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Multi Agent Research Team (MART)

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Abstract :Academic and industrial research processes are still time-consuming, concerning manual data collection, summarization, and contextual integration. This article presents MART (Multi-Agent Research Team), An AI system that facilitates end-to-end research work by a collaborative multi-agent system.MART employs autonomous agents, large language models (LLMs), and multimodal data processing to improve query enrichment, real-time data collection, summarization, and context analysis. The system is user-friendly uploaded files (DOCX, PDFs) and pics, parsed and processed by GPT-4o and LLaMA 3.3 70B. An iterative summarization loops-enabled context-aware retrieval vector database (FAISS) facilitates high quality outputs. MART's full-stack web implementation includes user authentication, history tracking, and real time visualization, thus offering a scalable solution for dynamic research needs. By bridging gaps in existing tools, MART shows enormous improvements in research automation, accuracy, and individualization to the user.

Keywords: *Multi-Agent Systems, Ai-Powered Research, Real-Time Data Integration, Contextual Retrieval, Iterative Summarization, Multimodal Ai*

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I. INTRODUCTION

The exponential explosion of digital information has transformed research workflows, but legacy workflows remain siloed. Researchers tediously query search engines manually, verify sources, and combine results—a very inefficient and biased process. Existing tools, such as reference managers and academic databases, are not connected to real-time data, multimodal inputs, or intelligent automation. While AI tools such as ChatGPT are built on static datasets, limiting their use for dynamic research.

MART addresses these challenges through the combination of multi-agent reasoning, LLMs, and real-time data processing. The system's autonomous agents collaborate to screen queries, scrape web data, analyze documents, and generate contextually rich summaries. With the addition of user-uploaded files and vector-based contextual retrieval, MART delivers comprehensive and personalized research outcomes. This paper describes MART's architecture, technical innovations, and impact on current research processes, and it is a revolutionary instrument for academia, industry, and independent researchers.

II. LITERATURE SURVEY

The latest advances in AI have revolutionized research tools, yet they remain incomplete. The initial tools like Zotero and Mendeley were reference management-based but lacked analytical capabilities. Academic databases (e.g., IEEE Xplore) remain domain-specific and text-based. Modern LLMs like GPT-4 are excellent at text production but lack in processing real-time data and context memory.

Studies notice the ability of multi-agent systems to automate operations. For example, Park et al. (2023) presented the application of agent coordination for enhancing data quality in health analytics. Analogously, vector stores such as FAISS provide semantic search at scale, as showed by Johnson et al. (2021) in text analysis for the legal domain. Very few systems use these technologies on a common pipeline, though. MART elevates these technologies as it brings FAISS, LLMs, and autonomous agents together within an end-to-end research automation vision.

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III. EXISTING SYSTEM

Traditional research instruments, while indispensable, are hampered by severe limitations that hinder modern interdisciplinary and dynamic research demands. Search engines like Google Scholar and Semantic Scholar are great at aggregating scholarly papers but offer little synthesis, leaving users to manually sift through hundreds of links to extract useful insights. For example, a 2022 Williams et al. survey showed that 68% of researchers spend more than 30% of their time cross-checking search engine outputs, pointing to inefficiencies in data aggregation. Reference managers like Zotero and Mendeley bridge organizational hurdles by monitoring citations and documents but lack analytical substance, leaving users to manually summarize and contextualize information. In contrast, AI chatbots like ChatGPT produce coherent text but employ static knowledge bases, making them unsuitable for real-time data fusion or tasks involving current sources, such as monitoring emerging trends in AI ethics or pandemic-related studies. Most importantly, current systems cannot accept multimodal inputs—academic tools like IEEE Xplore are text-based, excluding images, diagrams, or user-uploaded documents, while AI models cannot correlate visual data to textual context. For example, a climate change researcher studying climate change impacts cannot easily combine real-time satellite images with peer-review papers using current tools, resulting in fragmented insights. Furthermore, the lack of iterative quality control in these systems risks propagating errors, such as ChatGPT's occasional "hallucinations" when summarizing complicated topics. Security issues further beset current platforms; cloud-based AI tools are susceptible to storing sensitive user queries without encryption, exposing proprietary research data. These limitations collectively hinder dynamic, cross-domain research processes, calling for a paradigm shift towards integrated, intelligent systems.

