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Emotional Intelligence in Chatbots: A Study on Enhancing User Experience with Llama3 and Ollama

Salini Suresh
Bangalore, India
pnsalinisuresh@gmail.com

Rachna Rathore
Dept.of Mathematics
Jiwaji University
Gwalior, India
rachnarathore1109@gmail.com
https://orcid.org/0000-0001-8753-888X

Shailendra Thapliyal
Dept. of Management
Uttaranchal University
Dehradun, India
shailendra@uumail.in

Ajith Sundaram
Dept. of Business
Amrita Vishwa Vidyapeetham
Kochi, India
ajithsundaram@gmail.com

Saloni Bansal
Dept. of Computer Eng. & Applications
GLA University
Mathura, India
saloni.bansal@gla.ac.in

Kabir Gaba
Dept. of CSE (AIML), CSE-APEX
Chandigarh University
Chandigarh, India
kabirgaba002@gmail.com

***Abstract*—The field of emotional support chatbots has become a significant part of the tools designed to enhance mental well-being through human-like conversations. This paper introduces an innovative approach that prioritizes empathy and context continuity. The proposed solution, named ”SOLARA” utilizes the Llama3.2:3b model within the Ollama framework. By incorporating sentiment analysis powered by fuzzy logic, SOLARA delivers context-aware, personalized, and empathetic responses. The Llama3.2:3b model enhances SOLARA's ability to understand complex language and retain memory more effectively. With Ollama enabling offline functionality, SOLARA ensures user privacy and reliability. Compared to existing solutions, this approach demonstrates improvements in emotional accuracy, response quality, and conversational coherence. The solution highlights the potential of NLP in addressing emotional concerns while balancing performance and user privacy, paving the way for further exploration in this field.**

***Index Terms*—Ollama, Llama3.2**

I. Introduction

Background & Importance of NLP in Emotional Support:

This We are aware of NLP's emergence as a major tool for chatbots' development, specifically for the ones built for emotional support. Accessibility, empathy, and a communication which is not judgmental, all of this is provided by these systems to help users overcome mental and emotional challenges [1]. A continuous and personalized experience given by these support chatbots is something which even a human cannot match to, if we consider it in the terms of availability and comfort for users. Complex emotions cannot be understood by traditionally built, rule-based systems, as such systems are just made to follow a structured approach but emotions do not work in that way. Such systems mostly fail in understanding user's emotion or generating a response that can match a human intellect [2]. NLP has however achieved a great improvement and advancements as well which enhances its ability in handling such inputs. This feature is a must to have feature for an emotional support chatbot, as these chatbots need to analyze even a subtle change in the user's emotion while maintaining the understanding of context.

The Need for Advanced Models: Llama3.2:3b :

More parameters, more data, more understanding and generalization on a much better level is what an advanced model like Llama3.2 offers. Earlier models were trained well and had a great efficiency in handling complex inputs, but why to settle in less when you have a better option? These advanced models have a lot to offer along with removing the shortcomings of the earlier models. Sustaining coherence and providing a sensitive response are the things with utmost importance when it is about emotional support. And these are the key features of Llama3.2, its architecture makes it capable of achieving all of this, making it convenient and more preferrable option. By leveraging improved memory retention and natural language understanding, this model offers a deeper, more human-like engagement, making it a key tool in enhancing the user's emotional experience with the chatbot.

Role of Ollama Framework for Offline Availability:

Making emotional support available consistently, even offline is the key idea at the core of the work discussed in this paper. And that is where Ollama framework comes into action and makes this task possible, by allowing the

Llama3.2 model to run effectively offline. Which is essential in maintaining the privacy, making it more reliable, which is really a significant variable to keep in mind while dealing with sensitive emotional disclosures [3]. All of this makes sure that users can take benefit of such systems even in an environment without connectivity. And that too without giving away the performance or accuracy metrics, as the features of Llama3.2 will be made offline with Ollama framework. Trust is a variable that is given lesser weight many a time, but not in this proposal, the offline feature makes it more trustable than any other model available in this stream.

