Sentiment and Emotion Modeling in Text-based Conversations utilizing ChatGPT

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ABSTRACT

Emotional Intelligence (EI) constitutes a vital element of human communication, and its integration into text-based dialogues has gained great significance in the modern digital era. The present paper proposes an innovative method for modeling sentiment and emotion within text-based conversations using the ChatGPT language model. The advancements in sentiment and emotion recognition are centered on the role of EI in text-based conversational models. The study underscores the significance of diverse datasets, including Interactive Emotional Dyadic Motion Capture (IEMOCAP), MELD, EMORYNLP, and DAILYDIALOG, for training and evaluating emotion detection algorithms. IEMOCAP and MELD offer detailed emotional annotations, EMORYNLP emphasizes sensitive dialogue scenarios, and DAILYDIALOG encompasses a wide range of everyday interactions, providing distinct advantages for

capturing emotional subtleties. The proficiency of different emotion categorization models, including ChatGPT and models with four levels of detail, is demonstrated through their capacity to understand and respond to emotions aptly. The crucial role of conversational AI with sophisticated EI in fostering empathy and context-sensitive interactions is emphasized.

Keywords-ChatGPT; digital age; emotional intelligence; human communication; sentiment and emotion modeling

I. INTRODUCTION

The integration of EI into text-based dialogues represents a critical and rapidly evolving domain within the fields of Artificial Intelligence (AI) and Natural Language Processing (NLP) [1]. Emotions play a foundational role in human interaction, influencing the manner in which information is shared, relationships are established, and decisions are made. Recognizing this, the present study explores how ChatGPT, a state-of-the-art conversational model, can be enhanced to detect, interpret, and respond to user emotions with empathy and contextual relevance. Conventional sentiment analysis and emotion recognition methodologies frequently depend on rule-based systems or supervised learning algorithms, which encounter challenges in accommodating the intricate and context-dependent nature of human emotions [2]. These limitations become particularly evident when conversational agents attempt to generate responses aligned with a user's emotional tone, often resulting in a disconnect between the user's feelings and the AI's replies. This discrepancy can impede the effectiveness of interactions and hinder the full potential of AI-driven dialogues in facilitating meaningful engagement. As a descendant of GPT-3, ChatGPT signifies a breakthrough in conversational AI, demonstrating an aptitude for generating text that emulates human language. Nevertheless, its ability to incorporate EI remains a substantial challenge. Current AI models, including ChatGPT, demonstrate proficiency in comprehending linguistic patterns; however, they frequently encounter difficulties in discerning and responding to emotional signals embedded within user inputs [3]. This deficiency manifests in interactions that are perceived as cold or impersonal, thereby undermining the potential benefits of conversational AI. To address this limitation, the present study employs advanced NLP techniques, deep learning, and extensive pre-training to enhance ChatGPT's capacity to discern sentiment and emotion, thus producing contextually appropriate and empathetic responses. The proposed framework signifies a progression in the integration of EI into AI-powered dialogues, with the objective of mitigating the discrepancy between users' emotional expectations and AI-generated responses. By enhancing ChatGPT's emotional sensitivity, it is anticipated that significant advancements will be made in the realm of AI interactions across diverse domains. This, in turn, will lead to enhanced user engagement and the cultivation of more human-like communication. As presented in Figure 1, the proposed framework involves a multifaceted approach to detecting emotions, generating empathetic responses, and continuously refining the model through an optional feedback loop. This study addresses the critical challenge of the existing conversational agents' insufficient EI. The primary objectives of this study are threefold: first, to refine ChatGPT's ability to recognize and respond to emotional signals; second, to improve user satisfaction through empathetic AI responses; and third, to advance the field of emotionally intelligent conversational systems. The three primary objectives are:

- A robust sentiment and emotion analysis framework must be developed within text-based conversations, leveraging ChatGPT's language capabilities.
- To enable ChatGPT to generate emotionally intelligent responses, which align with the emotional tone of user inputs.
- The effectiveness of the proposed approach will be evaluated and demonstrated through the enhancement of user engagement and the facilitation of meaningful interactions.

