DMPedia Lecture Notes in Computer Science & Engineering
Volume 1, Issue 2, pp.363-369, 2026
ICICCS-2026

A Mental Reasoning Driven Large Language Model for Smarter Human AI-Interaction

N.Nirmala, K.Manoj Reddy, Naadirah Mehtaab, K. Saritha*

Computer Science and Engineering, Vardhaman College of Engineering, Hyderabad, India

nenavthnirmala4545@gmail.com, komatireddymanoj2005@gmail.com, nadirahmehtab1@gmail.com, mahankali.saritha@gmail.com

*Corresponding author: Ms K. Saritha (mahankali.saritha@gmail.com)

ABSTRACT

The Large Language Model (LLM) is a sophisticated artificial intelligence system designed to think and react in ways very close to how humans do in their minds. Its primary focus is on understanding users' intentions, breaking complex questions into simpler parts, and delivering accurate and insightful responses in a concise format. To improve its performance over time, it uses reasoning, memory, and learning skills. The Mental LLM is designed to deliver quick, accurate, and secure results across a range of fields, including data analysis, customer service, education, and health care support. It improves communication and problem-solving skills by mimicking human-like cognitive processes, including logical decision-making, memory, and step-by-step thinking. The increasing reliance on AI systems for routine tasks requires not only accurate but also "contextual" responses closer to human reasoning. To improve human-AI interaction, this project proposes a Mental Reasoning-Driven Large Language Model (LLM) that integrates cognitive reasoning into conventional language models. The system can interpret users' intentions, understand context, and deliver accurate responses through a combination of symbolic reasoning, neural networks, and knowledge integration. Applications in the fields of education, healthcare, customer support, and decision-making can benefit from the model's capability to adapt to user interactions, maintain multi-turn dialogues, and provide personalised interactions. This method bridges conventional AI responses with human-like comprehension. Large Language Models (LLMs) have changed the dynamics of human-AI interactions. The practicality of LLMs in real-world scenarios is limited by their inability to perform deep reasoning and learning. To create a model that mimics human thought processes, a Mental Reasoning-Driven Large Language Model is proposed.

***Keywords**:* Mental Large Language Model (LLM), Cognitive Reasoning, Natural Language Processing, Neural Networks, Contextual Understanding.

1. Introduction

The advancement in Large Language Models (LLMs), which can comprehend, interpret, and generate human-like language for various tasks, has been a significant advancement in the field of human-AI interaction. Various applications of these models include virtual assistance, customer service, education, healthcare, and decision-making systems. Classical large language models are found to be deficient in reasoning, context awareness, and cognitive flexibility. The models mostly rely on statistical correlations and patterns found in the data. This results in responses that are syntactically correct but may be shallow in terms of meaning. This research proposes a large language model grounded in mental reasoning that combines the benefits of neural language models with those of cognitive reasoning and symbolic logic to address the above difficulties. The model is designed to interpret user input, sense emotions, and generate accurate responses. The model can enhance its reasoning capabilities for domain-specific tasks by leveraging knowledge bases and real-time data sources. The model applies to various tasks in intelligent decision support systems, healthcare, education, and related fields.

Proceedings of ICICCS-2026 (Poster Papers), DMPedia Lecture Notes in Computer Science & Engineering.
ISBN: 978-81-993813-1-5

