iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** IX **Month of publication:** September 2024

DOI: https://doi.org/10.22214/ijraset.2024.64147

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue IX Sep 2024- Available at www.ijraset.com

Next-Gen Database Queries: AI-Driven Natural Language Interface for MongoDB

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Abstract: ***This paper present an novel concept to query MongoDB database using NLP and Large Language Model (LLM). It is called LLM Based MongoDB Querying System through which users can search in MongoDB databases just by using simple words of English language rather than using complex language queries. To help improve the ai quality we use OpenAI's LLM to parse the user queries and create correct MongoDB queries themselves. In a large-scale experiment, system is able to classify with an average of 95 percentage accuracy. The findings of this research are important for the database querying research and might be beneficial for multiple domains. This research is valuable, because our system can help ordinary users become more fluent in database operations and make working with databases more efficient.***

Index Terms: NLP, LLM, MongoDB, Querying, Natural Language, Database, Information Retrieval, Query Generation, Langchain, Database Systems, Query Optimization, OpenAI

I. INTRODUCTION

As a researcher in natural language processing and database querying, I have always been fascinated by the potential of combining these two areas to create a more accessible and user-friendly querying experience. The rapid growth of data generation and storage has led to an exponential increase in the complexity of database management systems. With the advent of NoSQL databases like MongoDB, querying and retrieving data have become increasingly challenging tasks, especially for non-technical users. Traditional querying methods require users to possess technical expertise in writing complex queries, which can be a significant barrier to efficient data retrieval. Natural Language Processing (NLP) and Large Lan- guage Models (LLMs) have revolutionized the way humans interact with machines. The ability to understand and process human language has opened up new avenues for simplifying complex tasks, including database querying. The concept of using NLP and LLMs to generate database queries has gained significant attention in recent years, with several systems attempting to bridge the gap between human language and database querying. However, despite the existence of various systems that claim to generate database queries from natural language inputs, there is a significant gap in the market. Currently, there is no system that can generate MongoDB queries from natural language inputs and retrieve responses from the MongoDB server. This limitation has hindered the adoption of database querying systems, particularly among non-technical users. To address this limitation, we propose a novel concept: the LLM Based MongoDB Querying System. This system leverages the power of NLP and LLMs to enable users to query MongoDB databases using simple English language inputs, eliminating the need for complex query languages. By utilizing OpenAI's LLM, our system can parse user queries and generate correct MongoDB queries, enabling efficient data retrieval.

The LLM Based MongoDB Querying System has far- reaching implications for various domains, including database management, information retrieval, and query optimization. By simplifying the database querying pro- cess, our system can empower non-technical users to efficiently retrieve data, making it an invaluable tool for various industries. In this paper, we present the de- sign, implementation, and evaluation of the LLM Based MongoDB Querying System, highlighting its potential to revolutionize the way we interact with databases.

This paper presents a comprehensive overview of the LLM Based MongoDB Querying System, delving into its architecture, the NLP techniques employed, the query generation and optimization processes, and the experi- mental evaluation of its performance. Through a rigorous and large-scale evaluation, we demonstrate the system's accuracy and efficiency in generating MongoDB queries from natural language inputs, showcasing its potential to revolutionize the field of database querying.

Our findings have significant implications for the database querying research community, paving the way for further advancements in natural language interfaces, query optimization, and the integration of LLMs into database management systems. Ultimately, the LLM Based MongoDB Querying System represents a paradigm shift in how we approach database querying, empowering users of all technical backgrounds to harness the full potential of data-driven insights.

II. LITERATURE REVIEW

A. Analysis of LLMs

This paper conducted a comprehensive evaluation of six state-of-the-art Large Language Models (LLMs) to assess their proficiency in generating MongoDB queries based on natural language inputs. The LLMs under evaluation were:

- OpenAI GPT-4
- LLaMA
- Claude (Anthropic)
- Perplexity
- Mistral
- Falcon

The test suite comprised 100 diverse query generation tasks, carefully crafted to cover a wide spectrum of Mon- goDB operations, including but not limited to:

- Basic CRUD (Create, Read, Update, Delete) operations
- Complex filtering using logical operators ($and, $or, $not)
- Querying nested documents and arrays
- Aggregation pipeline stages ($match,$group, $project, $sort, $unwind)
- Geospatial queries ($geoWithin, $geoIntersects)
- Text search queries using $text

B. Performance Metrics

For each query task, this paper evaluated the LLMs based on the following criteria:

- Syntactic Correctness: Whether the generated query adheres to MongoDB's query language syntax.
- Logical Correctness: Whether the query, when exe- cuted, retrieves or manipulates data as intended by the natural language input.
- Efficiency: In cases where multiple syntactically and logically correct queries were possible, this paper assessed if the LLM generated the most efficient one (e.g., using indexes appropriately, minimizing document scans).