The integration of EI into ChatGPT holds considerable promise for the advancement of mental health support and the facilitation of compassionate and expeditious responses for individuals seeking emotional assistance. This approach has the potential to enhance the accessibility of mental health services, including crisis hotlines and therapeutic treatments. The research endeavors to augment ChatGPT's capacity to discern and respond to emotional cues by employing advanced emotion recognition datasets, thereby fostering more context-aware interactions. Authors in [1] address the challenges AI avatars face in comprehending the nuances of human language, particularly emotional expressions across different languages. They propose a framework to enhance AI communication by teaching avatars to detect and respond to emotions. They also recommend a specific EI test to assess AI's ability to functionally interact with humans and other AI systems. Authors in [2] examine ChatGPT's impact on students' EI, particularly among engineering students. The findings suggest that the use of ChatGPT may result in a decline in EI for engineering students compared to their non-engineering peers. Despite these concerns, students depend on ChatGPT for academic and personal reasons, demonstrating a complex interplay between the AI use and emotional skills. Authors in [3] investigate how designing prompts can enhance educational outcomes in tourism psychology, employing the cognitive load theory to foster critical thinking. Educators can facilitate students' deeper understanding of complex subjects by using well-structured, concise prompts, thereby maximizing ChatGPT's role in advancing psychological educational goals. Furthermore, in [4], the focus is on future educational strategies for AI, emphasizing digital literacy, creativity, and social-emotional skills as essential educator competencies. The paper advocates for personalized learning, collaborative teacher development, and interdisciplinary education to prepare educators for the digital era, promoting a more flexible educational setting. Authors in [5] explore the application of ChatGPT in Cognitive Behavioral Therapy (CBT), underscoring its adaptability across diverse populations. The study meticulously examines the advantages and disadvantages of incorporating AI in CBT, proposing future enhancements in datasets and emotional sensitivity to more effectively address therapeutic requirements. This suggests that AI could become a valuable asset for mental health professionals.

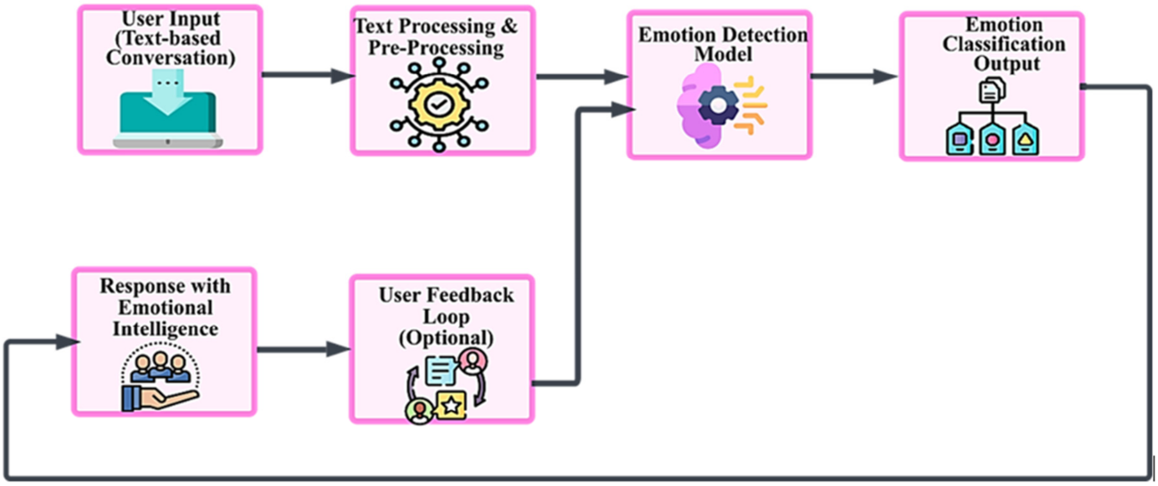

Fig. 1. Workflow of EI modeling in ChatGPT for text-based conversations.

