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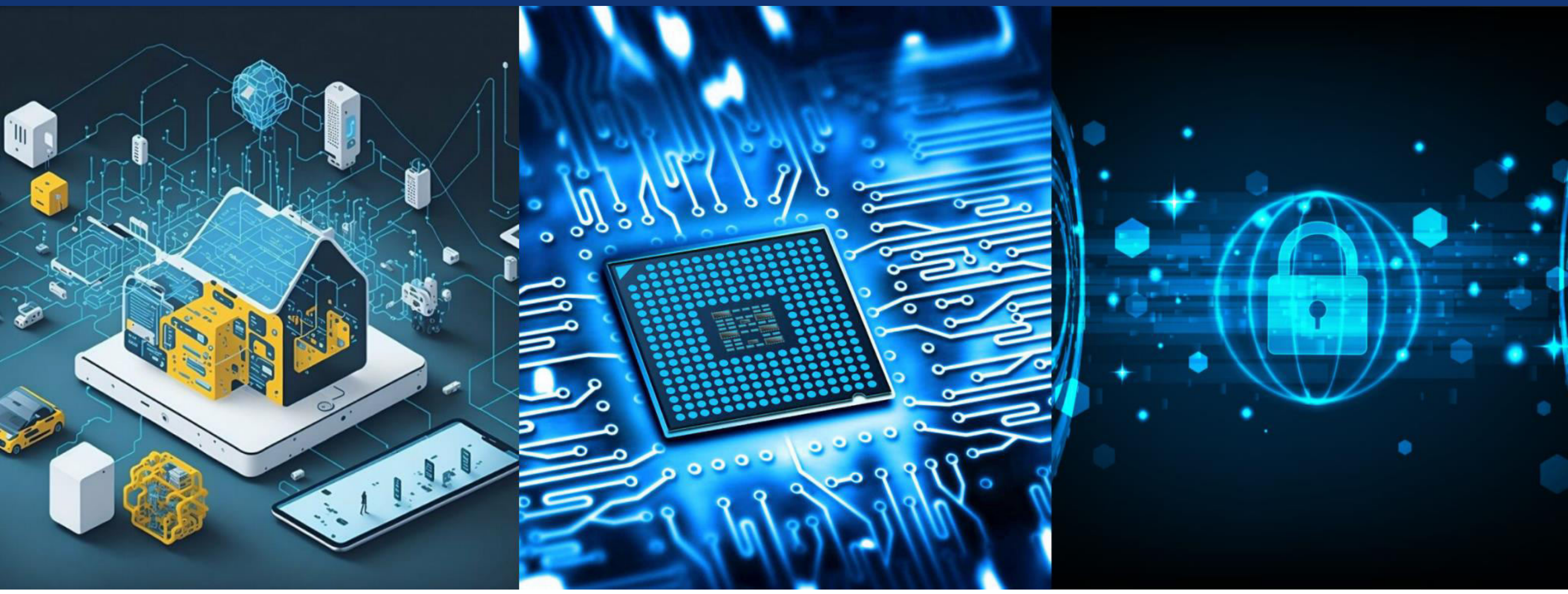

