IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 18, April 2026
Impact Factor: 8.2

Smart Troubleshooter: Real-Time AI System for Automated Technical Assistance

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Abstract: *This paper identifies a novel approach to address the challenges faced by industries which rely on complex machinery, where timely and accurate access to product information and troubleshooting guidance is critical. Traditional methods like referring manuals and seeking human support are often inadequate leading to downtime and hamper productivity. Our project introduces an AI-powered system that takes advantage of a multi-layered approach, combining fine-tuned language models, Retrieval-Augmented Generation (RAG) Fusion, and Corrective Retrieval-Augmented Generation (CRAG) to provide swift and precise responses. This system focuses on offering a solution that is scalable to a large extent for meeting the dynamic needs of modern industries.*

Keywords: Generative AI, RAG Fusion, Large Language Models, LLM Fine-Tuning, Synthetic Dataset Generation.

I. INTRODUCTION

In industries that depend heavily on complex machinery and equipment, ensuring smooth, uninterrupted operations is crucial to maintaining productivity and meeting customer demands[1]. However, when technical issues arise, the process of accessing reliable, accurate, and up-to-date product information can become a significant obstacle[2]. Traditionally, users rely on printed manuals or support from technical staff, which often entails searching through lengthy documents or waiting for human assistance[3]. Such methods are time-consuming and may provide limited guidance, leading to extended downtime and operational inefficiencies[4].

Additionally, with technological advancements occurring at a rapid pace, products and machinery are regularly updated or modified, making it difficult to keep printed manuals current[5]. This results in a growing gap between the information users need and the information available to them, especially when dealing with advanced machinery where technical details are complex[6]. For example, a technician working on an industrial robot might require precise troubleshooting steps or specific maintenance guidelines that may not be readily available in outdated resources[7]. This disconnect can cause delays, increase maintenance costs, and impact overall productivity[8].

To address these challenges, our approach proposes a real-time, AI-powered system designed to deliver precise, context-aware responses for product information and troubleshooting[9]. By leveraging advanced Natural Language Processing (NLP) capabilities, including fine-tuned Large Language models (LLMs) and RAG techniques, this system goes beyond traditional support methods[10]. The goal is to provide users with immediate, relevant assistance, thus reducing downtime, improving operational efficiency, and enhancing user satisfaction.[11]

Our approach integrates a multi-layered AI system that includes RAG Fusion and CRAG[12]. These techniques allow the system to generate accurate responses by combining knowledge from internal resources like product manuals with data from external sources when needed[13]. Through these capabilities, the system not only adapts to various user queries but also remains scalable and resilient, making it ideal for modern industrial environments where machinery, products, and user needs constantly evolve[14].

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II. RELATED WORK

Agent Based Work Flow

The AI-Based Agents Workflow (AgWf) paradigm provides a structured approach to enhance process mining applications using LLMs. AgWf combines deterministic tools and non-deterministic AI-based tasks, leveraging the divide-and-conquer principle to decompose complex inquiries into manageable sub-tasks executed by specialized agents[15]. This framework ensures improved task execution and higher quality outcomes by utilizing both traditional process mining techniques and the semantic capabilities of LLMs[16]. The framework supports various task types, such as routing inquiries, evaluating task outputs, and synthesizing insights into coherent results, thereby addressing limitations of existing LLM implementations in complex scenarios [17].

CrewAI

CrewAI is a collaborative AI framework that enables multiple AI agents to work together on complex tasks [18]. Each agent within the system is assigned a specific role, and to ensure accuracy and efficiency, agents are equipped with specialized tools like Serper's API for Google search and the RAG tool to enable RAG for tasks such as content creation, data research, and in-depth analysis [19].

CrewAI organizes agent interactions through various processes, including sequential, hierarchical, and a planned consensual approach that's currently in development[20]. In a sequential process, agents complete tasks one after another, handing over outputs as inputs to the next agent in line[21]. The hierarchical process allows agents to work under a structured order, where tasks are managed and delegated by a lead agent, establishing a clear chain of command and prioritization[22]. The planned consensual process is more collaborative, with agents discussing and agreeing on tasks before execution, pooling resources and insights for decisions to ensure an optimized outcome[23].