Vision for the Proposal:

A chatbot that is highly sensitive with its language, understands emotions on a high level and that can work both offline and online and that too efficiently. That is all this approach aims to achieve, with the help of Llama3.2:3b's fineness and accuracy in handling complex data like emotions, along with Ollama framework which makes it work offline with the same effectiveness as in online mode [4]. Integrating all this with fuzzy logic refines the working of chatbot offering a better response. With the help of this study, it is aimed to set high standards in the field of emotional support and self-help chatbots in the terms of empathetic, intellectual responses and a better understanding of emotional cues and making sure that privacy and security is there too on a high level. A solution that users can trust and they can feel extremely real.

II. RELATED WORK

Cabezas et al. (2024) integrated a LLaMA-based chatbot with augmented retrieval generation to assist students. The proposed system showed promise as a complementary educational tool for high school and college learners [5]. Kaushik (2024) investigated dynamic data scaling techniques for streaming machine learning, providing insights into optimizing chatbot frameworks for dynamic environments and large-scale operations [6]. Bilquise et al. (2022) conducted a systematic review on emotionally intelligent chatbots, outlining key methodologies for incorporating sentiment analysis and empathetic responses into conversational agents [7]. Shrivastava and Rathore (2024) analyzed a single server Markovian queuing model with specific features such as vacation interruptions and customer reneging. Their findings contribute to optimizing resource allocation in chatbot server frameworks [8]. Sasan (2024) introduced a medical chatbot based on LLaMA 2, showcasing its potential in patient consultation and medical information delivery while addressing accuracy and contextual challenges [9]. Rathore et al. (2024) investigated the integration of fog and edge computing into intelligent transportation systems for navigation. Their research provided a foundation for enhancing chatbot functionalities in transportation assistance [10]. Li and Klinger (2024) introduced iPrOp, a human-in-the-loop interactive prompt optimization framework for large language models. The study focused on improving model performance and adaptability through iterative optimization techniques, highlighting its applications in diverse domains [11].

Yigci et al. (2024) explored the use of large language model-based chatbots in higher education, emphasizing their potential to enhance personalized learning experiences while addressing the challenges of scalability and engagement [12]. Rathore et al. (2024) conducted a study on consumer sentiment analysis using advanced machine learning techniques. Their findings offered insights into understanding consumer behavior and preferences for business applications [13]. Ilieva et al. (2023) examined the effects of generative chatbots in higher education, highlighting their impact on student learning outcomes and the overall educational experience, particularly in interactive and collaborative learning settings [14]. Kooli (2023) critically analyzed the ethical implications of chatbots in education and research. The study proposed solutions to mitigate biases and ethical concerns while ensuring fair and responsible AI deployment [15]. Rathore (2023) assessed the role of AI in recruitment and selection processes, discussing its efficiency in automating tasks, improving decision-making, and reducing hiring biases in organizational settings [16]. Rane (2023) explored chatbot-enhanced teaching and learning, focusing on implementation strategies and challenges. The study highlighted the role of ChatGPT in improving interactivity and engagement in educational environments [17]. Thamilselvan et al. (2024) designed a LLaMA 2-powered chatbot for enhanced college website support. Their approach demonstrated improvements in user satisfaction and information retrieval for institutional purposes [18]. Rathore et al. (2024) proposed a smart ecosystem for skin cancer detection, integrating AI for accurate diagnostics. The study underlined the potential of chatbots in assisting healthcare services with rapid and accessible consultations [19].

III. METHODOLOGY

Ollama Framework: Overview and Offline Functionality-

Making emotional support available consistently, even offline is the key idea at the core of the work discussed in this paper. And that is where Ollama framework comes into action and makes this task possible, by allowing the Llama3.2 model to run effectively offline. Which is essential in maintaining the privacy, making it more reliable, which is really a significant variable to keep in mind while dealing with sensitive emotional disclosures.