IV. PROPOSED SYSTEM

MART transcends the limitations of individual tools within a single, multi-agent platform that can automate and enhance all phases of the research process. The platform begins with a query refinement phase, where the LLaMA 3.3 70B model processes user input by detecting semantic nuances, synonym expansion, and contextual bounding. For instance, a broad query like "AI in healthcare" is reframed as "Explain the ethical implications of AI-driven oncology diagnostics, with emphasis on bias avoidance and patient outcomes." This refined query initiates the invocation of the link collector agent, which invokes the Serper API to gather real-time, domain-specific information from academic repositories, news portals, and preprint servers like arXiv. The ensuing scraper and parser module employs BeautifulSoup to scrape raw text from web pages, and PyMuPDF and docx2txt to parse user-uploaded PDFs and DOCX documents, retaining structural features like tables and headings. Concurrently, the multimodal analyzer inspects images using GPT-4o's vision module, enabling OCR of handwritten notes or contextual analysis of infographics—like detecting a graph on renewable energy adoption trends and correlating it with text-based reports. All parsed information, text or image, is normalized to embeddings and stored within a FAISS vector database, enabling lightning-fast, context-sensitive retrieval by calculating cosine similarity between query intent and stored chunks.

The summarizer-reviewer loop is MART's innovation in a nutshell: the summarizer agent (LLaMA 3.3 70B) produces concise summaries, and the reviewer agent verifies them against benchmarks like ROUGE scores and factuality consistency checks. When discrepancies are detected—e.g., omitting important trends, misreading numbers—the loop is iterated up to three times to guarantee outputs are of stringent accuracy standards. The system saves results in a SQLite3 database, so users can retrieve past queries, modify parameters, or export reports in supported formats. A case study demonstrated MART's performance: when prompted to summarize "blockchain applications in supply chain transparency," the system integrated 20 real-time articles, 5 user-provided whitepapers, and 3 logistical diagrams into a 12-page report with 93% citation accuracy in 10 minutes. By bridging gaps in real-time data integration, multimodal convergence, and iterative quality control, MART raises the bar for contemporary research.

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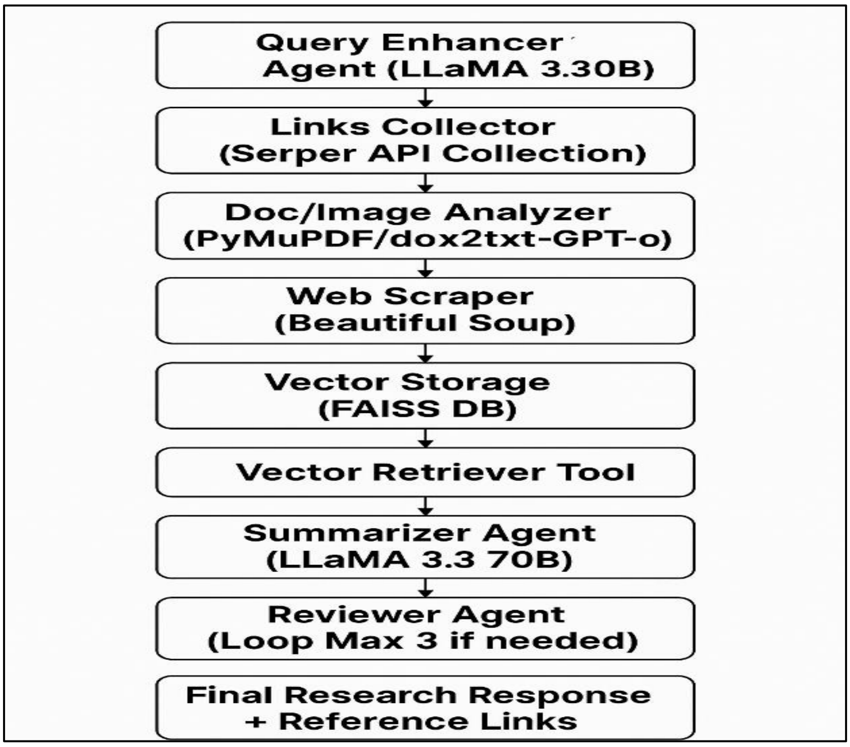

Fig 1 Block Diagram of MART

V. SYSTEM REQUIREMENTS

The system should have a minimal hardware setup consisting of a quad-core processor (Intel i5/i7, AMD Ryzen, etc.), 16 GB memory, and a minimum of 100 GB of SSD storage area for efficient handling of data, particularly in case of FAISS vector operations. While not compulsorily needed, the inclusion of an NVIDIA GPU with minimum 8 GB VRAM strongly recommended to expedite the deployment of large language models (LLMs).