Designed to streamline teamwork and improve efficiency, CrewAI's modular framework enables agents to manage complex decision-making seamlessly [24]. The system's adaptability makes it ideal for multi-agent tasks like content generation, data analysis, and email automation, where multiple agents collaborate to achieve goals that would be challenging for a single AI model to accomplish alone[25].

Large Language Models (LLMs)

A Large Language Model (LLM) is an advanced AI system designed to process and generate human-like text by leveraging large-scale neural architectures, primarily Transformers[26]. These models are trained on vast datasets, enabling them to learn complex linguistic patterns, context, and relationships within the text[27]. The size of an LLM, measured in parameters—the adjustable values learned during training—ranges from millions to hundreds of billions, with larger models often yielding superior performance but requiring substantial computational resources[28]. Prominent examples include OpenAI's GPT, Large Language Model Meta AI (LLaMA), and Google DeepMind's Gemini, each excelling in tasks like text generation, summarization, and language translation[29].

The authors in the LLaMa paper [30] demonstrate that LLMs can achieve state-of-the-art performance by training exclusively on publicly available datasets, emphasizing openness and efficiency[31]. LLaMA models, spanning sizes from 7B to 65B parameters, outperform larger counterparts like GPT-3 on several benchmarks despite their smaller scale. These advancements underscore the potential of LLMs in democratizing access to AI technologies while maintaining competitive performance[32].

The paper [33], leveraged the capabilities of LLMs as a component of automated synthetic data generation pipelines[34]. By automating the data generation process, the pipeline reduces reliance on manual data collection, offering a cost-efficient solution for building and refining Machine Learning models[35]. Our approach integrates multiple powerful agents based LLMs to enhance the dataset generation process[36].

In the paper [37], it is demonstrated how LLMs can be employed to generate troubleshooting trees, which are essential for diagnosing and resolving issues in industrial equipment[38]. By leveraging LLMs, the study aims to streamline the creation of troubleshooting guides, reducing the reliance on manual efforts and enhancing the efficiency of maintenance[39].

The study shown in the paper [40], revolves around multi-round prompt design and enabling LLM to connect the dots between different pieces of information[41]. They allow the LLM to iteratively process information for capturing the complexity of fault diagnosis encouraging the model to refine its understanding with each phase[42].

Fine-Tuning LLMs

Fine-tuning a LLM to serve as a user assistance system involves adapting a pretrained LLM to respond effectively to queries, resolve doubts, and offer step-by-step instructions based on a provided user manual[43]. This customized training equips the LLM to accurately interpret user questions and provide relevant guidance, making it a powerful tool for troubleshooting and instructional support[44].

The fine-tuning process leverages advanced techniques like Quantized Low-Rank Adapters (QLoRA) to reduce computational requirements and optimize performance [45]. These techniques enable the training of large models efficiently on consumer-grade hardware without sacrificing quality:

- Creating a Specialized Dataset: The process begins by gathering and structuring a dataset from the user manual. This dataset should cover common troubleshooting scenarios, step-by-step instructions, and detailed explanations of product features[46]. The dataset may also include FAQs, and example queries to train the LLM on the types of questions users might ask[47].
- Adapting Model Parameters: Instead of retraining the entire model, small trainable low-rank matrices are added to specific layers, such as attention layers[48]. These matrices focus on targeted fine-tuning for the specific task or domain, significantly reducing computational complexity and memory requirements[49]. This ensures that the LLM efficiently learns to understand the technical terminology, operational procedures, and typical issues covered in the manual, while keeping the base model unchanged[50].
- Quantization for Efficiency: Quantization reduces memory usage by converting model weights from a 16-bit floating-point format to a 4-bit format during training[51]. This technique allows large models, such as those with 13 billion or 70 billion parameters, to run on consumer-grade GPUs[52]. It preserves performance by keeping the base model frozen during training, thus avoiding degradation caused by quantization noise (a small error introduced when approximating data using lower precision)[53].
- Optimizing Performance: Fine-tuning involves careful adjustment of hyperparameters like learning rate, training duration, and batch size[54]. The goal is to enhance the LLM's ability to provide precise answers without making it overly reliant on the fine-tuning data, allowing it to retain some general language understanding[55]. Techniques like validation on user queries ensure that the model strikes the right balance between specificity and flexibility. The integration of QLoRA makes this process more resource efficient[56].
- Testing and Refinement: The fine-tuned model is tested with a set of validation queries that simulate real user interactions. This evaluation phase ensures the LLM can handle diverse questions, ranging from basic operational instructions to complex troubleshooting issues. Feedback from these tests may prompt further adjustments to the training data or model parameters [57].
- Iterative Improvement: Once deployed, the LLM-based assistant can continuously improve through user feedback. By periodically fine-tuning the model with new data reflecting common queries or misunderstood concepts, the assistant becomes more reliable and efficient over time[58].

