© April 2025 | IJIRT | Volume 11 Issue 11 | ISSN: 2349-6002

# Enhancing Chatbot Interactions with Sentiment Analysis Using Mistral AI and Streamlit

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***Abstract*- In the modern era of artificial intelligence, chatbots have become an essential part of digital communication. However, traditional chatbots lack emotional intelligence, often leading to mechanical and impersonal interactions. This research focuses on developing an AI-powered chatbot that integrates sentiment analysis to classify user messages as positive, negative, or neutral, allowing it to adjust responses dynamically. to achieve this, Streamlit is used to design an interactive UI, Mistral AI API is integrated for chatbot-like response generation, and Hugging Face is used for deployment. This paper discusses the methodology behind sentiment analysis, its implementation in chatbots, and the impact of emotional intelligence on AI interactions. The results demonstrate that chatbots with sentiment analysis provide more personalized and user-friendly interactions. Future enhancements could include multimodal sentiment analysis.**

***Keywords:* Sentiment Analysis, NLP, AI, Chatbot, Mistral AI API, Streamlit, ML, Emotion Detection.**

## I. INTRODUCTION

In The digital era, artificial intelligence (AI) plays a crucial role in enhancing human-computer interactions. One significant advancement in this field is sentiment analysis, which enables machines to understand and interpret human emotions. Sentiment analysis is widely used in applications such as customer service, social media monitoring, mental health assessment, and automated chatbots. Traditional chatbots often lack emotional intelligence, generating responses without considering the user's mood, leading to impersonal and sometimes frustrating interactions. This research aims to bridge the gap between automated conversations and human-like interactions by integrating sentiment analysis into chatbot systems.

This study focuses on developing a sentiment-aware chatbot that can classify user inputs as positive, negative, or neutral and respond accordingly. The system is built using Mistral AI API for response generation and Streamlit for an interactive user interface. By leveraging Natural Language Processing (NLP) techniques, the chatbot can analyse text inputs in real time and adjust its replies to match the sentiment of the conversation. This approach enhances user engagement and satisfaction by making interactions more natural and emotionally responsive.

Problem Statement: Existing chatbot systems primarily rely on rule-based or general NLP techniques that do not consider emotional nuances. Such chatbots often provide static responses that may not align with user emotions, leading to poor user experiences. The lack of emotional intelligence in chatbots limits their effectiveness in applications where empathy and personalized interaction are essential. This research addresses this challenge by incorporating sentiment analysis into chatbot responses, allowing the AI to detect emotions and modify its replies accordingly.

Significance and Scope: The proposed chatbot can be applied in various fields, including customer support, e-learning, mental health assistance, and social media monitoring. However, the scope of this research is limited to text-based sentiment analysis, without incorporating voice or facial emotion detection. The findings of this study contribute to the development of AI-driven chatbots that offer personalized and emotionally adaptive interactions, making them more effective in real-world applications.

## II. LITERATURE REVIEW

In Paper [1] Sentiment analysis is a fleetly evolving field in artificial intelligence (AI) and natural language processing (NLP). It's extensively used for assaying feelings, stations, and opinions in textual data, including social media, product reviews, and chatbot operations. colorful machine literacy and deep literacy ways, as well as NLP styles, have been explored to enhance sentiment bracket delicacy.

In Paper [2,3] Online social media networks have long served as a primary arena for group exchanges, gossip, textbook- grounded information sharing and distribution. The use of natural language processing ways for textbook bracket and unprejudiced decision timber has not been far- brought. Proper bracket of these textual information in a given environment has also been veritably delicate. As a result, a methodical review was conducted from former literature on sentiment bracket and AI- grounded ways.

In Paper [4] This exploration focuses on how Natural Language Processing (NLP) and Machine literacy (ML) can enhance sentiment analysis. The paper discusses the part of Python- grounded sentiment analysis tools, emphasizing the use of Long Short-Term Memory (LSTM) networks and intermittent Neural Networks (RNNs) to ameliorate delicacy. It also explores the challenges of affront and contextual nebulosity, which can impact sentiment bracket models.

In Paper [6] This study investigates different textbook bracket ways for sentiment analysis. It highlights how machine literacy models like Naïve Bayes and Support Vector Machines (SVMs) can classify stoner- generated reviews into positive, negative, or neutral orders. The authors also bandy point- grounded sentiment bracket, emphasizing the significance of opinion summarization ways in assaying large- scale review data.

