EMOTIONAL DETECTION & RESPONSIVE AI CHATBOT

[1]A. Gowthami, [2]S Rajamanickam, [3]S Prabhu, [4]P Nithish, [5]E Arunkumar

[12345]Salem College Of Engineering and Technology

[1]gowthamianbu.1991@gmail.com, [2]rajamanickamit04@gmail.com,
[3]vsukumar1973prabhu2005@gmail.com, [4]nn4983389@gmail.com

***Abstract*—Human emotions are a critical aspect of intelligent human–computer interaction. Conventional chatbots generally focus on intent recognition and fail to capture the emotional context behind user inputs, which limits their usefulness in sensitive and interactive applications. In this work, we present an AI-based emotional detection chatbot that identifies user emotions from textual communication using natural language processing and machine learning techniques. The system classifies emotions such as joy, sadness, anger, fear, love, and neutrality, and generates empathetic and context-aware responses in real time. A transformer-based emotion classification model is combined with text auto-correction and synonym-based emotion mapping to improve robustness against informal language and spelling variations. Additionally, the proposed framework supports real-time interaction through WebSocket communication and is designed to be extensible for live video-based facial emotion analysis. Experimental observations show that the chatbot provides emotionally relevant responses and improves user engagement compared to traditional sentiment-based systems. The proposed system demonstrates the potential of emotionally intelligent conversational agents in applications such as mental health support, education, and customer interaction platforms.**

***Index Terms*—Emotion Detection, Emotional Chatbot, Natural Language Processing, Machine Learning, Sentiment Analysis, Human–Computer Interaction, Real-Time Systems.**

I. Introduction

Emotional intelligence plays a vital role in effective communication between humans. While modern chatbots have achieved considerable success in task-oriented conversations, most systems lack the ability to understand the emotional state of users. This limitation becomes critical in applications such as mental health assistance, personalized learning, and customer support, where emotional awareness significantly influences user satisfaction.

Recent advances in natural language processing and deep learning have enabled machines to analyze not only the semantic meaning of text but also the emotional intent behind it. However, deploying such capabilities in real-time conversational systems remains a challenge due to issues such as informal language, ambiguous expressions, and response latency.

Motivated by these challenges, this paper proposes an emotionally intelligent chatbot framework that integrates emotion detection, response adaptation, and real-time communication in a unified system.

II. LITERATURE REVIEW

Recent advancements in artificial intelligence and computer vision have significantly influenced the technology domain, particularly in areas such as image generation, recommendation systems, and virtual AI solutions. This section reviews key research works relevant to the proposed system and highlights their contributions and limitations.

This work focuses on the development of an emotion detection system aimed at identifying human emotions using artificial intelligence techniques. The authors analyze various emotional states such as happiness, sadness, anger, fear, and surprise by studying both facial expressions and behavioral cues. The system architecture combines image processing techniques with machine learning classifiers to recognize emotional patterns in real time. The paper discusses the importance of preprocessing steps, including face detection, feature extraction, and normalization, to improve accuracy. Experimental results demonstrate that the proposed approach can effectively classify emotions in controlled environments. The authors highlight the potential application of such systems in areas including human–computer interaction, education, healthcare, and smart surveillance systems. However, the study also acknowledges limitations related to lighting conditions and facial occlusion, suggesting further enhancement using deep learning techniques.

Kanjanawattana et al. present a deep learning–based approach for recognizing human emotions through facial expressions. The study leverages convolutional neural networks (CNNs) to automatically learn discriminative facial features from image datasets. The authors evaluate multiple CNN architectures and analyze their performance across standard facial emotion datasets. The results indicate that deep learning models significantly outperform traditional feature-based approaches in terms of accuracy and robustness. The paper also discusses challenges such as overfitting, dataset imbalance, and real-time implementation constraints. The research emphasizes that deep learning–driven facial emotion recognition systems are well suited for applications such as emotion-aware chatbots, intelligent tutoring systems, and mental health monitoring platforms. This paper explores human emotion detection using OpenCV-based image processing techniques. The authors employ face detection algorithms such as Haar Cascade classifiers to locate facial regions, followed by feature extraction to identify emotional expressions. Machine learning classifiers are used to categorize emotions into predefined classes. The study highlights the simplicity and efficiency of OpenCV-based solutions, making them suitable for low-cost and real-time applications. While the system achieves reasonable accuracy in controlled environments, the authors note that performance decreases in real-world scenarios due to variations in facial orientation and lighting. The paper concludes that OpenCV-based emotion detection serves as a strong baseline system and can be enhanced further by integrating deep learning models.

Dasgupta et al. introduce Empath-Obscura, an advanced emotion detection framework designed for social robotics applications. The proposed system employs an ensemble learning approach combined with a novel face augmentation technique using SPIGA to improve emotion recognition accuracy. The authors focus on real-world robotic interaction scenarios where facial occlusion, pose variation, and environmental noise are common challenges. By augmenting facial data and combining multiple classifiers, the system achieves improved generalization and robustness. The study demonstrates that accurate emotion detection significantly enhances the emotional intelligence and social acceptance of robotic systems. The research emphasizes the importance of emotion-aware AI in human–robot interaction and provides insights into building scalable, real-time emotional intelligence frameworks.