Fine-tuning allows the creation of an effective LLM-based assistant that can interpret and respond accurately to user questions, delivering tailored advice and instructions derived directly from a user manual. This approach minimizes training costs while providing a high-quality support experience for users navigating technical information [59].

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The authors of the study [60], address the challenge of hallucinations by incorporating Knowledge Graphs (KGs) and fine-tuning models on industrial datasets[61]. They leverage multimodal data to create more detailed prompts for inference and utilize KGs to facilitate multi-hop reasoning when required[62].

RAG Fusion

Traditional RAG method has certain limitations which RAG Fusion helps overcome [63].

RAG Fusion combines both RAG and reciprocal rank fusion by generating multiple queries, re-ranking them with reciprocal scores and fusing the documents and scores[64].

RAG Vs RAG-Fusion:

Traditional RAG gathers the documents, generates vector embeddings which are stored in a vector database. The 'n' most relevant documents based on vector distance to original query via vector search. Then the query along with the retrieved documents are sent to a LLM to output a response[65].

RAG-Fusion adds a few extra steps[66]. Once the original query is received, the model sends the original query to the LLM to generate a number of new search queries based on the original query[67]. The algorithm then performs vector search to find relevant documents[68]. But instead of doing this the traditional way, it uses the reciprocal rank fusion algorithm in search to assign scores to every document and re rank them according to the scores[69].

The model sends the re-ranked results along with the generated queries and original query to the LLM to produce an output[70].

III. METHODOLOGY

Dataset Generation

Automating the process of generating data plays a crucial role in designing an efficient and accurate language model for domain-specific queries[71]. CrewAI is employed here for simplification of the process by allowing users to feed a product manual, specify the product name (e.g., a vehicle), and optionally mention a specific part or component [72]. The tool then automatically generates a semi-structured dataset in JavaScript Object Notation (JSON) format, consisting of relevant question-answer pairs[73].

This way, the manual effort is reduced in generating training data. The resultant dataset provides the model with the ability to model accurate and contextually appropriate responses related to troubleshooting and product-related queries[74]. This is valuable in large industrial environments where detailed manuals and documentation are common, as it allows for continuous updates as new products or equipment are introduced[75].

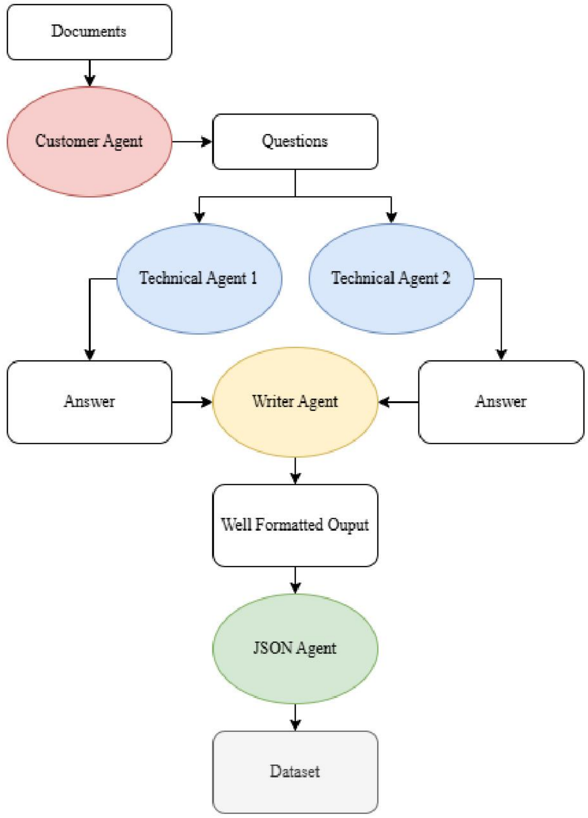

Fig 1: Workflow for dataset generation

As seen in Fig 1, the process begins with the Customer Agent, which analyzes the provided document to generate customer queries or questions. These questions are then processed by two Technical Agents, both employing RAG tools to find solutions within the document[76]. The two agents operate with different temperature settings, ensuring diversity in the answers generated[77].