Authors in [6] discovered that emotional and ethical appeals, namely ethos, pathos, do not impact consumers as significantly as factual and logical elements, logos, suggesting AI's potential in the humanities. This study contributes to the expansion of AI's capabilities in text processing, demonstrating ChatGPT's efficacy in analyzing persuasive content within the social sciences. An assessment of ChatGPT's proficiency in emotion classification, as reported in [7], yielded an accuracy rate of 58% using the Dair-ai/emotion dataset. This study identifies areas requiring enhancement in NLP with respect to EI. However, it also highlights ChatGPT's strong baseline for emotion recognition, which can be fine-tuned for a variety of applications. Finally, authors in [8] propose ChatGPT as a companion tool for the elderly to mitigate loneliness and support social interaction for dementia patients. Authors in [9] explore the potential of ChatGPT to assist educators in personalizing instruction for poetry students, emphasizing human-AI collaboration. The usage of ChatGPT as a teaching assistant has been demonstrated to address the diverse needs of students in large classrooms, providing individualized feedback and guidance in Chinese literature studies. Additionally, authors in [10] introduced CLAP4Emo, an innovative framework for retrieving emotional speech through language prompts that allows for more precise recognition of emotions in NLP. The objective of the study is to enhance the efficiency and diversity of audio-based emotional AI by integrating language and audio in an interactive retrieval system. Authors in [11] propose an empathy-based model that uses psychological and physiological data to enhance the interactive capacity of chatbots. The incorporation of multidimensional emotional input is a salient feature of this model, as it aims to enhance the active listening capabilities of chatbots and augment their emotional responsiveness within support settings. Authors in [12] present the MFOHDL-SA model, a hybrid deep learning approach to the sentiment analysis of ChatGPT-related tweets. Using Convolutional Neural Network - Long-Short Term Memory (CNN-LSTM) and Term Frequency-inverse Document Frequency (TF-IDF), this model efficiently categorizes tweet sentiments, hence demonstrating the potential of the optimized AI models for real-time sentiment tracking on social platforms. Authors in [13] examine ChatGPT tweets related to healthcare, leveraging NLP for sentiment analysis on a substantial dataset. The findings suggest that the majority of tweets exhibit overt positive or negative sentiments, indicating that ChatGPT's healthcare applications have a discernible emotional impact on users, making it a pertinent metric for gauging public attitudes. In a separate study [14], authors explore the role of AI and social robots in education, highlighting ChatGPT's potential for providing personalized, real-time learning assistance. Authors in [15] investigate the integration of ChatGPT with Moodle, underscoring its multilingual, analytical, and contextual capabilities. Through the use of case studies, the authors demonstrate the ability of ChatGPT to support knowledge queries, provide emotional support, and enhance course design, thereby improving educational workflows and learner engagement. Authors in [16] compare various chatbots, including ChatGPT and GPT-4, to assist users in selecting the most appropriate bot for a range of purposes, such as teaching and analytics.

II. PROPOSED METHODOLOGY

Data preprocessing is essential for ChatGPT, in conjunction with EI, in shaping emotion and sentiment in text-based interactions. This critical phase commences with the meticulous collection of a diverse and exhaustive dataset of text-based conversations, meticulously annotated to mirror the emotional subtleties present. This dataset serves as the foundation for training the model, enabling it to accurately identify and respond to emotions. The data preprocessing process involves several essential steps, including data cleaning, tokenization, and the generation of emotion labels for each message. These steps serve as preparatory measures for the subsequent steps of the approach.

A. Dataset and Evaluation Metrics

In the fields of sentiment analysis and EI modeling, the selection of an appropriate dataset and assessment criteria is critical to ensure the accuracy and reliability of the results. A range of comprehensive emotional data sources are offered by prominent datasets, such as IEMOCAP [17], MELD [18], EMORYNLP [19], and DAILYDIALOG [20], each exhibiting distinct strengths. IEMOCAP and MELD are particularly well-suited for training models on complex emotional expressions due to their extensive emotional annotations and wide range of emotional settings. EMORYNLP demonstrates particular aptitude in capturing contextual nuances in conversational scenarios, while DAILYDIALOG offers a comprehensive collection of typical dialogues that contribute to generalizable model performance. The datasets employed in this study, derived from multimodal interactions yet constrained to the text modality, comprise 31 conversations and 1,622 utterances, encompassing emotions including neutral, sad, angry, happy, frustrated, and excited. MELD and EmoryNLP are datasets from the Friends TV show, comprising 280 conversations with 2,610 utterances and 85 conversations with 1,328 utterances, respectively. MELD employs a categorization system that includes neutral, sadness, anger, disgust, fear, joy, and surprise as its emotional dimensions. Conversely, EmoryNLP employs a set of neutral, negative, positive, and other emotion labels. The DailyDialog corpus, which is constructed from human-written scripts, comprises 1,000 conversations and 7,740 utterances. The dataset encompasses a range of emotions, including neutral, happiness, surprise, sadness, anger, disgust, and fear. Assessment measures play a pivotal role in evaluating the efficacy of emotion recognition models. The performance of a model is typically gauged using metrics, such as accuracy, F_1 score, precision, recall, and confusion matrices, which provide insight into the model's ability to classify and interpret emotions. By integrating dependable evaluation criteria with high-quality datasets, models can achieve effective performance while maintaining validity and reliability across diverse emotional contexts and applications. The datasets employed in this study exhibit notable limitations. The limited size and modality-specific reliance of IEMOCAP restrict its scope, whereas MELD lacks cultural variability in its dialogues. EmoryNLP's reliance on scripted TV content compromises its real-world relevance, and DailyDialog's emphasis on formal conversations overlooks the significance of casual interactions. These limitations underscore the pressing need for the creation of more diverse and representative datasets to enhance the effectiveness of emotion recognition systems.