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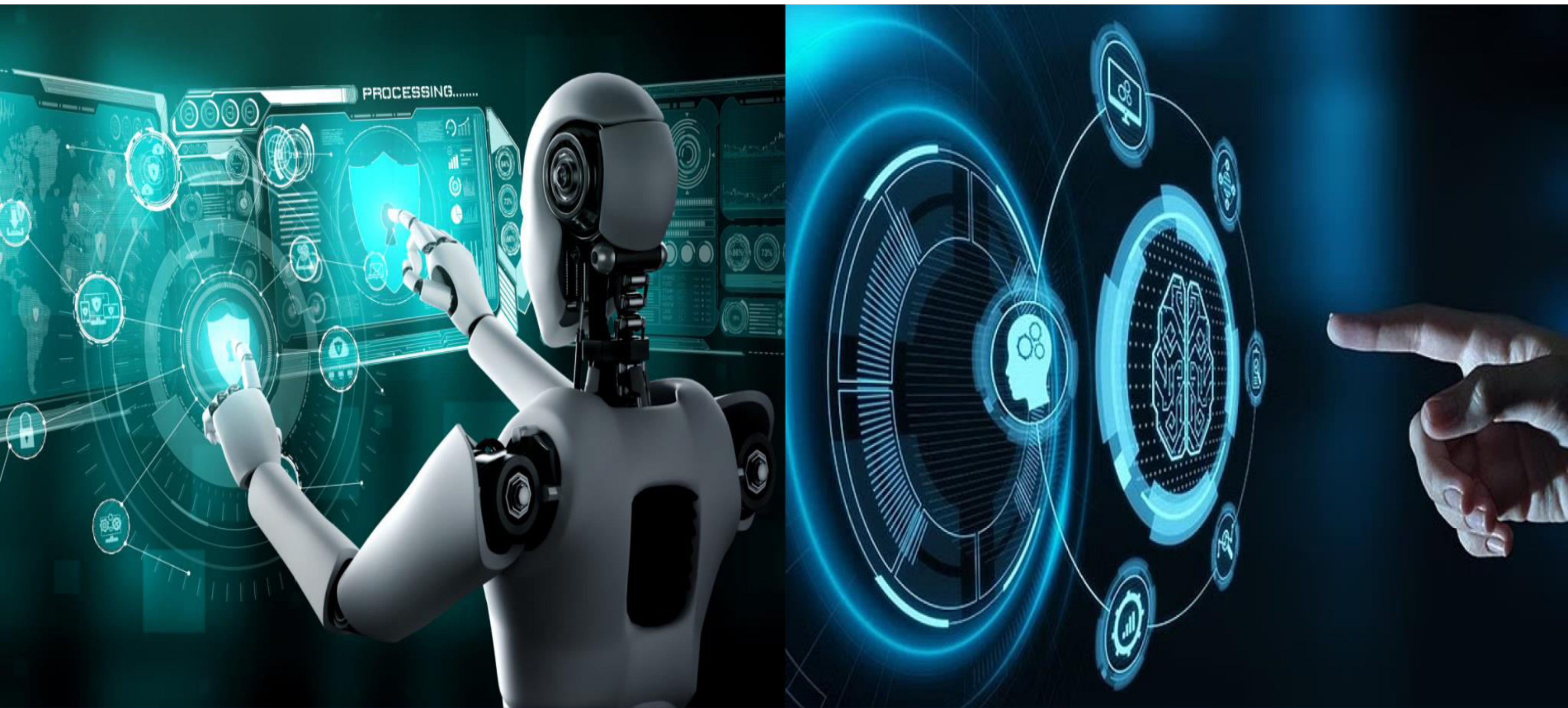

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ProTask AI: GenAI Integrated Task Manager

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ABSTRACT: ProTask AI: GenAI Integrated Task Manager is an intelligent task management system that combines generative AI, natural language processing, and artificial intelligence (AI) technologies to increase productivity. By enabling users to create, amend, and manage tasks using natural conversational inputs rather than tedious form-based interactions, the system gets beyond the drawbacks of conventional task managers. Through the Ollama framework, it makes use of a locally deployed Large Language Model (LLM), guaranteeing data privacy, lower latency, and real-time processing without depending on outside cloud services. The main feature is a conversational interface that allows users to give unstructured commands using both text and speech-to-text input. After interpreting user intent, the AI pulls task details—such as description, deadline, priority, and reminders—and transforms them into structured JSON format so that they may be processed. Secure REST APIs created with FastAPI manage this data and enable effective CRUD operations. Accuracy and consistency are improved through the integration of LangChain with rapid engineering, context management, and structured data extraction. FastAPI is used in the backend for scalability and high speed, and MongoDB is used to safely store task and user data. Along with visualization options like calendar views and progress charts for efficient tracking, the system also provides automated email and browser notifications for timely reminders. In contrast to current systems, ProTask AI ensures modularity, maintainability, and adaptability with a tiered architecture that includes User Interface, Application, AI, Database, and Notification levels. The system offers a user-friendly, effective, and privacy-focused solution that streamlines job management and boosts overall productivity by fusing conversational AI, speech recognition, and intelligent automation.