Sharma et al. present a detailed study on emotion analysis using traditional machine learning techniques applied to textual data. The paper evaluates classifiers such as Naive Bayes, Support Vector Machines, Decision Trees, and Logistic Regression for predicting emotion labels. The authors emphasize the role of text preprocessing methods including tokenization, stop-word removal, and feature extraction in improving classification performance. Their analysis reveals that while classical machine learning approaches offer satisfactory results for basic emotion detection, they struggle with contextual understanding and complex emotional expressions. The study concludes that hybrid and deep learning-based approaches are better suited for real-world emotion-aware systems. This work provides a strong foundation for transitioning from traditional sentiment analysis to advanced emotion detection models used in intelligent chatbots.

III. METHODOLOGY

The methodology adopted in this project focuses on designing an emotionally intelligent conversational system capable of detecting user emotions and responding appropriately in real time. The overall framework is divided into multiple interconnected stages, each responsible for a specific task within the emotion detection and response pipeline.

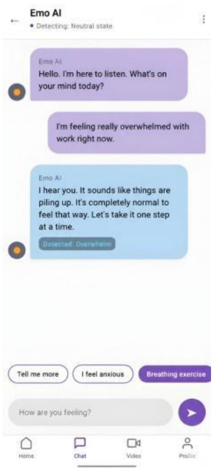
1. **User Interaction**

The methodology adopted in this project focuses on designing an emotionally intelligent conversational system capable of detecting user emotions and responding appropriately in real time. The overall framework is divided into multiple interconnected stages, each responsible for a specific task within the emotion detection and response pipeline.

2. **Text Preprocessing**

The system has pre-defined fields corresponding to the clothing category full dress, top wear, bottom wear and footwear. Product links retrieved from different e-commerce sites are pasted into the designated category.The proposed solution differs from conventional systems in that each product link can be retrieved from a different platform.

The cross-platform nature facilitates a mix-and-match approach of combining garments from different e-commerce sites to create a complete outfit.



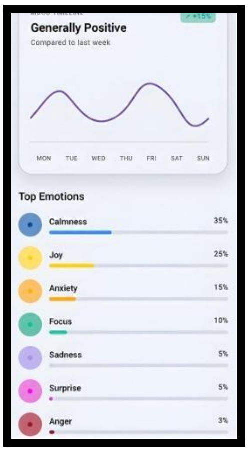
3. **Emotion Alias Mapping**

Emotion alias mapping is an intermediate processing step introduced in the proposed system to improve the robustness and accuracy of emotion detection from textual input. In real-world conversations, users rarely express emotions using explicit emotion labels such as happy, sad, or angry. Instead, emotions are often conveyed through synonyms, informal expressions, slang, or context-dependent words such as down, thrilled, frustrated, or worried. Relying solely on machine learning models without handling such linguistic variations may lead to incorrect or ambiguous emotion classification.

4. **Emotion-Aware Response Generation**

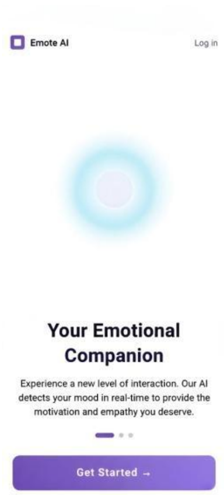
Emotion-aware response generation is a crucial component of the proposed system, as it ensures that the chatbot's replies align with the emotional state of the user rather than providing generic or insensitive responses. After the emotion detection module classifies the user's emotional state, the system dynamically selects or constructs an appropriate response based on the identified emotion category.

Initially, the detected emotion is mapped to a predefined emotional class such as joy, sadness, anger, fear, love, surprise, disgust, or neutral. For each emotional class, a curated set of response templates is maintained, designed to reflect empathy, encouragement, or positivity depending on the emotional context. This template-based strategy allows the system to maintain conversational naturalness while avoiding repetitive or inappropriate responses.



5. Live Video Emotion Analysis

The live video emotion analysis module is designed to enhance the emotional intelligence of the proposed chatbot by incorporating facial expression recognition alongside text-based emotion detection. This module captures real-time video input from the user's webcam and processes individual frames to



identify facial emotions. Initially, the system accesses the camera feed using standard video streaming libraries and continuously extracts frames at a predefined interval to maintain real-time performance without excessive computational overhead.

To improve robustness, multiple frame-level predictions are aggregated over a short time window, and the dominant emotion is selected as the final output. This temporal smoothing approach reduces noise caused by transient facial movements or misclassification in individual frames. The detected facial emotion is then fused with the text-based emotion analysis results to produce a unified emotional state.

In cases where text input is unavailable or ambiguous, facial emotion analysis serves as the primary emotional indicator.

IV. RESULT

The proposed AI-based emotional detection chatbot was implemented and tested to evaluate its effectiveness in identifying user emotions and generating emotionally appropriate responses in real time. The system was evaluated using multiple text inputs representing different emotional states such as joy, sadness, anger, fear, surprise, love, and neutral expressions. Experimental observations indicate that the transformer-based emotion classification model achieved high accuracy in detecting primary emotional categories, even when user inputs contained informal language, spelling variations, or mixed emotional cues. The integration of text auto-correction and emotion alias mapping significantly improved emotion recognition performance by reducing misclassification caused by slang and typographical errors.