All of this makes sure that users can take benefit of such systems even in an environment without connectivity. And that too without giving away the performance or accuracy metrics, as the features of Llama3.2 will be made offline with Ollama framework [20]. Trust is a variable that is given lesser weight many a time, but not in this proposal, the offline feature makes it more trustable than any other model available in this stream.

L1ama3.2 : 3b Model Architecture-

When GPT-2 was introduced, it was seen as a significant achievement as it could generate coherent text. But when we look at the advance models today, it looks too be the beginning. Being able to generate a coherent text, that makes sense, that too in real-time and then taking care of social and religious beliefs into account and not harming any of the beliefs, then being intelligent enough to handle emotional inputs, all of this was still like a dream. But with the pace all of this has happened shows we are leading to something getting true soon that seems to be unreal today.

Comprehending language on a better level, and retaining memory for a longer period was still needed to be achieved, that Llama3.2:3b have now achieved on a satisfactory level [21]. Multi-turn conversations along with keeping track of emotions, making it more human-like with the help of optimization in its architecture. Being able to analyze subtle and delicate, very fine cues in input texts with the help of a huge number of parameters. Llama3.2:3b proves to be a better version than all of its predecessors.

Key features of the model include:

- Enhanced Memory Retention.
- Improved Emotional Understanding.
- Resource Efficiency.

Fuzzy Logic in Sentiment Analysis for Emotional Recognitio

Integrating fuzzy logic with these simple models can be proven as a significant step towards a realistic mimicking of human mind in understanding and responding to emotional queries. Rather than having structured and fixed rigid options, we look forward to explore a more flexible and unexplored path in the field of sentiment analysis and responding in accordance to that. For example, a user may express queries that are partially ”anxious” and partially ”sad,” and fuzzy logic helps the system generate responses that acknowledge this uncertainty and complexity.

It has been done previously by many of the available solutions but there was a narrow scope explored and focused, for example focusing on binary or ternary states of mind. But here we have focused on having a much deeper understanding of emotions by having a complex pool of target values [22]. This makes it the best available option for applications in this field, in which users often express mixed or unclear feelings.

The fuzzy logic system integrated with Solara examines user inputs on the basis of a pre-planned emotional scaling, mapping the level of emotions and their combinations. For instance, a user statement like ”I'm feeling a little anxious but also better than previous” might be calculated as 60% anxious and 40% relieved. On the basis of this analysis, Solara can respond that takes care of both emotions, offering support that feels more personalized and empathetic.

Context Preservation and Response Generation in Solara:

This paper proposes an approach that may act as a game-changer, the empathy is given the maximum importance here along with continuity of the context. Maintaining context is one of the major challenges in an emotional helping chatbots. A user may start referring to something mentioned earlier in the past, in case our bot could not retain the data of the incident, it will lead to a spoiled conversation. Llama3.2 is the solution, that we offer in this approach, as it can help Solara to retain context across multiple conversation turns.

Continuous updating of memory state for keeping a record of necessary details from conversations is the key technique used to manage context preservation. Model references to this memory state every time it has to respond to some query, to maintain the feeling of personalization.

Flow Diagram ((or the architecture of Solara using Llama3.2:3b)-

The architecture of Solara, powered by the Llama3.2:3b model, is structured to handle user input in several steps:

- Input Processing: User inputs are first processed through an NLP pipeline, where tokenization and initial sentiment analysis take place.
- Fuzzy Logic Sentiment Analysis: The fuzzy logic system evaluates the emotional content of the input, determining the degree to which various emotions are present.
- Contextual Memory Update: The context memory is updated with the user's latest input, ensuring that previous conversation details are retained.