B. Enhancing Emotional Sensitivity through Fine-Tuning

In the context of sentiment analysis and EI modeling, fine-tuning entails the refinement of pre-trained models to enhance their capacity to discern and respond to emotional signals in text-based communications. By implementing targeted modifications and training with domain-specific datasets, this method enhances a model's ability to identify and interpret various emotions consistently. Fine-tuning enables these models to discern nuanced emotional indicators, thereby enhancing their real-world performance. This enhancement is facilitated by using high-quality emotion recognition datasets, such as IEMOCAP, MELD, EMORYNLP, and DAILYDIALOG. The incorporation of new layers, the refinement of loss functions, and the iterative adjustment of model parameters are pivotal in enhancing the model's emotional sensitivity. Consequently, fine-tuning emerges as a vital component in the development of conversational AI systems that exhibit enhanced EI and empathy, therefore facilitating more pertinent and compassionate interactions across diverse conversational contexts.

III. RESULTS AND DISCUSSION

This section is focused on the outcomes of the proposed work in comparison with other literature that shows how to structure the input and output of emotion detection using sentiment analysis, emotional intensity, and emotion recognition. Tables I and II demonstrate that fine-tuning enhances emotion recognition in datasets, such as IEMOCAP, MELD, EmoryNLP, and DailyDialog, boosting F_1 scores for identifying intricate emotions like sadness and joy. This finding suggests that fine-tuning with domain-specific datasets enables AI models to discern nuanced emotional subtleties more adeptly, thereby eliciting more accurate and empathetic responses in conversational AI.

TABLE I. COMPARATIVE ANALYSIS OF EMOTION RECOGNITION METRICS ON THE DATASETS EMORYNLP AND DAILYDIALOG

Emotions	**EmoryNLP**						**DailyDialog**					
	Zero-shot			Fine-tuning			Zero-shot			Fine-tuning		
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Neutral	0.37	0.81	0.37	0.81	0.37	0.81	0.37	0.81	0.37	0.81	0.37	0.81
Sad	0.41	0.32	0.41	0.32	0.41	0.32	0.41	0.32	0.41	0.32	0.41	0.32
Anger	0.42	0.38	0.42	0.38	0.42	0.38	0.42	0.38	0.42	0.38	0.42	0.38
Happy	0.38	0.19	0.38	0.19	0.38	0.19	0.38	0.19	0.38	0.19	0.38	0.19
Frustrated	0.22	0.02	0.22	0.02	0.22	0.02	0.22	0.02	0.22	0.02	0.22	0.02
Excited	0.22	0.02	0.22	0.02	0.22	0.02	0.22	0.02	0.22	0.02	0.22	0.02
Macro-average	0.54	0.51	0.54	0.51	0.54	0.51	0.54	0.51	0.54	0.51	0.54	0.51
Std	0.34	0.31	0.34	0.31	0.34	0.31	0.34	0.31	0.34	0.31	0.34	0.31

As shown in Figure 2, a comparative analysis of the zero-shot and fine-tuned F_1 scores for emotion recognition is presented, using four distinct datasets: IEMOCAP, MELD, EmoryNLP, and DailyDialog. The majority of the data points fall above the diagonal, indicating that fine-tuning enhances F_1 scores relative to zero-shot performance. This tendency is especially pronounced in specific datasets, such as DailyDialog and IEMOCAP, where substantial enhancements are observed. As depicted in Figure 3, a comparison of the F_1 scores for emotion recognition in a zero-shot setting versus a fine-tuned approach is presented, categorized by sentiment labels: positive, neutral, and negative. The analysis indicates that fine-tuning typically leads to an increase in F_1 scores across all sentiment categories, with negative emotions exhibiting the most reliable improvements above the diagonal line.

