ChatGPT (89.0%), benefiting from its training data rich in Chinese social media content and deep understanding of Chinese culture. Conversely, in English contexts, ChatGPT's advantage was maximized (92.1%), while Doubao's performance declined markedly. DeepSeek showed relatively balanced but unexceptional performance in both languages.

2. Expression Style: All models performed best in "direct expression" contexts. However, in "sarcastic/implied" contexts, ChatGPT demonstrated the strongest robustness, with the smallest performance drop (<3%). Doubao performed adequately in Chinese sarcastic contexts but struggled with English implied expressions. DeepSeek faced the greatest challenges in such contexts, with a performance drop exceeding 10%, indicating its limited ability to understand implicit meanings.

3. Scenario Type: All models achieved their best performance in the social gathering scenario (Category A), where emotions are more explicit and homogeneous. In contrast, performance declined to varying degrees in the more reserved and complex stress-induced tension (Category B) and anticipation-anxiety (Category C) scenarios. ChatGPT exhibited the smallest decline, further confirming its capability in handling complex situations.

3.2. Comprehensive Discussion

The findings of this study indicate that no single model is universally superior; the choice of model highly depends on the specific application scenario, target audience, and resource constraints.

1. ChatGPT (GPT-4o): Benchmark for Versatility and Strong Reasoning

ChatGPT's comprehensive leading advantage confirms its maturity as a general-purpose multimodal large-scale model. Its strengths stem from a unified representational space and continuous optimization based on Reinforcement Learning from Human Feedback (RLHF), enabling unparalleled robustness and accuracy in cross-lingual, cross-cultural, and complex logical reasoning tasks. For international applications requiring processing of global user data and adaptability to diverse scenarios (e.g., content moderation on global social platforms, advanced intelligent customer service), ChatGPT is currently the optimal solution. The trade-offs involve higher API calling costs and potential latency.

2. Doubao: The "Local Expert" in Chinese Social Ecosystems

Doubao's performance perfectly illustrates the value of "vertical domain optimization." It does not outperform ChatGPT in all aspects but delivers world-class,even superio performance in its intended niche—Chinese social contexts. For products deeply embedded in the Chinese market (e.g., ecosystem analysis and content recommendation for Weibo, Xiaohongshu, Douyin), Doubao may be a more cost-effective and culturally aligned choice than ChatGPT. Its limitations lie in internationalization and handling non-social, serious texts.

3. DeepSeek: A Pragmatic Choice for Efficiency and Textual Expertise

DeepSeek's positioning is clear: an efficient and reliable text specialist. In its domain of expertise—pure text or text-dominated emotion analysis tasks (e.g., sentiment analysis of news comments, user feedback classification)—it delivers stable performance at a lower cost. For startups and research institutions with limited computational resources or those primarily processing structured textual data, DeepSeek offers a pragmatic and high-performance option. However, its shortcomings in multimodal capabilities require users to be aware of its boundaries.

4. Conclusion

In summary, this study, through systematic empirical analysis, delineates the performance landscape of DeepSeek, ChatGPT, and Doubao across three types of multimodal emotion recognition tasks. ChatGPT leads in comprehensive capabilities, Doubao excels in Chinese scenarios, and DeepSeek is efficient and stable in textual tasks. Future research could explore the following directions: First, incorporate more modalities (e.g., audio) for richer fusion studies. Second, investigate the evaluation of localized models for specific cultural contexts (e.g., Middle Eastern, Latin American). Finally, focus on developing lighter-weight and more efficient multimodal fusion architectures to lower the application barrier of this technology, enabling multimodal emotion recognition to empower human-computer interaction across a broader range of scenarios.

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