KEYWORDS: Artificial Intelligence (AI), Generative AI, Natural Language Processing (NLP), Large Language Model (LLM), Ollama Framework, LangChain, FastAPI, MongoDB, Speech-to-Text, Conversational AI, Task Management System, REST APIs, CRUD Operations, Smart Task Prioritization, Real-Time Notifications, Intelligent Automation.

I. INTRODUCTION

Effective task management is crucial for increasing productivity and setting up personal and professional obligations in today's hectic digital world. Conventional task management programs mostly rely on rule-based reminder systems, manual data entry, and static prioritization techniques, all of which frequently lack intelligent automation and contextual awareness. The need for systems that can decipher natural language, comprehend user intent, and offer proactive support is rising as users handle more intricate and dynamic processes. ProTask AI: GenAI Integrated work Manager uses artificial intelligence (AI), natural language processing (NLP), and generative AI to overcome these difficulties and turn traditional work management into an intelligent dialogue. Using either text or voice commands, the system lets users create and manage tasks while automatically extracting important task parameters including priorities, deadlines, descriptions, and reminder schedules.

The Ollama framework powers a locally deployed Large Language Model (LLM) at the heart of ProTask AI, which guarantees improved data privacy, lower latency, and independence from outside AI services. Accurate user input interpretation is made possible by the inclusion of LangChain, which enhances prompt management, contextual comprehension, and structured task extraction. While MongoDB offers scalable and adaptable data storage, FastAPI functions as the backend foundation for managing task operations, authentication, and AI integration. With features like progress monitoring, calendar-based task visualization, automated email and browser notifications, and speech-to-text functionality, the platform further improves usability.

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II. RELATED WORK

A. Large Language Models for Conversational AI

Natural language processing has been transformed by large language models (LLMs), which allow machines to comprehend and produce text that is similar to that of a person. GPT-3 was presented by Brown et al. (2020) and showed good few-shot learning abilities on a variety of language tasks without needing task-specific training [1]. The model performed exceptionally well in conversational interactions, question responding, and text comprehension. But GPT-3 mostly depended on cloud-based deployment, which could cause latency and privacy issues for critical applications. The basis for incorporating LLMs into intelligent task management systems that can comprehend natural language commands was established by this work.

B. Foundation Models and Language Model Evaluation

The idea of Foundation Models was first presented by Bommasani et al. (2021), who emphasized how transfer learning and extensive pre-training might enable a variety of AI applications [2]. In a similar vein, Liang et al. (2022) suggested a comprehensive methodology for evaluating language models, emphasizing real-world usability, robustness, reliability, and fairness [3]. In order to guarantee reliable deployment in real-world settings, their research highlighted the significance of assessing AI systems beyond accuracy measures. These contributions offer crucial principles for creating dependable productivity tools powered by AI.

C. Reasoning and Tool-Augmented Language Models

The goal of recent work has been to improve language models' capacity for reasoning and making decisions. The ReAct framework, which combines reasoning and action generation to accomplish complicated problems through iterative decision-making, was proposed by Yao et al. (2022) [4]. Similarly, Schick et al. (2023) launched Toolformer, which allows language models to use external tools and APIs on their own to enhance information retrieval and task execution [5]. These methods show how AI systems may carry out intelligent task automation, and they served as inspiration for ProTask AI's task extraction and workflow management features.

D. Conversational AI and Context-Aware Interaction

The incorporation of proactive engagement mechanisms and context retention has led to a considerable evolution in conversational AI systems. Proactive conversational AI methods that enhance user engagement by anticipating user wants and comprehending context were surveyed by Deng et al. (2023) [6]. In their evaluation of conversational search systems, Al-Maskari et al. (2022) emphasized the significance of dialogue management for efficient information retrieval [7]. Additionally, effective dialogue state tracking techniques that enhance memory management and response consistency during discussions were developed by Casanueva et al. (2022) [8]. These research serve as the basis for ProTask AI's conversational and context-aware features.

