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A Multi-LLM Powered Expressive Assistant with Intelligent Task Execution

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Abstract: Rapid evolvement of artificial intelligence has powered innovations in conversational systems, intelligent Automation, and Immersive Training Platforms are enabling new forms of human-AI collaboration. This work presents A Multi-LLM Intelligent Task Execution aPowered Expressive Assistant system that integrates various large language models (LLMs) to enable the delivery of adaptive, multilingual, and context-sensitive interactions while Orchestrate complex workflows by combining natural language processing, multimodal understanding, and robotics automate processes to support dynamic decision-making, process optimization, and personalized guidance. Unlike traditional chatbots, Or single-model solutions, architecture uses the Complementary strengths of multiple LLMs in order to be expressive. Communication and execution of intelligent tasks over various domains. The fields that may be benefited from this are customer care, education, health care, and industrial training, where the assistant does the following: breaks down instructions, thereby automatically generating step-by-step instructions. It will help the accountants to reduce repetitive tasks, improves efficiency and accuracy, and ensures compliance. The work points to the potential of multi-LLM architectures to advance intelligent automation and shape the next generation of more expressive and human-centric AI systems.

***Index Terms* -** Artificial Intelligence, Robotic Process Automation (RPA), Mixed Reality (MR), Generative AI, Large Language Models (LLMs), Customer Service Chatbots.

INTRODUCTION

Through automation, immersive technologies, and generative models, artificial intelligence (AI) has rapidly advanced, revolutionizing the digital landscape and spurring innovation across industries. In business and industrial settings, the integration of AI with Robotic Process Automation (RPA) has evolved into Intelligent Process Automation (IPA), enabling organizations to automate routine tasks while incorporating cognitive capabilities such as data analysis, pattern recognition, and decision-making to improve efficiency, reduce costs, and enhance innovation. Simultaneously, AI-powered Mixed Reality (MR) platforms are redefining training methodologies by allowing experts to record demonstrations once and automatically generate interactive, step-by-step tutorials, thus addressing challenges of content creation while delivering scalable, immersive, and cost-effective learning experiences in sectors like healthcare, defense, and education. At the same time, generative AI chatbots built on Large Language Models (LLMs), With context-aware, multilingual, and adaptive communication that outperforms conventional rule-based systems while guaranteeing compliance with data privacy regulations, platforms like ChatGPT are transforming customer service. Collectively, these advances highlight the transformative role of AI in reshaping automation, education, and user interaction, paving the way toward more intelligent, efficient, and inclusive digital ecosystems aligned with the vision of Industry

I. RELATED WORK

It is also used in the field of robotic process automation (RPA), with an emphasis on its evolution from basic rule-based task execution to more sophisticated intelligent process automation (IPA) through the incorporation of artificial intelligence (AI). Previous studies show that integrating machine learning, natural language processing, and predictive analytics greatly increases the scalability and adaptability of business operations in sectors like manufacturing, healthcare, finance, and auditing. These works collectively emphasize both the benefits, such as efficiency, and the drawbacks and cost reduction, and challenges such as ethical considerations, data security, and issues of interoperability. Conversational systems and technological advancements in immersive learning have also occurred concurrently. Artificial intelligence (AI)-enhanced mixed reality (MR) solutions have been investigated for their potential to automate tutorial processes through speech recognition. eye and gaze tracking, and large language models, hence cutting costs while also interactivity and accessibility. In a similar fashion, research on these, in effect, have juxtaposed conventional approaches to chatbots with which rely on strict domain-related rules, with generative Examples include models such as ChatGPT that rely on transfer learning, self-supervised learning, and reinforcement learning from "human feedback to enable multilingual, context-aware, and regulation-compliant communication. When taken as a whole, these collections highlight how AI is transforming automation, immersive learning, and consumer interaction, providing a foundation for future integrated and humanity-focused Ecosystems Digital.

II. METHODOLOGY

This study uses a thorough methodology that incorporates ideas from generative AI-driven conversational systems, intelligent automation, and mixed reality training. In order to examine the development of robotic process automation (RPA) and its integration with artificial intelligence (AI), a literature review methodology inspired by systematic review techniques was used. Targeted keywords were used to search important databases like IEEE Xplore and SpringerLink in order to find pertinent works. These were then evaluated critically for their approaches, uses, and constraints. The analysis concentrated on how AI-enabled RPA forms the foundation of Intelligent Process Automation (IPA) by enhancing conventional rulebased automation with machine learning, predictive analytics, and natural language processing. For Mixed Reality (MR) training and generative AI chatbots, a design-oriented methodology was applied. In the MR domain, the system was implemented using Unity 3D and the Mixed Reality Toolkit (MRTK3), incorporating speech-to-text, gaze tracking, and gesture recognition modules to automatically generate instructional materials from expert demonstrations. Similarly, for the generative AI chatbot, a ChatGPT-based architecture was developed, integrating natural language understanding, dialogue control, and API-based backend communication. Emphasis was placed on multilingual capabilities, GDPR compliance, and user-centered design, with evaluations conducted through user acceptance testing and iterative refinement. Collectively, these methodological approaches ensure a holistic perspective on how AI can drive innovation across automation, education, and customer interaction.