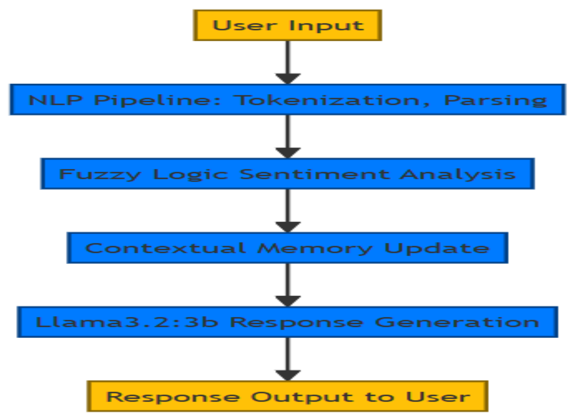

Fig. 1. Solara Architecture Flow Diagram

IV. EXPERIMENTAL SETUP

Dataset and Preprocessing for Sentiment Analysis:

The dataset proposed to be used is an amalgamated version of publicly available datasets and custom conversations manually tailored for maintaining sensitiveness. Emotion Lines and Daily Dialog are the few of the popularly used datasets also used in this approach.

Preprocessing:

1) Tokenization
2) Lowercasing and Lemmatization
3) Stopword Removal
4) Emotion Labeling

Tools and Platforms (Llama3.2:3b and Ollama Framework)-

The experimental setup leverages the Llama3.2:3b model for natural language understanding and response generation, while the Ollama framework ensures offline functionality.

Llama3.2:3b -

Comprehending language on a better level, and retaining memory for a longer period was still needed to be achieved, that Llama3.2:3b have now achieved on a satisfactory level. Multi-turn conversations along with keeping track of emotions, making it more human-like with the help of optimization in its architecture. Being able to analyze subtle and delicate, very fine cues in input texts with the help of a huge number of parameters. Llama3.2:3b proves to be a better version than all of its predecessors.

Ollama Framework:

Making emotional support available consistently, even offline is the key idea at the core of the work discussed in this paper. And that is where Ollama framework comes into action and makes this task possible, by allowing the Llama3.2 model to run effectively offline. Which is essential in maintaining the privacy, making it more reliable, which is really a significant variable to keep in mind while dealing with sensitive emotional disclosures

Software Stack:

- Python 3.9
- Pytorch
- FuzzyWuzzy

Evaluation Metrics (Response Quality, Latency, Emotional Ac

To assess the effectiveness of Solara, several evaluation metrics were employed:

- Response Quality: This was calculated with the help of reviews and feedbacks taken from users.
- Latency: How quickly the responses are generated.
- Emotional Accuracy: This metric evaluates how nicely the chatbot understands a user's emotions and inputs.

Qualitative Metrics:

- Empathy Score
- Continuity

Testing Environment (Online vs. Offline):

To evaluate the performance of Solara in both connected and offline settings, two primary testing environments were established:

Online Testing:

A remote server and an online interface were used to host Solana and take queries from the users. How it will perform while having access to high computational power could be tested easily in this environment.

Offline Testing:

In this mode a normal consumer system was used to evaluate working of the approach discussed in this paper. Latency and memory usage were evaluated in this mode to check whether there is any degradation in performance in this mode. And, if there is any, is it significant enough to suggest a major change or refinement of the architecture.

V. RESULTS

Model Performance of Llama3.2:3b Compared to Llama2- The Llama3.2-

3b model has shown major and significant betterments over its predecessor, Llama2, specifically in handling emotional support conversations. Key areas of performance that were evaluated include context retention, response coherence, and emotional sensitivity.

Context Retention:

There was a lesser context loss observed as compared to Lllama2 and there was a better memory retention generally. Llama3.2 could go up to 92% of accuracy in retaining context, while Llama2 could manage to have only 78%. Which suggests Llama3.2 is better in terms of maintaining and handling longer conversations.

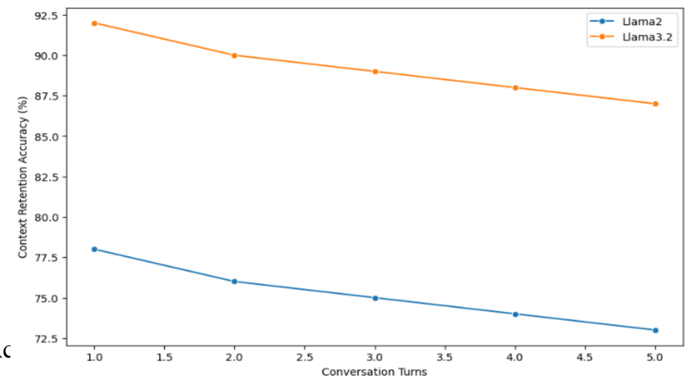

Fig. 2. Context Retention Comparison

Response Coherence:

To evaluate this metric, user feedbacks were used. To avoid any misjudgment, a team of neutral human evaluators was set up for evaluating this metric. On a scale of 5 both were evaluated and even here Llama3.2 outperformed with a score of 4.6, while Llama2 got only 3.9.