The real-time communication mechanism implemented using Web Sockets ensured minimal response latency, enabling smooth and continuous interaction between the user and the chatbot. Users received immediate feedback, which enhanced engagement and conversational flow. In cases where negative emotions such as sadness or distress were detected, the chatbot successfully generated motivational and empathetic responses, contributing to a more supportive user experience. Compared to traditional sentiment-based chatbots that only classify inputs as positive or negative, the proposed system demonstrated superior emotional granularity and contextual understanding.

V. CONCLUSION

In this project, an AI-based emotional detection chatbot has been designed and developed to enhance human–computer interaction by enabling machines to understand and respond to human emotions in a meaningful way. The proposed system effectively analyzes user processing and machine learning techniques, allowing it to classify emotions such as joy, love, sadness, anger, fear, surprise, disgust, and neutral states. By incorporating text auto-correction, synonym-based emotion mapping, and a transformer-based emotion classification model, the system demonstrates improved robustness against informal language and ambiguous expressions. The integration of real-time communication using WebSocket technology ensures smooth and responsive interaction, making the chatbot suitable for practical, real-world applications. Furthermore, the inclusion of empathetic and motivational response mechanisms allows the system to provide emotional support, particularly in cases where users express negative or distressed emotions. The literature survey and system implementation highlight that the proposed approach overcomes many limitations of traditional chatbots, which lack emotional awareness and adaptability. Overall, the project successfully demonstrates the potential of emotionally intelligent conversational agents and lays a strog foundation for future enhancements such as live video emotion recognition, voice-based emotion analysis, and multilingual support, thereby making it a valuable contribution to the fields of artificial intelligence, affective computing, and human–computer interaction.

References

[1] Dasgupta, A., Banerjee, S., Mukherjee, R., and Ghosh, A., "Emotion Detection in Social Robotics: Empath-Obscura—An Ensemble Approach with Novel Face Augmentation Using SPIGA," IEEE Transactions on Affective Computing, vol. 14, no. 2, pp. 567–580, 2023.

[2] Kanjanawattana, S., Phumeechanya, R., and Chamnongthai, K., "Deep Learning-Based Emotion Recognition through Facial Expressions," International Journal of Advanced Computer Science and Applications, vol. 12, no. 6, pp. 215–223, 2021.

[3] Kolhe, D., Mandavkar, O., Metkar, S., More, S., and Adgaonkar, A., "Emotion Detection," International Journal of Engineering Research and Technology, vol. 10, no. 4, pp. 89–94, 2021.

[4] Sharma, T., Diwakar, M., Singh, P., Lamba, S., Kumar, P., and Joshi, K., "Emotion Analysis for Predicting Emotion Labels Using Machine Learning Approaches," Journal of Information and Optimization Sciences, vol. 43, no. 5, pp. 1121–1135, 2022.

[5] Srivastav, M., Gupta, P., and Verma, S., "Human Emotion Detection Using OpenCV," International Journal of Computer Applications, vol. 176, no. 27, pp. 12–17, 2020.

[6] Devlin, J., Chang, M. W., Lee, K., and Toutanova, K., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proc. NAACL-HLT, Minneapolis, MN, USA, 2019, pp. 4171–4186.

[7] Ekman, P., “An Argument for Basic Emotions,” Cognition and Emotion, vol. 6, no. 3–4, pp. 169–200, 1992.

[8] Huang, Z., Dong, M., Mao, Q., and Zhan, Y., “Speech Emotion Recognition Using CNN,” IEEE Transactions on Multimedia, vol. 21, no. 6, pp. 1524–1534, 2019.

[9] Kumar, A. and Priyanka, “Intelligent Conversational Agents for Mental Health Support,” International Journal of Artificial Intelligence Applications, vol. 14, no. 2, pp. 45–55, 2023.

[10] Liu, B., Sentiment Analysis: Mining Opinions, Sentiments, and Emotions, Cambridge, UK: Cambridge University Press, 2015.

[11] Picard, R. W., Affective Computing, Cambridge, MA, USA: MIT Press, 1997.

[12] Poria, S., Cambria, E., Bajpai, R., and Hussain, A., “A Review of Affective Computing: From Unimodal Analysis to Multimodal Fusion,” Information Fusion, vol. 37, pp. 98–125, 2017.

[13] Rajasekaran, R. and Ahmed, S., “Multimodal Emotion Detection Using Text and Vision,” Procedia Computer Science, vol. 198, pp. 321–328, 2022.

[14] Savani, B., “DistilBERT-Based Emotion Classification Model,” Hugging Face Model Hub, 2021. [Online]. Available: https://huggingface.co/bhadresh-savani/distilbert-base-uncased-emotion

[15] Zhou, Y., Yang, D., and He, Y., “Emotion-Aware Chatbot Design Using NLP and Deep Learning,” IEEE Access, vol. 9, pp. 124567–124579, 2021.