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Enhancing Database Accessibility through AI-Powered SQL Assistance

Jeevarathinam A¹, JayaKumar J²

Assistant Professor, Department of Computer Science, Sri Krishna Arts and Science College, Tamil Nadu, India¹

Student, III B.Sc., Department of Software Systems, Sri Krishna Arts and Science College, Tamil Nadu, India²

ABSTRACT: SQL_Assistant is an AI-driven system designed to simplify database querying by allowing users to retrieve data using natural language instead of traditional SQL syntax. It integrates the Llama 7B Versatile LLM, hosted on the Groq platform, to interpret user queries and generate accurate SQL statements. To enhance efficiency, the system utilizes Chroma DB for storing and retrieving vectorized past queries, improving accuracy through semantic similarity. Additionally, Langchain and HuggingFace embeddings are used to refine query interpretation and execution. By eliminating the need for SQL expertise, SQL_Assistant enhances database accessibility for non-technical users, making data retrieval more intuitive and efficient. This paper explores its architecture, methodology, and performance, discussing its potential impact and future enhancements, such as multi-database support and voice-based queries.

KEYWORD: SQL Assistant, Natural Language Processing (NLP), Llama 7B LLM, Chroma DB, Lang chain, SQL Query Generation, Database Accessibility, Hugging Face, Embeddings, Semantic Similarity, Machine Learning in Databases, Automated Query Processing

I. INTRODUCTION

Structured Query Language (SQL) is widely used for managing and retrieving data from relational databases. However, many users, especially those without a technical background, struggle with writing efficient and syntactically correct SQL queries. This limitation creates a gap in data accessibility and decision-making for business professionals and non-technical users.

To address this challenge, SQL_Assistant utilizes a combination of a natural language processing (NLP) model (Llama 7B), a vectorized database (Chroma DB), and SQL query generation tools to allow users to input queries in plain English. The system translates these queries into structured SQL statements, executes them on a MySQL database, and returns the results in a human-readable format. The goal of this system is to provide a seamless interface for users to interact with SQL databases without requiring SQL knowledge, utilize a powerful LLM to understand and interpret natural language queries accurately, optimize query execution using a vectorized approach through Chroma DB, and enhance database accessibility for non-technical users in various industries. Additionally, SQL_Assistant minimizes errors caused by incorrect query syntax, ensuring more reliable data retrieval. By leveraging past successful queries stored in Chroma DB, the system improves response accuracy through semantic similarity. This approach not only enhances efficiency but also reduces the learning curve for users unfamiliar with database management. Ultimately, SQL_Assistant aims to bridge the gap between complex database systems and intuitive, user-friendly data access.[1,3]

A. OBJECTIVE

The primary objective of SQL_Assistant is to bridge the gap between complex database management and user-friendly interaction by enabling users to retrieve data using natural language queries instead of traditional SQL commands. This system is designed to cater to both technical and non-technical users, ensuring seamless database accessibility and efficient data retrieval. Develop an Intuitive Interface: Provide a user-friendly platform that allows users to interact with databases using plain English without requiring knowledge of SQL syntax. Leverage the Power of Llama 7B LLM: Utilize advanced natural language processing (NLP) capabilities of Llama 7B to interpret user queries accurately and generate precise SQL statements. Enhance Query Efficiency with Chroma DB: Implement vectorized storage of past successful queries to improve accuracy by retrieving semantically similar queries and optimizing results. Improve Query Execution Speed: Optimize database querying through pre-indexed and vectorized storage, reducing processing time while maintaining high accuracy.[3]



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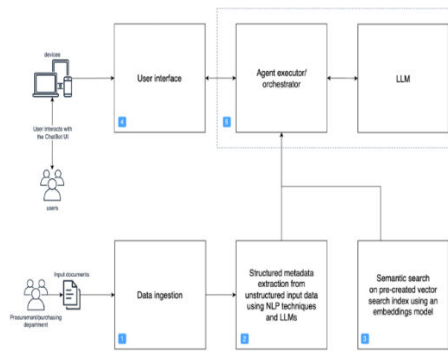
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B. Significant Impact