Emotional Sensitivity:

Llama3.2 was observed to be more empathetic, backed by the diverse emotional conversation-based datasets used to train it. Even this metric suggested the same thing that Llama3.2 is much better than Llama2, as it could 87% times accurately capture emotional needs and could tailor a response in accordance to that.

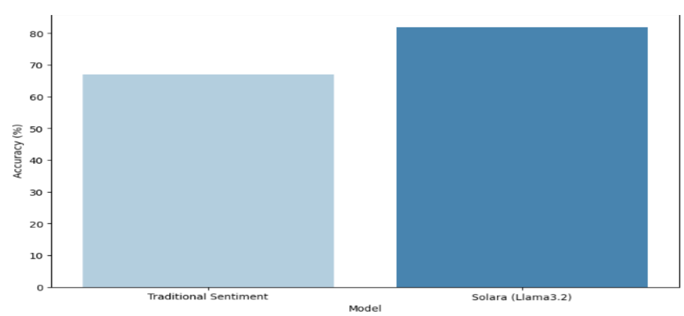

Fig. 3. Accuracy Comparison of Traditional Sentiment vs Solara (Llama 3.2)

Sentiment Analysis & Fuzzy Logic Impact on Emotional Awareness:

The integration of fuzzy logic in Solara's sentiment analysis significantly improved the chatbot's emotional awareness. This approach allowed the system to interpret user emotions on a spectrum rather than assigning them to rigid categories, resulting in more nuanced and accurate emotional responses.

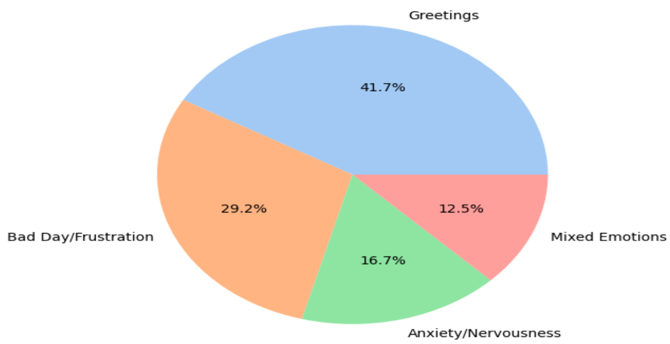

Fig. 4. Intent Category Distribution

TABLE I
TRADITIONAL SENTIMENT ANALYSIS VS SOLARA

Metric	**Traditional Sentiment Analysis System**	**Solara**
Sentiment Recognition Accuracy	67%	82%
Multi-Emotion Responses	-	Exists
Emotional Depth in Responses	4.1/5.0	4.8/5.0

VI. Conclusion

Paper presents a significant advancement in emotional support chatbots by introducing SOLARA, which integrates the Llama3.2:3b model and the Ollama framework to enhance user interaction through improved emotional intelligence. The methodology employed includes the use of advanced NLP techniques for context preservation and fuzzy logic for nuanced sentiment analysis, allowing for more accurate and human-like interactions. The experimental setup demonstrated SOLARA's superiority over previous models in terms of emotional accuracy, context retention, and response coherence. Results from both online and offline testing environments affirmed the effectiveness of the SOLARA system in providing empathetic and contextually aware responses, highlighting its potential to operate independently of network connectivity, thus ensuring privacy and constant availability. This innovative approach sets a new benchmark for chatbots in mental health support, combining technological sophistication with deep emotional understanding, thereby enhancing the overall user experience.