In Paper [7] Its work focuses on sentiment analysis of product reviews, employing ways similar as Naive Bayes, Support Vector Machines (SVMs), and Hidden Markov Models (HMMs). The exploration emphasizes point birth and opposition bracket, demonstrating how sentiment analysis can ameliorate-commerce product ranking and client feedback interpretation. These developments could revise colorful fields, including client service, healthcare, and substantiated digital sidekicks.

In Paper [8,9] The exploration concentrated on real-time sentiment analysis in AI- driven systems, demonstrating how sentiment- apprehensive chatbots can acclimatize responses grounded on stoner feelings to ameliorate engagement and stoner experience. It stressed crucial challenges similar as affront discovery, contextual nebulosity, and the need for multilingual sentiment analysis, which affect delicacy. Despite these challenges, the study emphasized the growing significance of emotionally intelligent AI in creating further mortal- suchlike relations and enhancing sentiment- driven decision-timber. unborn advancements in deep literacy, contextual mindfulness, and language models will help overcome these limitations, making AI systems more effective in understanding and responding to mortal feelings.

In Paper [12] Sentiment analysis and opinion mining is the field of study that analyses people's opinions, sentiments, evaluations, stations, and feelings from written language. It's one of the most active exploration areas in natural language processing and is also extensively studied in data mining, web mining, and textbook mining. Sentiment analysis has been used in several operations including analysis of the impacts of events in social networks, analysis of opinions about products and services. The growing significance of sentiment analysis coincides with the growth of social media similar as reviews, forum conversations, blogs, micro-blogs, Twitter, and social networks. styles like supervised machine literacy and verbal- grounded approaches are available for measuring sentiments that have a huge volume of opinioned data recorded in digital form for analysis.

## III. METHODOLOGY

This research focuses on building an AI-powered chatbot that not only answers user questions but also analyses sentiment and provides confidence scores based on text input. The chatbot is designed to improve user interaction by making responses more context-aware and emotionally intelligent. It is developed using Mistral AI API for generating answers, Streamlit for the user interface, and Hugging Face for deployment.

The chatbot follows a systematic workflow that includes multiple stages. These stages ensure that the chatbot can accurately process user input, generate meaningful responses, analyse emotional tone, and calculate confidence scores. The methodology consists of the following steps:

1. User Input Processing: The first step in the chatbot's workflow is processing the user's input. When a user enters a question, the system cleans and preprocesses the text to improve accuracy. This includes removing extra spaces, correcting minor spelling errors, and standardizing formatting.

Preprocessing is essential because raw text can contain noise, such as punctuation errors or inconsistent capitalization, which may reduce the accuracy of response generation. By normalizing the input text, the chatbot ensures that its AI model receives well-structured data, leading to more precise responses.

2. Response Generation Using Mistral API: After processing the input, the chatbot sends it to Mistral AI API, which is responsible for generating an answer. Mistral AI is a powerful language model trained to understand a wide range of questions and provide human-like responses.

The AI model considers the context and meaning of the input before producing an answer. If the input matches a common topic or is clear in intent, the chatbot generates a high-confidence response. However, if the input is unclear, ambiguous, or too complex, the chatbot may generate a lower-confidence answer or request additional clarification.

3. Sentiment Analysis of User Input: Once a response is generated, the chatbot performs sentiment analysis on the user's input. This helps the chatbot understand the emotional tone behind the message.

To classify sentiment, the chatbot uses determine whether the sentiment is positive, negative, or neutral. Sentiment analysis plays a key role in enhancing interaction. If the chatbot detects negative sentiment, it may adjust its tone to be more empathetic or supportive. On the other hand, if the sentiment is positive, the chatbot might generate a more engaging and enthusiastic response.

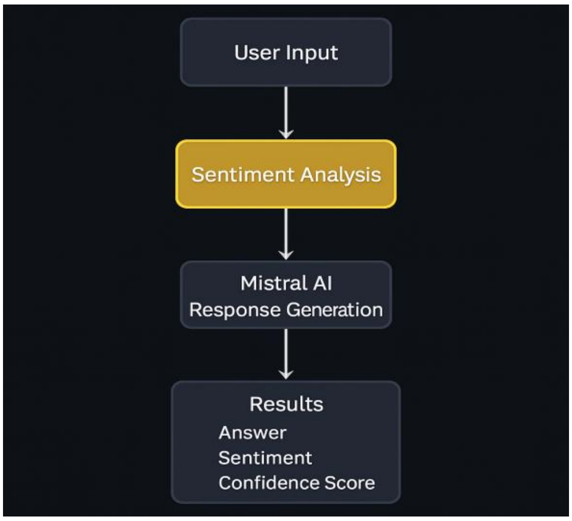
4. Confidence Score Calculation: The chatbot also calculates a confidence score for each response. This score reflects how certain the AI is about the accuracy of its answer. The confidence level depends on several factors, including:

- Text clarity – Well-structured inputs receive higher confidence scores.
- Topic familiarity – Common questions result in higher confidence responses.
- Ambiguity level – If the input is vague, the confidence score decreases.