E. AI-Driven Productivity and Task Management Systems

Intelligent task organization, scheduling, and automation have been made possible by the increasing use of AI in productivity applications. The main features of current task management systems include rule-based reminders, static prioritization, and manual task creation. The advantages of using speech recognition, natural language processing, and automated alerts to improve user experience and productivity have been shown by recent developments in AI-powered productivity products. Building on these developments, ProTask AI unifies a locally deployed LLM utilizing Ollama with rapid orchestration based on LangChain, speech-to-text processing, task storage based on MongoDB, and automatic email notifications. This method offers a more effective and user-friendly productivity solution through intelligent task extraction, conversational task management, and privacy-preserving AI processing.

III. PROPOSED ALGORITHM

Figure 1 illustrates the proposed architecture of the ProTask AI system. The architecture consists of several interconnected modules that work together to provide intelligent task management through conversational AI and automated reminders.

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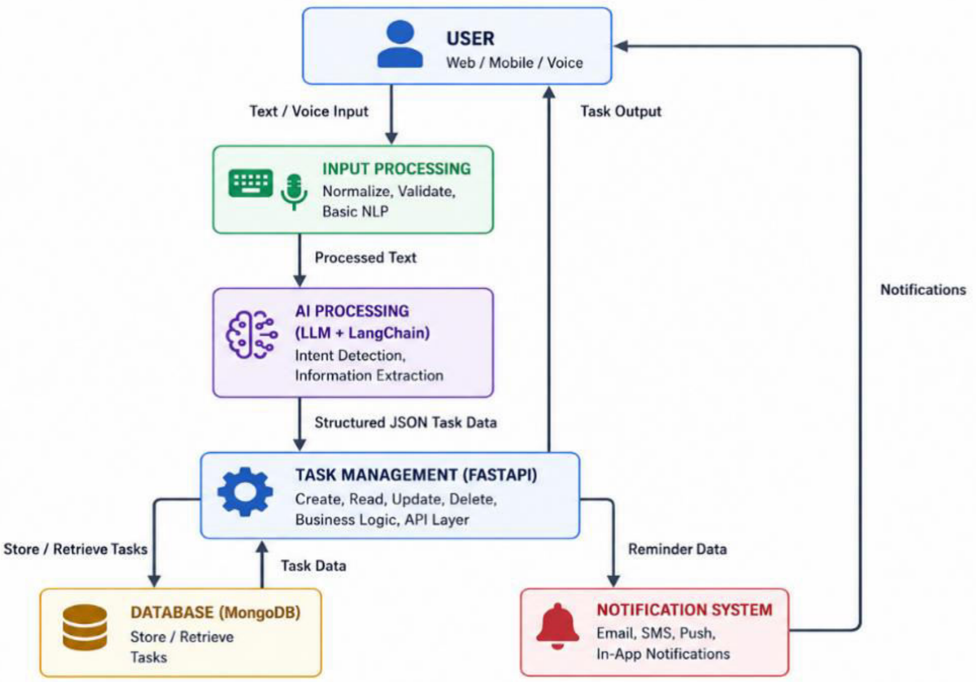

Figure1: Proposed architecture of ProTask AI

- **User Input Module:** The user can input text or voice commands into the system. While textual instructions are sent straight for processing, voice commands are translated into text utilizing the Speech-to-Text module.
- **AI Processing Module:** The Ollama-based Large Language Model (LLM) analyzes the processed input to determine task-related information and user intent. The interpreted data is subsequently processed by LangChain, which transforms it into a structured JSON format appropriate for backend operations.
- **Task Management Module:** The FastAPI-based API layer receives the structured task data and handles the creation, updating, retrieval, and deletion of tasks.
- **Database Module:** Task details, due dates, reminder timetables, and user-related data are stored in MongoDB. Task records can be efficiently stored and retrieved thanks to the database.
- **Notification Module:** To guarantee that tasks are completed on time, the Notification Manager keeps track of reminder data and creates email alerts and browser notifications.
- **Output Module:** The application interface provides an intelligent and user-friendly task management experience by returning the processed task details, confirmations, and reminders to the user.

IV. IMPLEMENTATION & EXPERIMENTAL RESULTS

System Implementation

ProTask AI was implemented using FastAPI for backend services, MongoDB for persistent storage, and a locally deployed LLM through Ollama for natural language understanding. The system accepts text and voice inputs, extracts task information, stores structured task data, and generates automated reminders.

➢ **Dashboard and Task Management**

The dashboard provides centralized task management with task status tracking, priority visualization, and calendar-based scheduling for improved productivity.