VII. DISCUSSION AND ANALYSIS

Llama3.2:3b's Role in Improving Emotional Response Generation-

More parameters, more data, more understanding and generalization on a much better level is what an advanced model like Llama3.2 offers. Earlier models were trained well and had a great efficiency in handling complex inputs, but why to settle in less when you have a better option? These advanced models have a lot to offer along with removing the shortcomings of the earlier models.

Sustaining coherence and providing a sensitive response are the things with utmost importance when it is about emotional support. And these are the key features of Llama3.2, its architecture makes it capable of achieving all of this, making it convenient and more preferrable option. By leveraging improved memory retention and natural language understanding, this model offers a deeper, more human-like engagement, making it a key tool in enhancing the user's emotional experience with the chatbot.

Advantages of Fuzzy Logic in Classifying User Emotions:

Integrating fuzzy logic with these simple models can be proven as a significant step towards a realistic mimicking of human mind in understanding and responding to emotional queries. Rather than having structured and fixed rigid options, we look forward to explore a more flexible and unexplored path in the field of sentiment analysis and responding in accordance to that. For example, a user may express queries that are partially ”anxious” and partially ”sad,” and fuzzy logic helps the system generate responses that acknowledge this uncertainty and complexity.

It has been done previously by many of the available solutions but there was a narrow scope explored and focused, for example focusing on binary or ternary states of mind. But here we have focused on having a much deeper understanding of emotions by having a complex pool of target values. This makes it the best available option for applications in this field, in which users often express mixed or unclear feelings.

The advantages of using

- fuzzy logic include
- Improved Emotional Accuracy
- Personalized Interactions

Overall, fuzzy logic has proven to be a valuable tool for improving the chatbot's emotional intelligence, allowing it to handle a wider range of emotional expressions and deliver more personalized responses.

Insights from Offline Availability for User Privacy and Reliability:

Making emotional support available consistently, even offline is the key idea at the core of the work discussed in this paper. And that is where Ollama framework comes into action and makes this task possible, by allowing the Llama3.2 model to run effectively offline. Which is essential in maintaining the privacy, making it more reliable, which is really a significant variable to keep in mind while dealing with sensitive emotional disclosures.

All of this makes sure that users can take benefit of such systems even in an environment without connectivity. And that too without giving away the performance or accuracy metrics, as the features of Llama3.2 will be made offline with Ollama framework. Trust is a variable that is given lesser weight many a time, but not in this proposal, the offline feature makes it more trustable than any other model available in this stream.

Offline availability, therefore, not only enhances privacy but also ensures that Solara can provide reliable and continuous emotional support, independent of external connectivity factors.

VIII. Limitations and Challenges

Despite the mentioned achievements and betterments achieved by Solara, there are still some limitations and challenges, as mentioned below:

Increased Latency in Offline Mode:

Ollama framework is especially used in this approach to make Solana available offline but with that functionality comes an issue in terms of response time. In low-end devices it was worse than those with higher resources available. The 1.8-second average response time in offline mode, while acceptable, was higher than the 1.2 seconds achieved in the online mode. This slight latency could affect user experience in cases where real-time responsiveness is crucial.

Hardware Limitations:

To run the Llama3.2:3b model on a local device needs significant memory and processing power, which may lead to limited accessibility of the chatbot for users with devices with low-end resources. Enough optimizations have been made in this approach to reduce the memory need but still a 1.6 GB of memory usage is high for certain devices with low level resources, potentially which may hinder the usability for some users.

Complexity of Emotion Interpretation:

Despite the fact that fuzzy logic has been implemented in this approach, but emotional complexity still remains a hurdle. There were cases where it struggled to accurately weigh overlapping emotions, particularly when the inputs were vague or ambiguous. For instance, phrases like ”I don’t know how I feel” posed challenges for the system, which sometimes led to inaccurate emotional analysis.

Addressing these challenges in future iterations of the chatbot will be essential in improving Solara’s scalability, response time, and emotional accuracy.

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