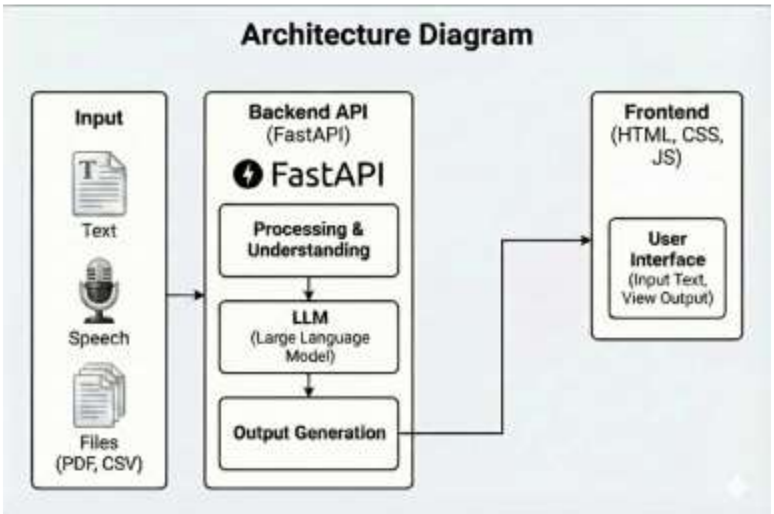

Figure 1: Block Diagram for A Multi-LLM Powered Expressive Assistant with Intelligent Task Execution

Figure 1 Block Diagram for the system is designed as a unified block where users provide inputs in the form of text, speech, or files (PDF, CSV), which are processed in the backend using Django to handle preprocessing and understanding. These inputs are then pass to large language models (LLMs) that perform reasoning, natural language understanding, and intelligent task execution. A frontend interface enables seamless human-AI interaction within a single integrated workflow and provides an interactive user interface for both input and output. It arranges the generated results into useful outputs and presents them to the user in an understandable manner.

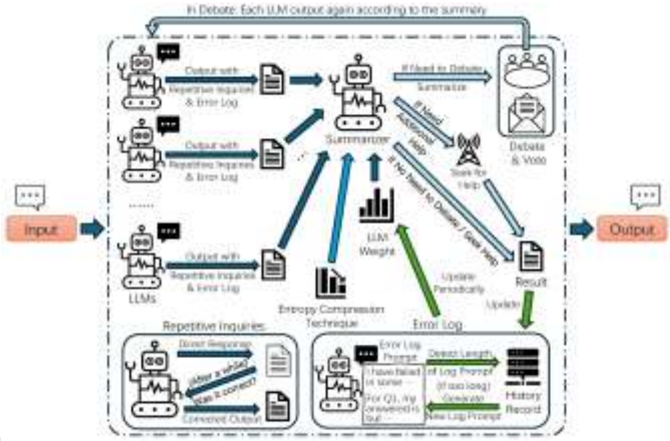

Figure 2: Multi-Agent LLM Refinement Framework

Figure 2 presents an in-depth architecture of the proposed multi LLM collaboration system. The framework is made up of a number of interrelated parts that cooperate to provide reliable, precise, and flexible responses. The major components are characterized as follows

A. Input Module: This is the entry point of the framework, where user queries or tasks are introduced. The input is directed simultaneously to multiple Large Language Models (LLMs) for parallel processing, ensuring diversity in generated outputs.

B. Large Language Models (LLMs): Multiple LLMs operate concurrently to process the same input. Each model produces an output along with a record of repetitive inquiries and an error log. This redundancy introduces variation in responses, enabling the system to compare and validate multiple perspectives.

C. Repetitive Inquiries Subsystem: This module ensures iterative validation of responses. An LLM provides an initial direct response, which is later rechecked for correctness. If discrepancies are detected, the system generates a corrected output. This feedback loop enhances reliability by refining responses over time.

D. Error Log Subsystem: Each LLM generates an error log describing failures or inaccuracies. These logs are analyzed to detect issues such as prompt length overflow or incomplete outputs. If logs become too lengthy, the subsystem compresses them and generates new log prompts for efficiency. This mechanism continuously learns from past mistakes, minimizing repeated errors.

E. Summarizer Module: In order to eliminate duplication and emphasise consensus information, the summariser combines outputs from all LLMs using entropy compression techniques. Additionally, it ensures that more dependable models are given priority in upcoming tasks by updating LLM weights based on historical accuracy.

F. LLM Weighting Mechanism: Each model is dynamically assigned a weight that reflects its past performance. These weights are updated periodically, allowing the system to adaptively emphasize outputs from consistently accurate LLMs.