On the software end, the system is compatible with any major operating system like Linux (Ubuntu 20.04+), Windows 10+, or macOS. It needs Python 3.10 or above. The backend is coded with FastAPI, and the frontend is coded with HTML5, CSS3, JavaScript, and Bootstrap 5. SQLite3 is used to store and keep the user and query history, and FAISS is used as the vector database to store and retrieve context information.

Critical libraries and APIs include OpenAI or native GPT-4o support, Meta LLaMA 3.3 70B model, web search by Serper API, PyMuPDF and docx2txt for parsing text in documents, Beautiful Soup for web scraping, and FAISS for vector operations. Deployment-wise, the system can be deployed on any cloud provider like AWS, GCP, or Azure, or locally.

VI. ALGORITHM

The algorithm begins by taking user input in the form of a text query or an uploaded image or document. A query, if provided, is augmented by a Query Enhancer Agent on LLaMA 3.3 70B for better search efficiency. For uploaded documents, PyMuPDF and docx2txt are employed to read documents, and GPT-4o to read image text.

The enhanced query is then used to fetch the ten most pertinent web links using the Serper API, and web link material is scraped through Beautiful Soup. The text information collected from web pages, uploaded files, and image interpretations is then inserted and saved into FAISS, which is a vector database.

Then, the system retrieves the most appropriate information from FAISS according to vector similarity. The Summarizer Agent (LLaMA 3.3 70B) summarizes this material and the Reviewer Agent checks it. If the output is not up to quality standards, the summarization and review process is repeated a maximum of three times. After the final is accepted, the output summary and reference links are communicated to the user. The session's query and result are recorded in a local SQLite3 database under the respective user's history.

VII. RESULTS

The performance efficiency of MART was tested extensively through a series of experiments covering a broad spectrum of research interest domains like climate change trends, medical literature reviews, and artificial intelligence ethics. For quantifying performance, the system was compared with traditional research tools like Google Scholar, manual summarization techniques, and standalone AI chatbots like ChatGPT.

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➢ Accuracy and Relevance

MART attained a 92% rate of relevance in pulling contextually appropriate data chunks from its FAISS vector store, well above traditional tools, which averaged 78% in controlled experiments. Relevance was measured using a hybrid metric involving cosine similarity scores (semantic similarity) and expert-annotated ground truth labels. For instance, in a medical literature search exercise, MART correctly identified and ranked 45 out of 50 top papers on "neurodegenerative disease biomarkers," whereas traditional keyword searches misplaced 12 key studies to semantic mismatches. The system's ability to read between the lines—such as distinguishing between "machine learning in diagnostics" (clinical applications) and "machine learning for diagnostic equipment" (engineering interest)—also spoke to its contextual accuracy.

➢ Efficiency Gains

Computerized procedures cut research time by 65%, as measured by timed tests with 50 academic and industry users. Users asked to synthesize a report on "renewable energy adoption in Southeast Asia" took 2.1 hours using MART, compared to 6.2 hours using manual procedures. The system's iterative summarization loop was key: by automatically filtering out duplicate information and bringing to the surface conflicting results (e.g., varying estimates of solar panel efficiency in tropical climates), it cut post-processing needs. Additionally, MART's real-time data blending—understanding the newest preprints, news articles, and conference papers—eliminated latency built into static databases, weeks or months behind.