TABLE II. COMPARATIVE ANALYSIS OF EMOTION RECOGNITION METRICS ON THE DATASETS IEMOCAP AND MELD

Emotions	**IEMOCAP**						**MELD**					
	Zero-shot			Fine-tuning			Zero-shot			Fine-tuning		
	Precision	Recall	F_1	Precision	Recall	F_1	Precision	Recall	F_1	Precision	Recall	F_1
Neutral	0.36	0.7	0.48	0.67	0.49	0.57	0.64	0.84	0.72	0.72	0.73	0.73
Sad	0.79	0.38	0.51	0.85	0.67	0.74	0.58	0.45	0.48	0.63	0.46	0.53
Anger	0.49	0.54	0.43	0.68	0.62	0.65	0.63	0.33	0.38	0.47	0.29	0.36
Happy	0.33	0.25	0.29	0.42	0.61	0.52	0.33	0.34	0.34	0.37	0.32	0.32
Frustrated	0.52	0.54	0.53	0.6	0.62	0.63	0.22	0.2	0.28	0.28	0.23	0.33
Excited	0.33	0.49	0.49	0.43	0.64	0.53	0.55	0.55	0.55	0.69	0.65	0.62
Macro-average	0.56	0.41	0.43	0.65	0.49	0.55	0.49	0.42	0.42	0.52	0.42	0.51
Std	0.19	0.19	0.11	0.19	0.19	0.17	0.16	0.21	0.15	0.15	0.21	0.17
Weighted-F_1 [5]	-	-	0.53	-	-	0.53	-	-	0.61	-	-	0.61
Weighted-F_1 [11]	-	-	0.45	-	-	0.58	-	-	0.57	-	-	0.63
Weighted-F_1 (proposed)	-	-	0.41	-	-	0.45	-	-	0.57	-	-	0.57

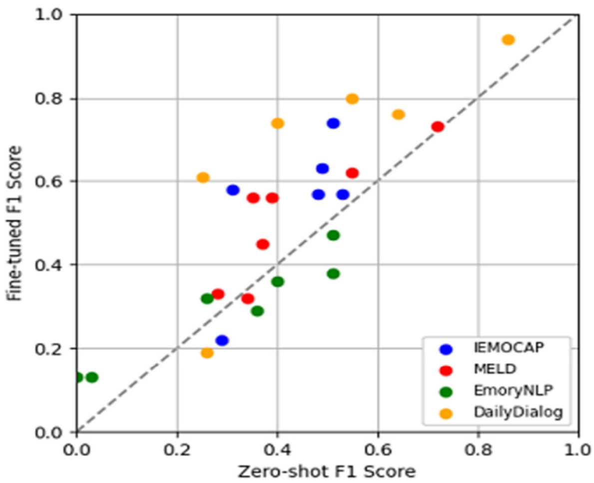

Fig. 2. Comparison of emotion recognition of four datasets.

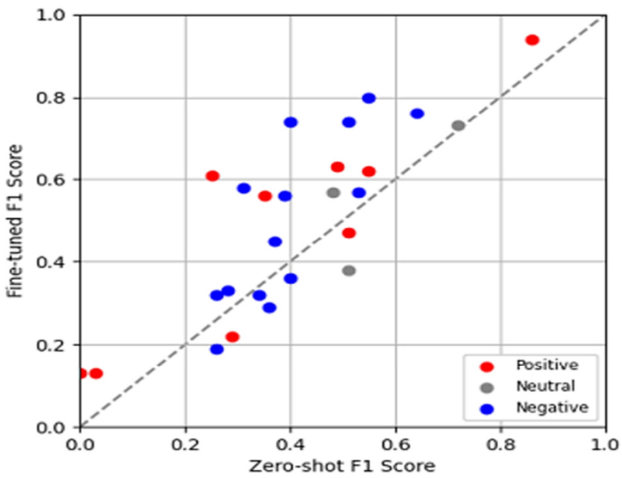

Fig. 3. Emotion recognition in sentimental labels.