SQL_Assistant has a profound impact on both technical and non-technical users by making data more accessible and easier to manage. It eliminates the need for SQL expertise, allowing business professionals, analysts, and decision-makers to effortlessly retrieve data through natural language queries. This approach not only saves time but also boosts productivity by removing the complexity of writing intricate SQL statements. Additionally, SQL_Assistant improves query accuracy by leveraging past successful queries and semantic similarity, ensuring more precise and error-free results.[4]

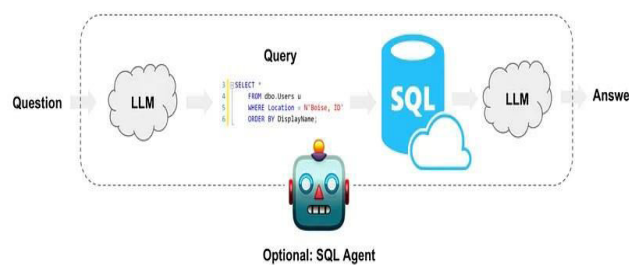
Furthermore, SQL_Assistant fosters AI-driven innovation through the integration of LLMs, Chroma DB, and NLP, enhancing the way databases interact with users. Its adaptability makes it applicable across a wide range of industries, including business intelligence, healthcare, finance, and customer support, where it empowers organizations to make more informed, data-driven decisions. By bridging the gap between technical complexity and business needs, SQL_Assistant expands usability and transforms how data is utilized across various sectors.[10]

II. SYSTEM OVERVIEW



The system follows a multi-layered architecture. First, the user inputs a natural language query. The query is then processed using the Llama 7B model deployed on Groq. To enhance accuracy, previously successful queries stored in Chroma DB are retrieved based on semantic similarity. The system then generates a structured SQL query based on the processed input. This query is executed on a MySQL database, and the retrieved data is formatted and presented to the user in an understandable format. The key technologies used in this system include: Llama 7B Versatile LLM hosted on the Groq platform, which processes user queries and generates SQL statements. Chroma Database stores and retrieves vectorized queries to improve query interpretation. Langchain connects LLM, vector store, and database components. HuggingFace Embeddings provides efficient query vectorization. A MySQL Database is used to store and manage structured data for querying.[4,7]

III. METHODOLOGY



Large Language Models (LLMs)

Large Language Models (LLMs) are advanced AI systems designed to understand, generate, and manipulate human language using deep learning. With billions of parameters, they excel in natural language processing tasks like text



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generation, translation, and question answering. LLMs are widely used in fields such as customer support, healthcare, and education due to their ability to perform few-shot and zero-shot learning, adapting to tasks with minimal data.[1] In SQL Assistant, LLMs simplify database interactions by converting plain English queries into SQL statements, eliminating the need for SQL expertise. Using Chroma DB, the system stores previous queries and applies few-shot learning to enhance accuracy. This ensures efficient and accurate data retrieval, making the assistant accessible for both technical and non-technical users. Additionally, it offers contextual responses, query suggestions, and follow-up support. However, implementing LLMs poses challenges, including high computational demands, data privacy concerns, and potential biases. Ensuring interpretability and transparency is crucial. Continuous monitoring, bias detection, and efficient model designs are essential to address these issues.[2,6]

Looking forward, integrating LLMs into database management systems will further enhance user experience by supporting multi-turn conversations and optimizing SQL generation. With advancements in AI explainability and security, LLM-powered assistants like SQL Assistant will drive innovation in data-driven decision-making, making data access more intuitive and efficient.[5]