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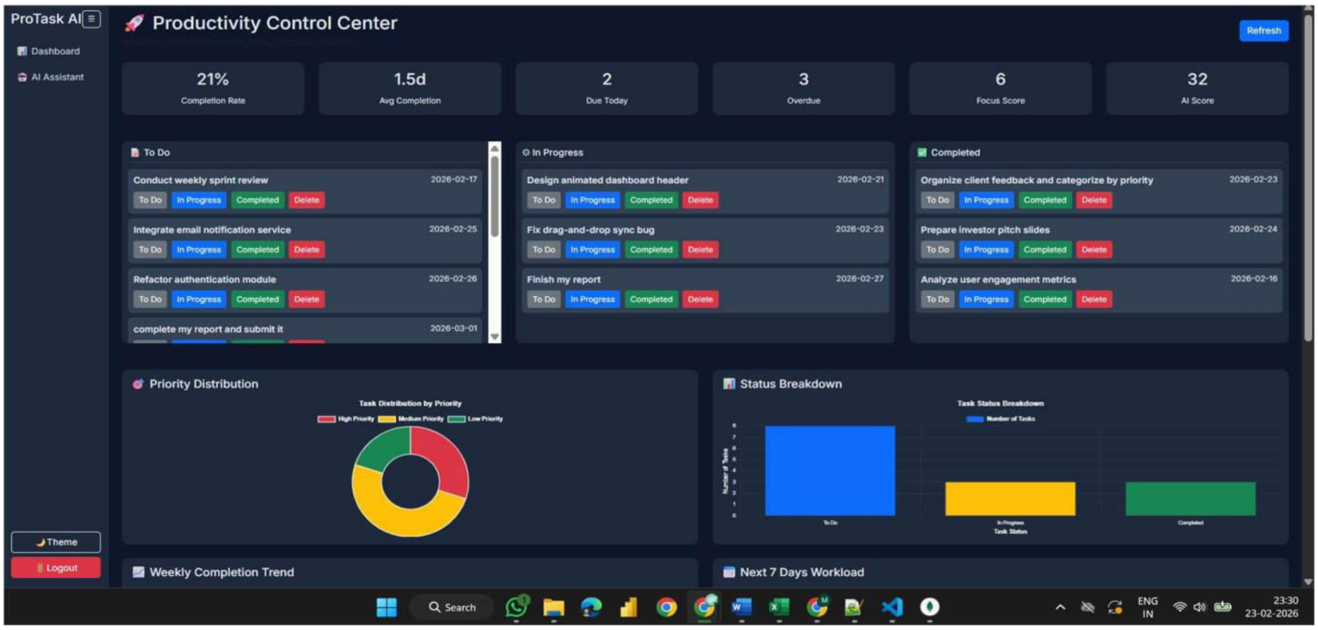