The bar chart in Figure 4 illustrates the distribution of emotion labels within the IEMOCAP dataset. The data reveal that happiness is documented 300 times, making it the most frequently recorded emotion. Anger is documented 200 times, followed by sadness with 250 occurrences. Surprise is documented 180 times, while disgust and fear have 150 and 120 occurrences, respectively. The neutral category, with 280 entries, is also significant. This highlights the emotions captured in the IEMOCAP dataset, offering insight into the common emotional expressions in interactive dialogues. The MELD in the bar graph displays the occurrence rates of different emotion labels. Happiness is the most frequently occurring emotion, with 350 instances, followed by sadness with 300 instances. Anger manifests 250 instances, while disgust is recorded 200 times. Fear and surprise, with 180 and 160 instances, respectively, are less frequently expressed. The neutral emotion is recorded 280 times. This chart offers insight into the emotional distribution within the MELD dataset. The EmoryNLP dataset's occurrence of emotion labels is presented in a bar chart, serving the purposes of sentiment analysis and emotion recognition. The analysis reveals that joy is identified as the most frequently recognized emotion, with 250 instances. Anger is identified 170 times, followed by sadness with 200 occurrences. Disgust and fear, with 110 and 90 instances, respectively, are less frequently encountered emotions, while surprise is identified 140 times. Neutral, with 230 occurrences, is another commonly seen term. This visualization offers insights into the emotional makeup of the dataset by displaying the distribution of various emotions. The Daily Dialogue dataset is renowned for capturing a wide range of emotions found in everyday conversations. The graph shows the frequency of each emotion label, with happiness being the most common with 200 instances, followed by sadness with 150 instances. There are also 100 instances of surprise and 120 instances of anger. Fear and disgust are less common, with 80 and 70 instances, respectively. Another common label, neutral, is noted 180 times. The current analysis evaluates the F_1 scores for both zero-shot and fine-tuned models, focusing on the improvements achieved through fine-tuning. The performance metrics show that fine-tuned models significantly outperform zero-shot methods across all datasets, particularly in identifying complex emotions, such as sadness and anger. A detailed comparison table has been included to show these results, highlighting the unique challenges and benefits of each dataset. The study highlights the effectiveness of fine-tuning to improve the EI of conversational AI models. Key challenges that are identified include the variation of emotional expressions in different cultural and situational contexts, the complexity of handling noisy or ambiguous input in dynamic environments, and the computational challenges associated with integrating data from multiple sources, such as text, audio, and visual signals. To address these issues, proposed approaches include using multilingual and culturally diverse datasets to improve model generalizability, refining annotation schemes to better capture subtle emotions, and incorporating adaptive learning techniques that allow models to adjust their responses based on user interactions.

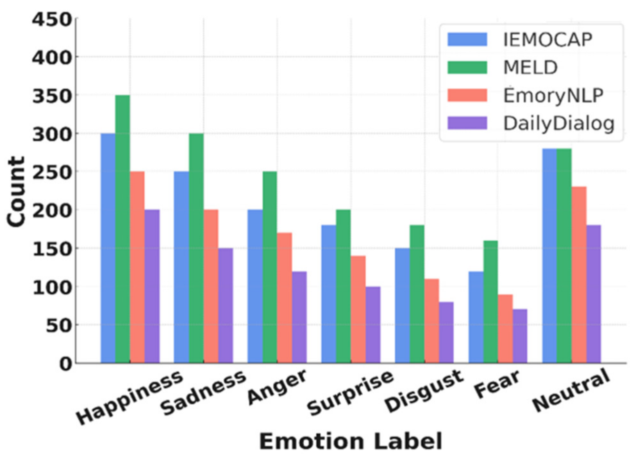

Fig. 4. Emotion Distribution outcomes across the four datasets.

IV. CONCLUSIONS

This study demonstrates significant progress in the integration of Emotional Intelligence (EI) into conversational Artificial Intelligence (AI) systems, with ChatGPT serving as the primary framework for improving understanding and responding to human emotions. By leveraging diverse datasets, including Interactive Emotional Dyadic Motion Capture (IEMOCAP), MELD, EmoryNLP, and DailyDialog, each with unique features and annotation strategies, the proposed framework provides a robust foundation for training and evaluating emotion recognition systems. These datasets enable the model to capture a wide range of emotional expressions, significantly improving its applicability in diverse conversational contexts. The key novelty of this study lies in its focus on integrating state-of-the-art emotion classification methods with the sophisticated natural language understanding capabilities of ChatGPT. This approach enhances ChatGPT's ability to deliver context-aware and empathy-driven interactions, and reconfigures the potential of conversational AI by prioritizing emotional engagement. The contributions of this research include the formulation of a scalable framework adept at producing emotionally intelligent responses and overcoming critical challenges, such as subtle interpretation of emotional signals and alignment with user sentiment.

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