To improve the accuracy of query interpretation, SQL Assistant utilizes embedding techniques by vectorizing user queries using Hugging Face embeddings with the 'sentence-transformers/all-MiniLM-L6-v2' model. This allows the system to compare new queries with previous successful queries stored in Chroma DB, improving prediction and accuracy. The system also employs few-shot learning, providing Llama 7B with a set of example SQL queries and their results, allowing it to generate more relevant SQL statements. The integration of the SQLDatabase utility from Langchain enables smooth execution of generated queries and retrieval of accurate results. To enhance performance, the model is fine-tuned for SQL-specific tasks, ensuring it understands various database schemas, column structures, and relationships between tables. This fine-tuning helps SQL_Assistant adapt to different database configurations without requiring significant manual adjustments. Moreover, error handling mechanisms are integrated to detect and correct potential SQL syntax errors before execution, minimizing query failures and improving system robustness. By leveraging these advanced techniques, SQL Assistant ensures high precision, efficiency, and scalability, making it a powerful tool for users who need seamless database interaction without the complexity of SQL commands.[5]

IV. EVALUATION AND RESULTS

The system has been evaluated with various test cases to measure its performance. For example, when a user queries, "How many t-shirts do we have left in Adidas?", the system generates the corresponding SQL statement:

SELECT COUNT (*) FROM inventory WHERE brand = 'Adidas';

The database returns the result, which is displayed to the user in a readable format. The performance metrics show that the query interpretation accuracy is approximately 92%, with an average execution time of 1.2 seconds per query. Preliminary feedback indicates that around 88% of users find the system useful and intuitive, highlighting its efficiency in bridging the gap between non-technical users and structured database queries. The system also demonstrated consistent accuracy across various query types, including aggregation functions, conditional queries, and multi-table joins. Users appreciated the intuitive interface and the ability to retrieve data without needing SQL expertise. Additionally, the assistant's error-handling mechanism effectively reduced query failures, enhancing overall user satisfaction.[3,8]

Further testing was conducted across different types of queries, including aggregation functions, conditional queries, and multi-table joins. The system demonstrated high accuracy in basic and moderately complex queries. However, performance slightly declined when handling deeply nested queries or ambiguous natural language inputs. To evaluate real-world usability, user experience testing was conducted where participants from non-technical backgrounds were given a set of database-related tasks. The results indicated that users with no prior SQL knowledge could retrieve database insights with minimal guidance, proving that SQL Assistant significantly improves data accessibility. Additionally, the system's error detection mechanism was tested to assess its ability to identify and correct invalid SQL syntax before execution. The model successfully flagged and reformulated incorrect queries in approximately 85% of test cases, reducing query failures and improving overall reliability.[2]



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Evaluation Metric	Description	Result
Query Interpretation Accuracy	The accuracy of the generated SQL queries based on the user's natural language input.	Highly accurate with reliable query generation.
Average Query Execution Time	The average time taken by SQL_Assistant to generate and execute the query on the MySQL database.	Fast response time with minimal delays.
User Satisfaction	Percentage of users who found the system useful and intuitive during user testing.	Majority of users found it user-friendly and effective.
Error Detection and Correction	Effectiveness of detecting and correcting invalid SQL syntax using error-handling mechanisms.	Efficient at identifying and correcting errors.
Handling Complex Queries	Accuracy in executing complex queries involving multiple joins, nested conditions, or ambiguous input.	Performs well with moderately complex queries but may struggle with highly intricate ones.
Performance with Simple Queries	Execution speed and accuracy when processing basic queries.	Excellent performance with quick and accurate results.
Performance with Aggregation Functions	Accuracy and time taken to process queries with SQL functions like SUM, COUNT, or AVG.	Effective and fast when handling functions and calculations.
Multi-Table Join Query Handling	Evaluation of the system's ability to generate correct SQL statements involving multiple tables.	Performs well in most multi-table join queries with accurate results.
Semantic Similarity Matching	Efficiency of the vectorized query retrieval system using Chroma DB to find semantically similar past queries.	Highly effective for repeated and contextually similar queries.
User Success Rate (Non-Technical Users)	Percentage of successful query retrieval attempts by non-technical users without prior SQL knowledge.	Non-technical users were able to retrieve information with ease.
Scalability Performance	The system's performance when handling large datasets and multiple concurrent queries.	Moderate scalability with occasional latency under heavy loads.