The outputs from the Technical Agents are subsequently passed to the Writer Agent, which synthesizes the responses into a single, coherent, and easily understandable answer[78]. This refined answer is forwarded to the JSON Formatter Agent, which structures the data into a JSON format. The JSON Formatter Agent integrates the original questions generated by the Customer Agent with their respective answers, thereby creating a well-organized dataset[79].

Additionally, the framework allows for the inclusion of specific information, such as vehicle components, within the document. This enables the system to tailor questions accordingly, ensuring relevance and specificity[80]. Through this iterative and systematic process, the CrewAI framework facilitates efficient and high-quality dataset generation for LLM fine-tuning[81].

Fine-Tuned Model Development

We have utilized the pretrained **LLaMA 3** model with 8 billion parameters from Hugging Face and fine-tuned it using **Unsloth** library which is designed to optimize and accelerate the fine-tuning and inferencing of LLMs (in our case training the LLM on custom dataset for car troubleshooting) [82].

To prepare the dataset as mentioned above we have used CrewAI a tool designed to streamline dataset generation from PDFs or documentations of the car manuals along with the conversion of the data into the particular trainable format[83].

Quantized Low-Rank Adapters (QLoRA):
The fine-tuning process leverages combination of two key techniques: Quantization and Low Rank Adaptation (LoRA) [84]:-

Quantization:
It reduces memory usage by converting 16-bit floating point number to a 4 bit format while preserving performance[85].
It enables the training and deployment of larger models like 13 billion or 70 billion parameters on consumer grade GPUs[86].
It ensures that the base model is frozen during training, avoiding degradation from quantization noise (a small error introduced when we approximate a continuous data using a limited number of discrete levels (in our case steps) to a reduced lower precision data)[87].

LoRA:
It adds small, trainable low-rank matrices (used to reduce the complexity and computational requirements) (rank = r) to specific parts of a large language model (e.g., attention layers)[88].
This enables targeted fine-tuning for specific tasks, domains, or datasets without retraining the entire model, making the adaptation process efficient and cost-effective[89].

Optimized Gradient Checkpointing:
To further optimize the memory usage during training we utilized Optimized Gradient Checkpointing which recomputes intermediate values when needed instead of storing them saving up to 30% of VRAM [90], [91].
After preparing the dataset a system prompt and the relevant car model is specified to guide the LLMs behavior. This will be the prompt given to the LLM model every time a user asks his/her query making the answer domain-specific and accurate[92].
Along with this we define the steps, learning rate and other hyperparameters[93].
Finally, our LLM gets trained on the dataset we provided[94].
We can also locally store the weights of this trained LLM and then load those weights to get the solutions to our queries[95].

Implementation of Retrieval-Augmented Generation (RAG) Fusion
RAG Fusion extends the capabilities of vanilla RAG [96]. It improves the traditional approach by creating variations from the base query to broaden the search perspective, allowing the system to capture results that may not have been possible with only the base query[97]. The term "fusion" refers to how the system re-ranks these search results by comparing their relevance across multiple versions of the user query. This improves the final result as different interpretations of the query are also used for answer retrieval[98].
In this project, RAG Fusion is used when the initial response from the fine-tuned model isn't quite sufficient, i.e., when the model assigns a low relevance score to the query. Whenever this is encountered, the system generates similar queries to the query prompted by the user to capture different perspectives of the same query (as depicted in the flow diagram's "Generate similar questions" node), which helps to give a better response. The system then performs a vector search within a document database (e.g., a Chroma Vector Database), where documents are stored as high-dimensional vectors for better efficiency while searching[99].
The documents retrieved are ranked using reciprocal rank fusion (as shown in Fig 2), where the relevance of results is calculated across multiple queries[100]. This improves the robustness of the system, making it more likely to retrieve the correct information, even in ambiguous or difficult-to-answer queries. If a highly relevant result is found, it is presented to the user, along with the exact page or section from the product manual for additional context, such as diagrams or tables (as shown in the flow's "High relevance" path leading to "Print Response").

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ISSN: 2581-9429 Volume 6, Issue 18, April 2026 Impact Factor: 8.2

CRAG Approach

When RAG Fusion does not yield a satisfactory result, the system switches to the CRAG approach [101]. CRAG further increases the scope for retrieval of data by using external web sources rather than only internal documents.