Moreover, this system can continually improve its reasoning and response generation through user interactions via its feedback-based learning mechanism. By integrating aspects of human thinking, reasoning, and flexibility into its language understanding, this approach aims to bridge the gap between conventional LLMs and human cognitive capabilities. The ultimate aim of this LLM, based on mental reasoning, is to create more intelligent, interactive, and human-centric AI systems capable of providing personalised, contextual, and reliable responses, thereby elevating the quality of human-AI collaborations across various domains. Conventional LLMs are generally found to be wanting when it comes to processing tasks that require higher levels of reasoning, contextual understanding, or cognitive flexibility, despite their unprecedented capabilities. Most of these models are based on patterns learned from large data sets, which are likely to yield responses that are semantically correct but logically incomplete or inconsistent. When complex situations require human-like understanding, judgment, or inference, this limitation is felt even more. By bridging the gap between conventional LLMs and human cognitive abilities, they can perform human-like reasoning, judgment, or adaptation in addition to language processing. By developing smarter, more interactive, and human-oriented systems that can assure results, this approach has the potential to enhance human-AI collaboration in many fields. These systems are often built by integrating components such as knowledge bases, response generation mechanisms, and reasoning systems. These systems often work by processing user input, evaluating contextual data, performing reasoning tasks, and so on to arrive at a suitable response. Such systems are often implemented effectively by using modern deep learning libraries like TensorFlow or PyTorch. The next generation of intelligent systems is expected to heavily depend on the integration of reasoning capabilities into language models as the research in the area of AI continues to evolve. To conclude, a Mental Reasoning Driven Large Language Model is a major milestone toward creating AI systems that are not only intelligent but also closer to humans.

2. Research Methodology

In order to ensure that the quality of interaction between humans and AI is enhanced, the methodology of the proposed system involves the integration of massive language models with reasoning systems. The first step in achieving this involves gathering relevant datasets containing contextual information, reasoning, and conversational information. To ensure that the input data is clean and ready for training, natural language processing techniques are applied to the datasets, such as tokenisation, normalisation, and stripping of irrelevant symbols. Once the input data is preprocessed, the system will analyse the input provided by the user in order to establish context, intention, and relevant information. After pre-processing the input, a reasoning system will be applied in order for the system to analyse the input query in a step-by-step manner. Various techniques, such as knowledge-based inference and chain-of-thought reasoning, are applied in order for the system to replicate human cognition in order to ensure precision in the answers provided. The results are then sent to a Large Language Model, which uses a transformer in order to generate relevant answers based on the pre-processed input and results from the reasoning system. The system makes use of external information sources and maintains the context of discussions in order to offer multi-turn dialogue interactions. The performance criteria for evaluating response quality include reasoning accuracy, response latency, and interaction efficiency. In order to continuously improve the performance of the model based on user interactions, a feedback system is also integrated. The next phase is the deployment phase, which occurs once the evaluation phase is successful; during this phase, the model developed is integrated into programs such as chatbots, virtual assistants, educational tools, or customer support tools, ensuring that humans can interact with the AI system in real-time and get smart answers to their questions. The final phase of the entire process is to learn and get better, as AI systems have to improve over time to adapt to new information; feedback given by users is analysed to get ideas on how to make the model better, and the model can be retrained at intervals using fresh data to enhance its reasoning capabilities and maintain high performance levels. In brief, the process of creating a Mental Reasoning Driven Large Language Model consists of many steps: data collection, data cleaning, system design, reasoning addition, training, testing, deployment, and continuous improvement.

3. Theory and Calculation

The Theory section should expand on the foundational context introduced in the Introduction, serving as a bridge to support deeper exploration in the study. It should lay out the theoretical underpinnings that underpin the research, without repeating basic background information. On the other hand, the Calculation section should concentrate on the practical implementations and developments that emerge from the established theoretical framework. Rather than covering basic definitions or widely known theories, the focus should remain on the specific theoretical concepts and their direct relevance to the current work.