Figure 2: Productivity Control Centre

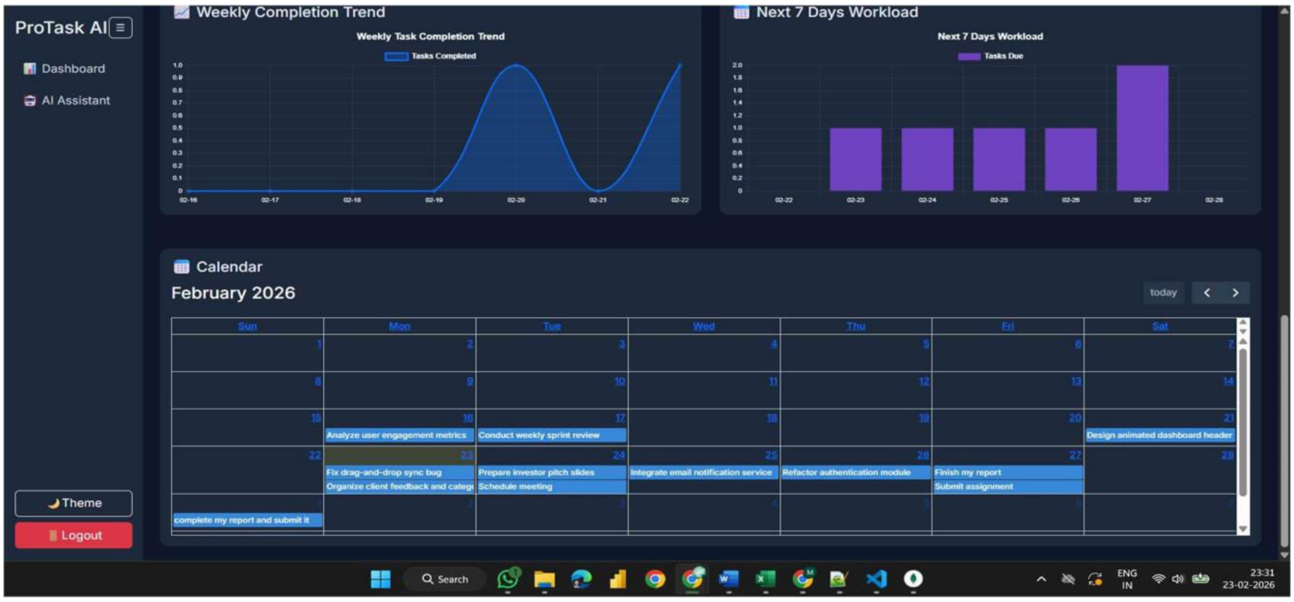

Figure 3: Calendar Integration for Upcoming Productivity Analysis

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➢ AI-Powered Task Processing

The AI module processes voice and text commands. Speech inputs are converted into text using speech-to-text technology, and the LLM extracts structured task information including task description, deadline, and priority.

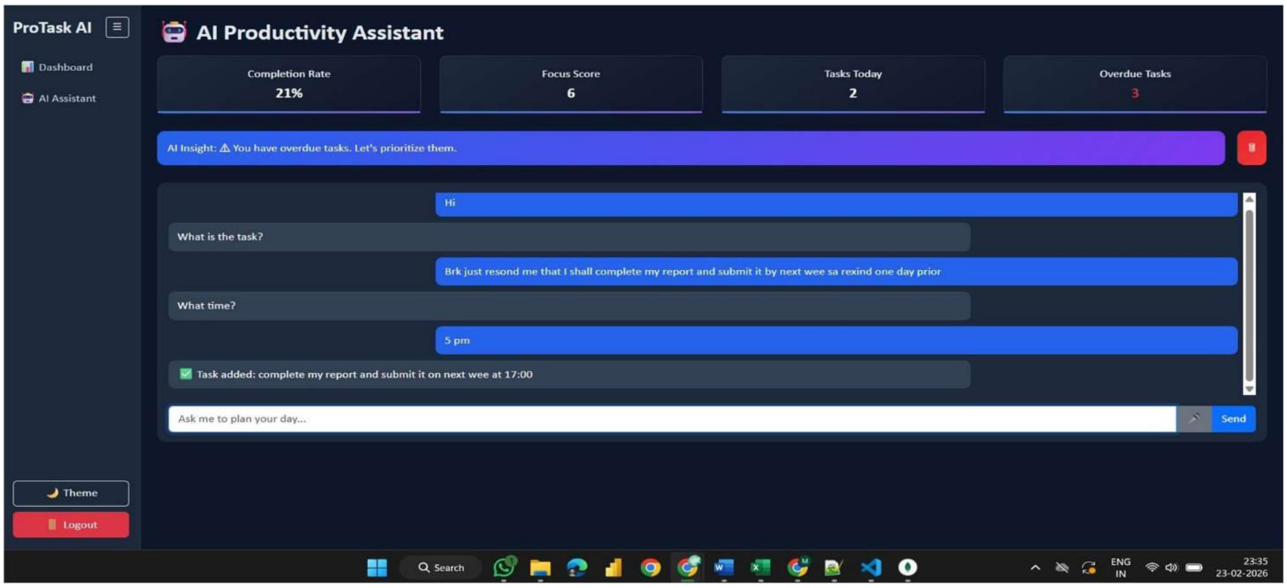

Figure 4: Conversational AI for Task Recognition and Storage

➢ Task Storage and Notifications

Structured task data is validated and stored in MongoDB. Automated email reminders are generated through the notification service.