G. Debate and Voting Mechanism: When outputs contain conflicts or uncertainties, the summarizer initiates a debate process among LLMs. Each model re-outputs its reasoning in light of the summarized content, followed by a voting procedure to converge on the most reliable answer.

H. Seek-for-Help Module: If the summarizer identifies a query beyond the capacity of the available LLMs, this module is triggered. It seeks external support (e.g., from additional knowledge bases, APIs, or human experts) to fill gaps and ensure comprehensive responses.

I. History Record: The framework maintains a history of prior inputs, outputs, and error corrections. This knowledge repository serves as a reference for future responses, reducing redundancy and improving accuracy by learning from previous experiences.

J. Output Module: After aggregation, debate, error correction, and weighting adjustments, the final refined response is delivered to the user. This output is designed to be context-aware, accurate, and less prone to errors compared to single-model outputs.

IV. RESULTS AND DISCUSSION

The outcomes from all three areas show how AI can revolutionise customer service, automation, and training. AI-enhanced Robotic Process Automation (RPA) improved efficiency, accuracy, and scalability in industries such as banking, healthcare, and manufacturing, though challenges of integration, ethics, and data privacy persist. In education and training, AI-powered Mixed Reality (MR) platforms effectively generated step-by-step tutorials from expert demonstrations, enhancing engagement, retention, and safety, but adoption is limited by hardware costs and customization complexity. Generative AI chatbots, particularly ChatGPT-based systems, outperformed traditional conversational models by enabling multilingual, context-aware, and regulation-compliant communication while reducing development effort, though issues of bias and reliance on external APIs remain. All of these results show that AI-driven systems greatly improve productivity and user experience. However, in order to ensure sustainable and responsible adoption, these systems must overcome ethical, technical, and financial obstacles.

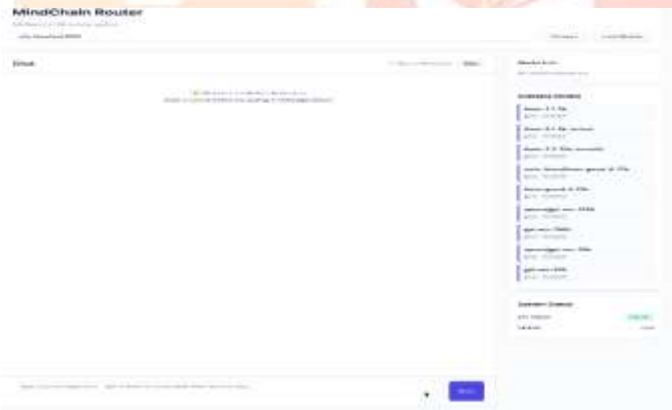

Figure 3: Front Page

The implementation of the proposed framework demonstrates the effectiveness of integrating Artificial Intelligence across automation, training, and customer interaction domains. The incorporation of AI-enhanced Robotic Process Automation (RPA) led to significant improvements in efficiency, accuracy, and cost reduction by automating repetitive business tasks while enabling intelligent decision-making through predictive analytics and natural language processing. Similarly, the Mixed Reality (MR) training system successfully generated step-by-step tutorials from expert demonstrations using speech recognition, gaze tracking, and gesture monitoring, resulting in greater learner engagement, knowledge retention, and safer training environments compared to traditional methods. In parallel, the generative AI chatbot based on Large Language Models (LLMs) proved capable of delivering multilingual, context-aware, and regulation-compliant communication, thereby reducing development effort and improving customer satisfaction. Collectively, the results confirm that the integration of these AI-driven approaches enhances operational efficiency, enriches training experiences, and strengthens customer service, while also revealing challenges related to scalability, hardware cost, data privacy, and ethical considerations that must be addressed for sustainable deployment.

V. CONCLUSION

The Beyond Needles: Blood Group Detection via Infrared (IR) Spectroscopy project effectively illustrates a clever and non-invasive method of blood group identification. Without the use of chemical reagents or conventional blood sampling, the system efficiently detects blood group types by fusing IR imaging with machine learning techniques. The developed model is particularly helpful in emergency and remote healthcare situations where laboratory facilities are limited because it produces results quickly, accurately, and hygienically. Real-time blood group prediction is now possible thanks to an effective pipeline that combines image preprocessing, feature extraction, and classification. By enabling users to log in, upload IR images, and view their results instantly, the web-based interface further improves usability. Thus, the system offers a dependable, portable, and affordable solution that can significantly cut down on the time and effort required for blood typing. Real-time blood group prediction is now possible thanks to an effective pipeline that combines image preprocessing, feature extraction, and classification. By enabling users to log in, upload IR images, and view their results instantly, the web based interface further improves usability. Thus, the system offers a dependable, portable, and affordable solution that can significantly cut down on the time and effort required for blood typing.

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