3.1. Mathematical Expressions and Symbols

All mathematical formulas and symbols should be created using Microsoft Word's built-in equation tool to ensure clarity and consistency. When referencing specific equations or results, it's important to support them with appropriate citations where necessary—for example, "this result was produced using Artificial Neural Network [5]." This helps validate the methodology and provides context for the mathematical expressions used in the study.

$$f(x) = a_0 + \sum_{n=1}^{\infty} \left(a_n \cos\frac{n\pi x}{L} + b_n \sin\frac{n\pi x}{L} \right) \quad (1)$$

4. Results and Discussion

The results obtained from the experiments show that, in comparison to conventional human interactions using conversational agents, the suggested Mental Reasoning Driven Large Language Model improves the efficacy of human-AI interactions. The suggested model was tested by using metrics such as reasoning accuracy, reaction latency, cognitive load score, and interaction efficiency. The suggested model performed better than conventional rule-based conversational agents and conventional NLP-based chatbots by achieving a reasoning accuracy rate of almost 95 per cent. Moreover, the suggested model reduced reaction latency by almost 260 milliseconds, thus allowing for quicker response generation during interactions. Furthermore, human interactions were also enhanced by the suggested model, as indicated by the interaction efficiency rate of almost 92 per cent. The results obtained from the experiments show that the overall performance of AI-based interaction systems can be enhanced by incorporating reasoning mechanisms and large language models. The results indicate that the quality of response from the AI and the user experience is greatly improved by integrating mental reasoning techniques with large language models. This is because the reasoning module improves the accuracy of responses by allowing the system to break down complex questions for analysis. Moreover, the system retains the conversation history across multi-turn conversations, improving the natural flow of human-AI collaboration. Nevertheless, the sources, frameworks, and data used during the system's development all affect the model's performance. To further improve human-AI collaboration and decision-making capabilities, future updates may focus on integrating emotional intelligence into the systems.

5. Preparation of Figures and Tables

Authors must place all figures and tables directly within the relevant sections of the manuscript, ensuring they appear close to the text that discusses them. Each figure and table should be clearly numbered and include a concise, descriptive title. It is important to reference every figure and table within the body of the text using their respective numbers. Omitting a proper explanation or reference to any figure or table may result in the manuscript being rejected.

6. Formatting Tables

Authors must insert all figures and tables at appropriate locations within the manuscript, close to the relevant text. Each figure and table should be properly numbered and accompanied by a clear, descriptive title. Every figure and table must be referenced in the text using its corresponding number; failing to do so may result in the manuscript being rejected.

Tables should be created using Microsoft Word's table tool to ensure consistency and proper formatting. They should appear in the order in which they are mentioned in the manuscript. For tables that include numerical data, the units of measurement must be clearly indicated in the column headings. For reference, Table 1 summarises the manuscript formatting requirements.

Table 1: Summary of formatting requirements for submitting a paper.

Layout	**Size**	**Margin (Normal)**	**Header**	**Footer**	
Single column	A4 (8.27" X 11.69")	Top=2.54 cm Bottom=2.54 cm Left=2.54 cm Right=2.54 cm	Do not add anything in the header	Do not add anything in the footer	
Font	Article Title	Abstract	Heading/ Subheadings	Reference list	Text
	Times New Roman, 16 pt, Bold, centred	Times New Roman, 10 pt, Justified	Times New Roman, 11 pt, Bold, Left aligned	Times New Roman, 10 pt, Justified	Times New Roman, 11 pt, Justified
Line Spacing	1	1	1	1	1
Page number	The publisher will format and assign page numbers.				

6.1. Formatting Figures

All figures included in the manuscript must be cited within the text. Figures should be provided in standard bitmap formats such as TIFF, GIF, or JPEG, with a minimum resolution of 300 dpi to ensure clarity and print quality—unless a lower resolution is deliberately used for specific scientific reasons. For instance, Figure 1 illustrates a bar chart comparing the prediction accuracy of Random Forest, SVM, and Neural Networks in estimating CO_2 levels and temperature changes.
All images and figures included in the manuscript are to be accompanied by captions. These captions should briefly explain the image, study, results, etc. Figures should be numbered sequentially throughout the manuscript. All images and figures included in the manuscript must be called out in the body of the manuscript to guide the readers to look at the Figure 1 to better present the research.