CRAG is initiated when RAG Fusion's results have low relevance (as shown in the flow diagram's "Low relevance" path). The query is first transformed to allow for a broader search space (seen as the "Transform query" node in the diagram). The transformed query is then used to search the web, and then the collected data is integrated and returned to the user with a disclaimer that web-sourced information may carry a risk of inaccuracy due to its external nature[102].

The CRAG approach helps in scenarios where internal documentation is incomplete or outdated, providing a fallback mechanism that ensures users are still able to receive answers. Although external data is not always as reliable as internal, curated sources, it ensures the system can handle a wide range of queries, even those that go beyond the scope of the available manuals[103]

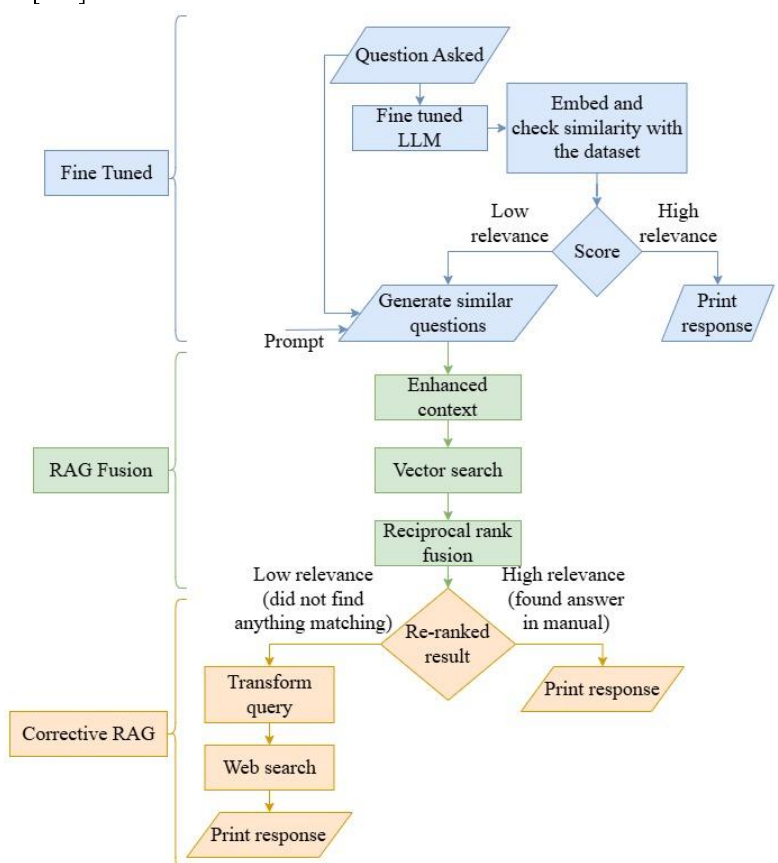

Fig 2: Flowchart of Workflow

Page Display

The authors have developed a method to locate the page or section containing the most relevant content based on the system's generated response, following the flow in Fig 3. The steps are as follows:

- ➢ **Keyword Generation**: When the LLM generates a response, it provides five associated keywords[104]. Each keyword is assigned a relevance weight based on its importance in the response context. More critical

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keywords get higher weights, while supplementary keywords receive lower weights. This weighting system allows the search algorithm to prioritize certain keywords more heavily during matching[105].

- **Semantic Keyword Expansion**: To account for variations in wording, the system performs a semantic expansion on each keyword[106]. This involves generating similar words and phrases that capture the same meaning, such as synonyms or contextually related terms. These expanded terms are also assigned weights based on their similarity to the original keywords[107].
- **Page Matching with Weighted Semantic Search**: The system assigns weights to keywords based on their parts of speech, emphasizing certain types of words that typically hold more relevance in search queries. Using the weighted keywords (and their semantic expansions), the system searches each page and computes a weighted match score for each page. A higher score is given when a page contains the original keywords or highly similar terms. This scoring is adjusted based on the weighted importance of each keyword, allowing more relevant keywords to influence the result heavily.
- **Diagram/Image Analysis**: Among the top 10 pages with the highest match scores, any page containing diagrams or images is further analyzed by examining the captions of these visuals.