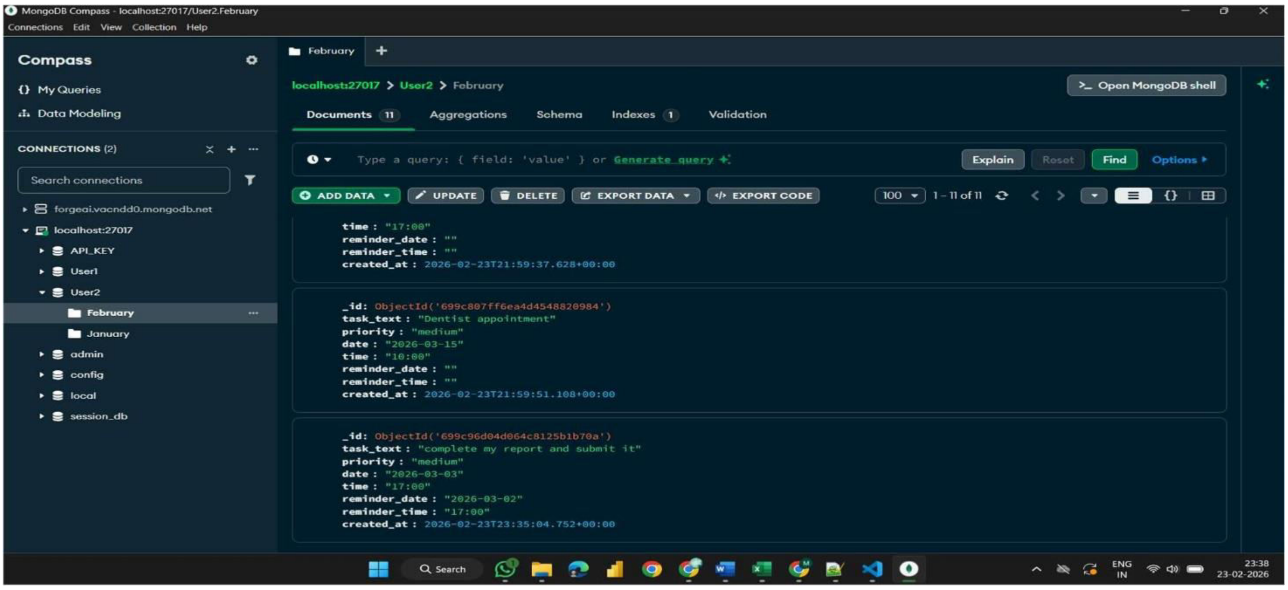

Figure 5: Task Storage with successful API call to MongoDB

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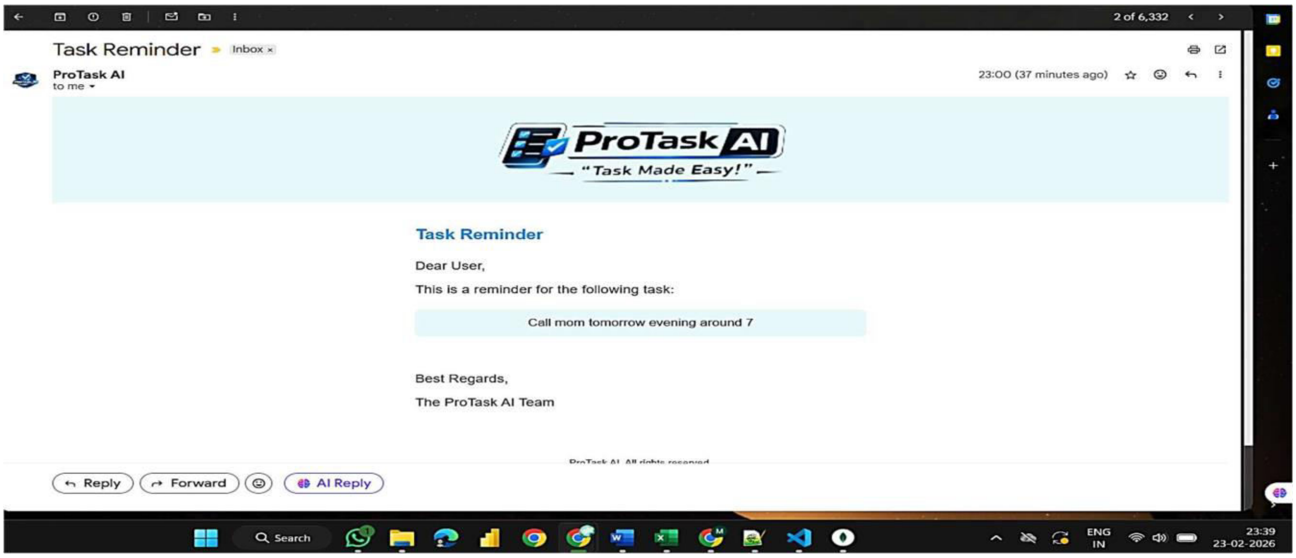