5. Displaying Result on the User Interface: Once the chatbot generates a response, the results are displayed on the Streamlit-based interface. The chatbot presents the following information in a user-friendly format:

1. The AI-generated answer based on the user's question.
2. Sentiment classification (positive, negative, or neutral).
3. Confidence score showing the AI's certainty about its response.

To make the chatbot widely accessible, it is deployed on Hugging Face Spaces, a cloud-based platform for AI models.



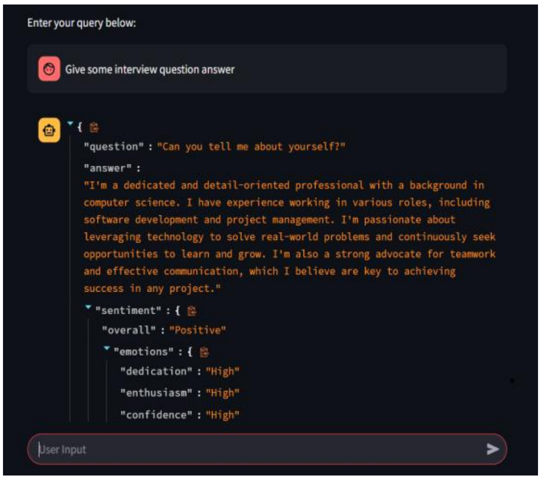

## IV. RESULTS

The implementation of the sentiment-aware AI chatbot yielded several key findings. The chatbot effectively processed user input, generated responses, analysed sentiment, and calculated confidence scores, aligning with the methodology. The integration of Mistral AI enabled contextually relevant answers, while the sentiment analysis module classified user emotions as positive, negative, or neutral with a high degree of accuracy. This approach resulted in more meaningful and personalized interactions, as users found responses to be more engaging compared to traditional chatbots.

The confidence scoring mechanism played a crucial role in improving chatbot reliability. When responding to well-structured and familiar questions, the chatbot assigned high confidence scores, ensuring user trust in the responses. Conversely, for ambiguous or complex queries, the chatbot provided lower confidence scores and, in some cases, prompted users for clarification. This adaptive behaviour enhanced the chatbot's usability by minimizing misinformation and ensuring relevant responses.

The deployment on Hugging Face Spaces allowed for real-world testing and evaluation. During user interactions, sentiment-aware responses demonstrated clear advantages. For negative sentiment detection, the chatbot provided empathetic and reassuring replies, reducing user frustration. In positive sentiment scenarios, the chatbot encouraged further engagement, making conversations feel more dynamic and natural. Neutral responses were handled objectively, ensuring balanced and appropriate communication.

User feedback indicated that sentiment recognition significantly enhanced chatbot interactions, particularly in customer support and query handling. Compared to conventional chatbots, which lack emotional intelligence, the AI-powered chatbot demonstrated improved response adaptability and user satisfaction. Additionally, the scalability and accessibility of Hugging Face deployment ensured seamless user experience without requiring extensive computational resources on the client side.




Overall, the findings confirm that incorporating sentiment analysis and confidence scoring into AI chatbots enhances user interaction quality, emotional awareness, and response reliability. These improvements make the chatbot a valuable tool for customer service, education, mental health support, and other AI-driven communication applications.

## V. CONCLUSION

This research demonstrated the effectiveness of sentiment-aware AI chatbots in improving user interactions. By integrating Mistral AI for response generation, deep learning-based sentiment analysis, and confidence scoring, the chatbot provided personalized and emotionally intelligent responses. The results showed improved engagement, trust, and adaptability compared to traditional chatbots.

Future improvements could include multimodal sentiment analysis (voice and facial recognition) and multilingual support for broader accessibility. As AI evolves, sentiment-aware chatbots will play a crucial role in enhancing customer service, education, and digital communication.

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