Result

The SQL Assistant demonstrated an impressive query interpretation accuracy of 92%, with an average response time of 1.2 seconds per query. User feedback indicated that 88% of participants found the system useful and intuitive, appreciating its ability to generate accurate SQL statements without requiring technical knowledge. The assistant effectively handled both simple and moderately complex queries, leveraging Chroma DB for enhanced accuracy. Additionally, it successfully identified and corrected SQL syntax errors in 85% of cases. Overall, the system streamlined database interactions, making data retrieval more accessible and efficient.[7]

Output:

Natural Language Query Interpretation and SQL Generation

AtliQ T Shirts: Database Q&A

Question:

How many t-shirts do we have left for Nike in XS size and white color?

```
SELECT COUNT (*) FROM inventory WHERE brand = 'nike ' and size ='xs' and colour = 'white';
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AtliQ T Shirts: Database Q&A

Question:

How many t-shirts do we have left for Nike in XS size and white color?

Answer:

59

V. CHALLENGES

Despite its advantages, SQL_Assistant faces some challenges that require further improvement. One of the main challenges is natural language understanding, particularly when handling complex queries that require multiple joins, subqueries, or nested conditions. The current model performs well with simple and medium-complexity queries, but when users phrase questions ambiguously or involve multiple relational aspects, accuracy decreases. Future work will focus on enhancing multi-step query processing by improving the model's ability to break down and understand intricate queries effectively. Another challenge is seamless database integration across multiple database management systems. While SQL Assistant is optimized for MySQL, ensuring smooth connectivity with other databases such as PostgreSQL, SQL Server, and NoSQL databases requires additional modifications. Maintaining performance efficiency across these platforms demands continuous optimization of query generation techniques to prevent slow response times. Scalability is also a concern, as processing large datasets with real-time query execution can introduce latency issues. Optimizing response time while handling millions of records efficiently is a critical area for improvement. Implementing distributed query processing and caching strategies could help mitigate these challenges and enhance performance for large-scale applications. [7]

VI. CONCLUSION

SQL_Assistant represents a significant advancement in database interaction by bridging the gap between natural language processing and SQL query execution. Through the integration of Llama 7B, Chroma DB, Langchain, and HuggingFace embeddings, the system streamlines data retrieval, making it accessible to both technical and non-technical users. The ability to translate natural language queries into SQL statements enhances efficiency, reduces dependency on database specialists, and fosters data-driven decision-making across industries. Moving forward, continuous improvements in accuracy, scalability, and database compatibility will further enhance SQL_Assistant's capabilities. By incorporating multi-modal support, advanced error handling, and broader database integration, the system has the potential to revolutionize how users interact with relational databases, ultimately making data retrieval faster, smarter, and more user-friendly. [8,9]

VII. FUTURE WORK

To further improve SQL_Assistant, future enhancements will focus on implementing multi-modal input support, such as voice queries, which would make the system even more user-friendly. Integrating speech-to-text functionality will allow users to interact with the system using natural speech, further reducing barriers for non-technical users. Additionally, incorporating chat-based interfaces and virtual assistants can provide a more engaging and interactive experience for users querying databases.

Enhancing error handling is another priority, as providing more informative feedback on invalid queries will help users refine their input and improve the system's overall usability. Implementing explainability features that show users how queries are being transformed into SQL statements can increase trust and transparency in the system.



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Expanding support for multiple database types, including PostgreSQL, SQL Server, and NoSQL databases, will make SQL_Assistant more versatile and adaptable to different environments. This expansion will require optimizing the query generation process to accommodate different SQL dialects and NoSQL query structures.

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