Figure 6: Email Notification for Task Reminder

Experimental Evaluation

The framework was evaluated using 1,000 heterogeneous user prompts representing realistic productivity scenarios involving below categories:

CATEGORY	COUNT OF PROMPTS TESTED
Explicit and implicit temporal expressions	150
Ambiguous relative time references	150
Urgency-indicating keywords	150
Partial task descriptions	150
Multi-intent conversational inputs	150
Missing scheduling constraint inputs	100
Noisy / real-world informal input	150

The evaluation measured task completion, dialogue efficiency, storage integrity, reliability, and latency.

- **Task Completion Performance**

Metric	Value
Final Completion Rate	92.3%
Failure Rate	7.7%

Table 1: Task Completion Performanace Metrics

- **Dialogue Efficiency**

Metric	Value
Clarification Rate	83.2%
Recovery Success Rate	90.76%
Average Turns per Task	1.83

Table 2: Dialogue Efficiency Metrics

The clarification mechanism improved task completion, demonstrating effective conversational refinement. The low average dialogue length indicates efficient user interaction with minimal conversational overhead.

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- **Storage Integrity**

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Stored Documents	1000
Duplicate Rate	11.5%
Field Completeness	33.92%

Table 3: Storage Integrity Metrics

- **Reliability Metrics**

Metric	Value
Precision	0.95
Recall	0.95
F1 Score	0.95

Table 4: Reliability Metrics

Results confirm reliable data persistence with complete schema validation and zero duplicate records. High precision and recall values demonstrate accurate task extraction and reliable storage operations.

- **Latency Analysis**

Metric	Value
Average Latency	11.33 sec
Median Latency	10.61 sec
95th Percentile Latency	12.85 sec
Standard Deviation	17.29 sec

Table 5: Latency Performance Metrics

The system maintained stable response times, with LLM inference contributing most of the processing delay.

- **Overall Robustness**

A composite robustness score was calculated using completion rate, recovery success, precision, recall, and storage consistency.

Robustness Score = 0.94

This result demonstrates strong reliability, semantic consistency, and robustness across diverse user inputs.

V. CONCLUSION

ProTask AI: By combining Artificial Intelligence (AI), Natural Language Processing (NLP), and Generative AI into a single platform, GenAI Integrated Work Manager offers an intelligent and conversational approach to task management. The suggested solution improves usability, efficiency, and productivity by allowing users to create and manage tasks through natural text and voice interactions, in contrast to standard task management systems that rely on manual input and rule-based operations. Through the Ollama framework, the implementation makes use of a locally deployed Large Language Model (LLM), guaranteeing improved data privacy, decreased reliance on external APIs, and reduced response latency. The system successfully converts unstructured user inputs into actionable task data by integrating LangChain to conduct intent recognition, contextual comprehension, and structured task extraction. A scalable, dependable, and responsive task management architecture is offered by the FastAPI-based backend, MongoDB database, and automatic notification systems. The framework's efficacy and dependability are validated by experimental evaluation, which shows great performance with high task completion rates, outstanding precision and recall, robust conversational handling, and steady latency characteristics. Additionally, the modular architecture improves future expansion, scalability, and maintainability. All things considered, ProTask AI effectively converts traditional task management into an automated, intelligent, and user-focused experience, demonstrating the usefulness of generative AI in contemporary productivity applications and offering a solid basis for upcoming AI-driven work management systems.

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