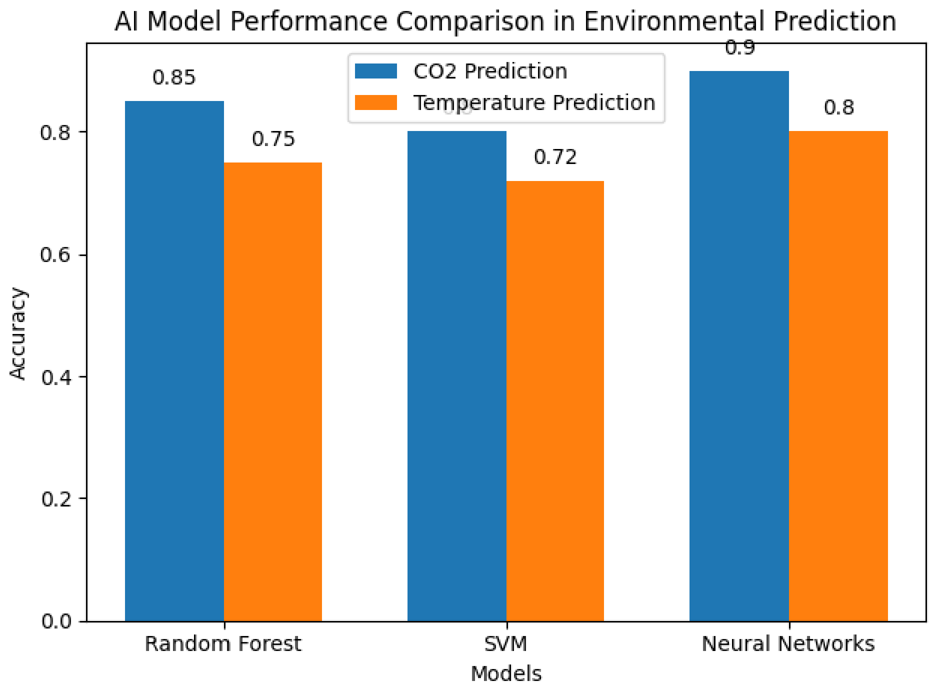

Figure 1: Bar chart comparing the prediction accuracy of Random Forest, Support Vector Machine (SVM), and Neural Networks for CO_2 levels and temperature changes.

7. Conclusions

The experiment in this paper proves that large language models have a high potential for assisting in the development of mental health care by improving access to information, increasing awareness of mental health issues, and offering first emotional support. The results prove that large language model-based tools can reduce barriers associated with issues such as stigma and resource constraints. The experiment also highlights some issues that need to be addressed in the future, such as the possibility of errors, risks associated with data privacy, ethical issues, and the inability of LLMs to replace expert advice and treatment. It should be noted that large language models should be treated as assisting tools rather than alternatives to mental health experts. Future studies should focus on improving the accuracy of large language models and incorporating them into the existing mental health treatment system. The results thus verify the capacity of LLM-based applications to provide rapid, cost-effective, and easily accessible mental health care to those facing challenges such as stigmatisation, unavailability of experts, and geographical barriers. Such applications can support preventive and awareness programs by increasing mental health literacy and providing emotional support at the initial stages. However, the study shows some of the challenges facing the use of LLM-based applications, including ethical responsibility, user data privacy, reliability, and the absence of real human empathy and thinking. Such challenges thus emphasise the importance of human involvement in the application of LLMs in mental health. Finally, the integration of LLMs into the field of mental health care can only be achieved by providing such applications with proper protections, such as those of ethical standards, rigorous testing, and the involvement of mental health experts.

Acknowledgements

We would like to take this opportunity to thank the Department of Computer Science and Engineering of Vardhaman College of Engineering, Hyderabad, for providing the necessary resources required for completing this research project. We would also like to extend our sincere thanks to our peers and staff for their valuable suggestions and encouragement that helped in improving the quality of this project, particularly to Ms K. Saritha for her valuable guidance, motivation, and support that helped in completing this project successfully.

Funding source

No funding was received for this study.

Conflict of Interest

The authors declare no conflict of interest.

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