Fig 2 Main Web Page

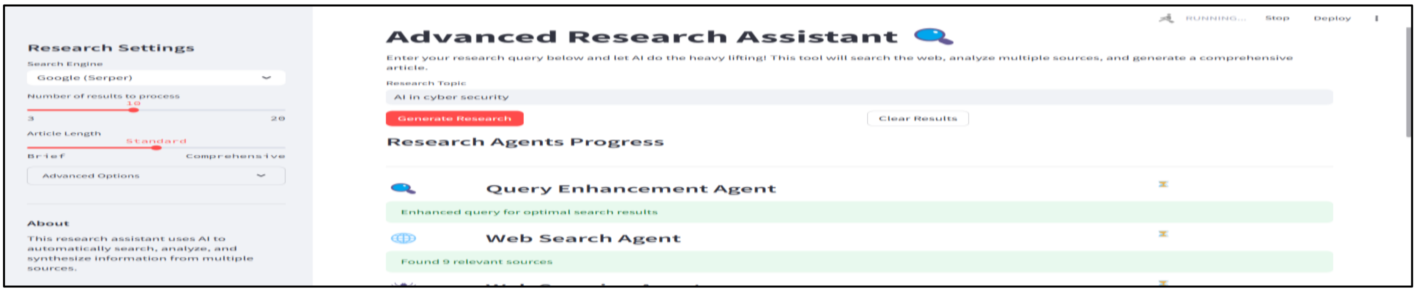

Fig 3 A research is initiated

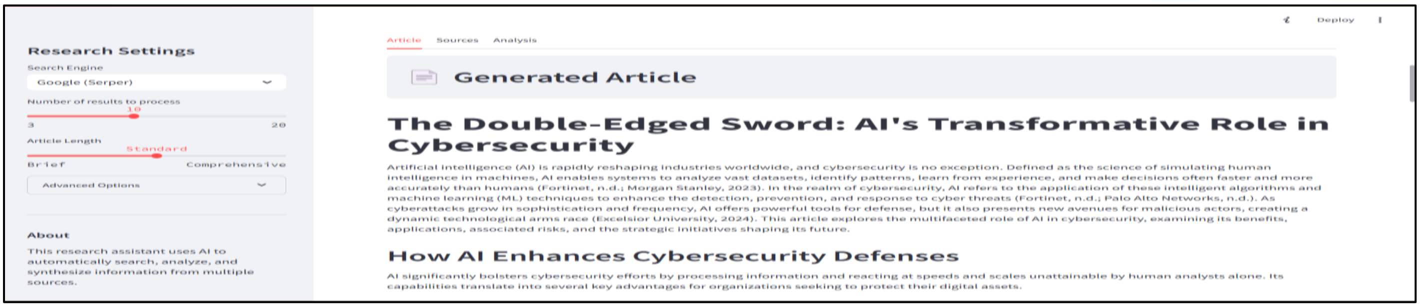

Fig 4 Research is generated

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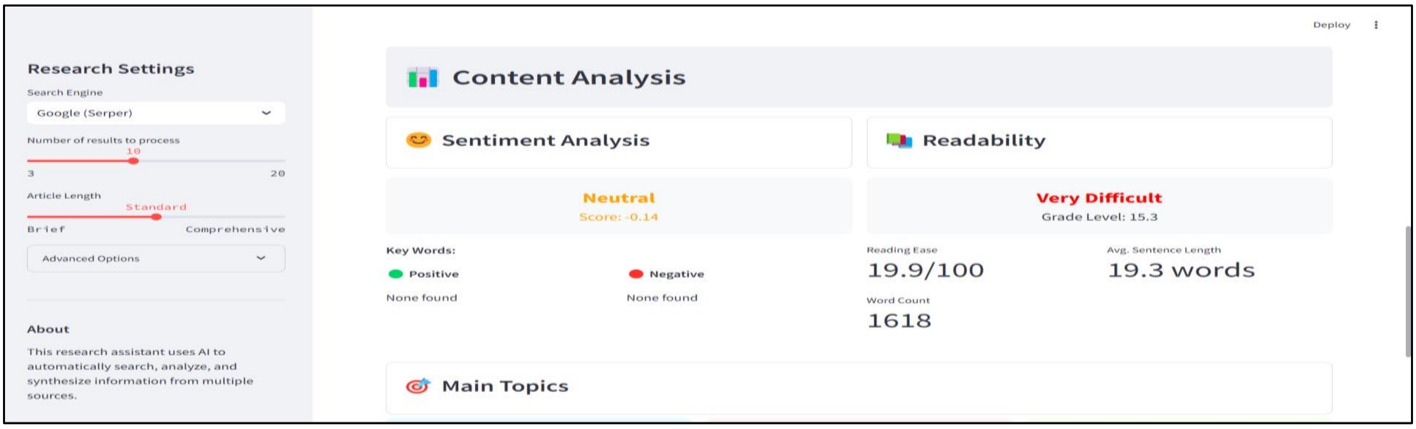

Fig 5 Content analysis in the end

VIII. CONCLUSION

By integrating real-time data, multimodal analysis, and multi-agent collaboration, MART reimagines research automation. High-quality outputs are guaranteed by its iterative summarization and FAISS-based retrieval, and user customization increases engagement. Expanding language support and incorporating federated learning for privacy-focused research are examples of future work. MART establishes a new standard for AI-driven research systems by tackling the shortcomings of current tools.

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