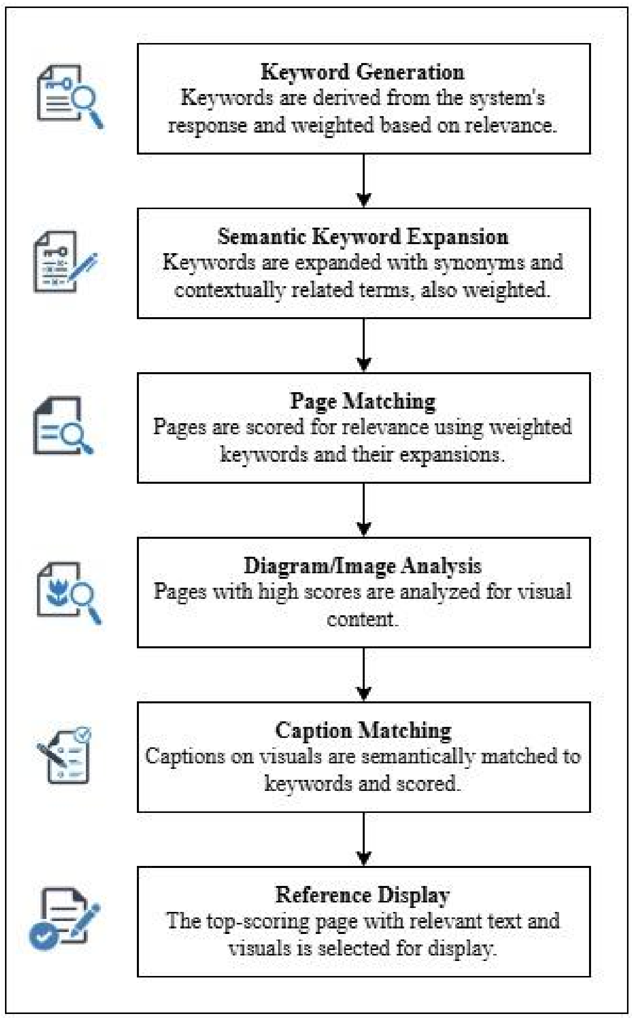

Fig 3: Page Display Flowchart

- **Caption Matching with Keyword Weights**: Similar to page matching, the system applies weighted semantic search on captions. It calculates a match score for each caption based on the presence of keywords and their expanded terms. The caption with the highest weighted match score is identified, and the page containing this relevant image is selected.
- **Reference Display**: The page with the most relevant content, supported by both text and images, is displayed to the user as a reference. This page includes the visual elements that align with the response, enhancing the user's understanding.

IV. RESULT AND DISCUSSION

- Experimental results indicate that **PARAM Shavak** demonstrates a marginally faster performance compared to **Google Colab**. The time reductions observed for **Llama 3**, **Mistral**, **Gemma**, and **Phi** were 65.3%, 66.2%, 46.5%, and 2.4%, respectively.
- The use of CrewAI for dataset generation from manuals for Fine tuning of LLMs is a novel approach that leverages the power of existing models like Gemini to easily train more specialized LLMs like a troubleshooting Assistant
- Our initial attempts at training a Large Language Model from scratch proved to be computationally expensive, so we looked towards UnSloth for fine-tuning, which provided an easier approach. UnSloth's boilerplate-like methodology simplified the process of fine-tuning a LLM for beginners.
- We have done benchmarking on PARAM Shavak supercomputer in a box solution by Center of Development for Advance Computing (C-DAC) with the following Hardware:
    - Processor: Dual Intel Xeon Gold 6132
    - RAM: 96 GB DDR4 2666 MHz in balanced configuration
    - GPU: RTX A4500 with 20 GB GDDR6 VRAM

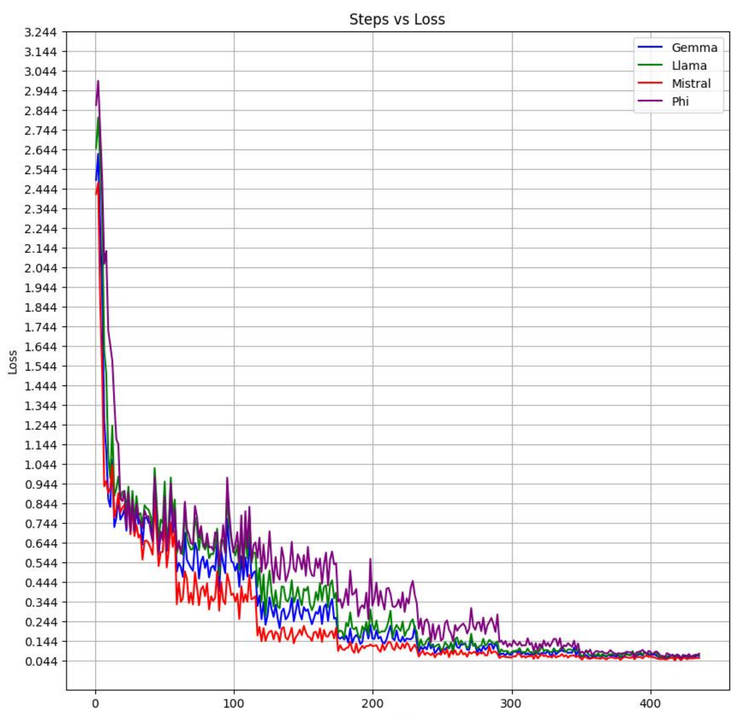

Fig 4: Loss Curve of Fine-Tuned LLM Model

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- As seen in Fig 4, the Mistral model converged faster. We believe this was due to its training on instruction-based tasks and having 7B parameters, offering an effective balance between performance and computational efficiency.
- The use of provenance tracking to predict the source of generated text proved to be largely effective, leveraging threshold-based page-wise weight calculations. However, an improvement could be made by highlighting the relevant text within the identified page for enhanced interpretability.

Table 1. Comparison of Google Colab and PARAM Shavak for Fine-Tuning Metrics

System	Model	Time Taken (in minutes)	Peak Memory (In Gigabytes (GB))	RAM (In GB)	GPU (In GB)
Google Colab	**Llama 3**	40.58	11.049	13	15
	Mistral	123.76	13.631		
	Gemma	50.95	8.117		
	Phi	20.89	2.643		
PARAM Shavak	**Llama 3**	14.09	6.904	93	40
	Mistral	41.87	13.568		
	Gemma	27.25	9.131		
	Phi	20.39	2.74		

As shown in Table 1, the time taken for fine-tuning various models on two different machine configurations varies significantly due to the number of parameters and the hardware capabilities of the systems. Larger models, such as Mistral, with 22 billion parameters and a vocabulary size of 32,768, require considerably more time to fine-tune on both Google Colab and PARAM Shavak. In contrast, smaller models like Phi exhibited similar fine-tuning times on both platforms. However, on PARAM Shavak, which features superior hardware with higher RAM and VRAM, the fine-tuning time was significantly reduced for all models. For instance, Llama 3 being a medium sized model required only 14.09 minutes on PARAM Shavak compared to 40.58 minutes on Colab. This highlights that more powerful computational resources greatly enhance the efficiency of fine-tuning larger models, leading to substantial reductions in processing time.

V. CONCLUSION

In conclusion, our real-time AI-powered product information and troubleshooting system represents a significant advancement in addressing the operational challenges faced by industries reliant on complex machinery. By leveraging fine-tuned language models, RAG Fusion, and CRAG, our system provides a scalable and contextually aware solution that meets the dynamic needs of modern industrial environments. Traditional troubleshooting methods are often inefficient, leading to extended downtimes and increased operational costs. In contrast, our AI-based solution offers swift, precise responses by integrating internal product documentation with external resources when needed.

The integration of CrewAI for automated dataset generation, along with LLaMA's fine-tuning and advanced techniques such as Quantized LoRA, enables our system to handle a wide array of user queries with high accuracy and minimal computational overhead. Furthermore, the page display mechanism enhances user experience by presenting the most relevant sections and visuals from the manuals, thus facilitating quick understanding and effective troubleshooting.

This system's architecture not only reduces the time required to resolve technical issues but also provides a sustainable framework that can be adapted as machinery and products evolve. Future improvements, such as incorporating additional AI agents or exploring multimodal data sources, could further enhance the system's versatility. Ultimately, this AI-powered approach sets a new benchmark for real-time technical support, paving the way for more efficient and resilient industrial operations.

DOI: 10.48175/IJARSCT-34326

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Volume 6, Issue 18, April 2026
Impact Factor: 8.2

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