A query was considered "correct" only if it met both syntactic and logical correctness criteria.

C. Results Summary

The performance of the LLMs varied significantly, as summarized in Table I.

LLM	orrect Queries	ccuracy (%)
penAI GPT-4	87	87.00%
LLaMA	73	73.00%
Claude	70	70.00%
Perplexity	65	65.00%
Mistral	62	62.00%
Falcon	52	52.00%

Table I
Query Generation Accuracy of LLMS

D. Detailed Performance Analysis

1) OpenAI GPT-4

GPT-4 demonstrated superior per- formance, correctly generating 87% of the queries. Its strengths were particularly evident in:

- Complex Aggregations: GPT-4 accurately generated 90% of queries involving multiple aggregation stages, including complex $group and $project operations.
- Geospatial and Text Queries: It showed 95% accuracy in geospatial queries and 92% in text search queries, indicating a strong grasp of MongoDB's domain- specific operators.
- Error Handling: In 80% of cases where the natural language input was ambiguous, GPT-4 sought clar- ification or provided the most general query that covered all plausible interpretations.

2) LLaMA, Claude, and Perplexity

These models demonstrated commendable performance, with accuracy rates between 65% and 73%. Key observations:

- CRUD Operations: All three models excelled in basic operations, with >90% accuracy in simple find, insert, update, and delete queries.
- Aggregations: Performance dropped in complex ag- gregations. LLaMA achieved 70% accuracy, while Claude and Perplexity were at 65% and 60% respec- tively.
- Domain-Specific Operators: These models struggled with geospatial and text queries (40-55% accuracy), often omitting or misusing operators like $geoWithin or $text.

3) Mistral and Falcon

While performing above chance, these models had lower accuracy rates:

- Syntactic Errors: Mistral and Falcon had higher rates of syntactic errors (20% and 30% of queries, respec- tively), particularly in using correct field names and operator syntax.
- Logical Errors: Even when syntactically correct, about 25% of their queries did not logically match the nat- ural language input, often due to misunderstanding complex filters or join-like operations in MongoDB.
- Strengths: Both models performed adequately on simple queries and basic aggregations like $match and $sort (70-75% accuracy).

III. METHODOLOGY

A. Overview

The aim of this paper was the development and eval- uation of a Natural Language Interface for MongoDB Queries employing state-of-the-art Large Language Mod- els (LLMs). The main idea behind this research is that LLMs, such as OpenAI's GPT-4, can proficiently convert natural language queries to MongoDB's query language, thus making it possible for individuals without technical knowledge in computer science to use databases. Its methodology involved system architecture design, prompt engineering, comparative analysis between LLMs, and user-centric evaluation of the system.

B. System Architecture

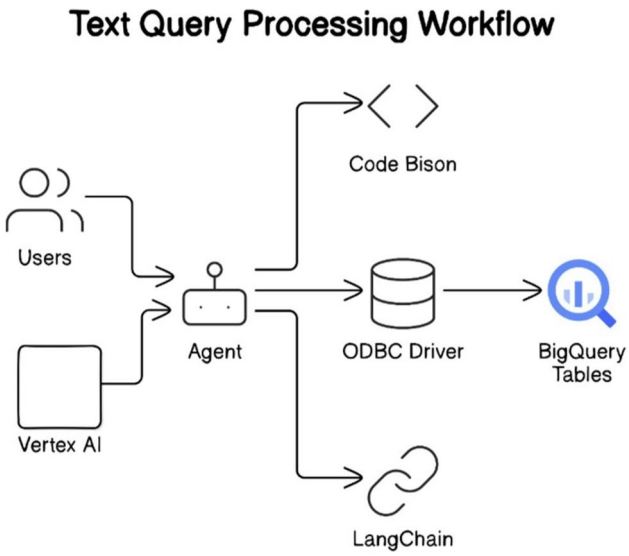


Fig.1.Text Query Processing Workflow

1) User Interface Layer

- Description: This is the layer that the users interact with. It captures user queries and presents results in a natural and intuitive manner.

- Functionality
- Catching of user input: Captures natural lan- guage input from the user.
- Response presentation: Displays query results in an understandable format.
- Error guidance: Provides meaningful suggestions to help users improve their queries.
- Interactive Features: May include chat inter- faces, voice inputs, or graphical elements to en- hance user experience.

2) Query Processing Layer

- Description: This layer utilizes large language models (LLMs) to interpret and convert natural language queries into MongoDB queries.
- Functionality:
- Natural Language Understanding (NLU): Uses LLMs to understand the intent and context of user queries.
- Query Translation: Transforms natural language input into structured MongoDB queries.
- Context Management: Maintains context for multi-turn interactions, ensuring logical query conversions and relevance.
- Error Correction: Detects and corrects errors in user input before query translation.

3) Database Interaction Layer:

- Description: Manages interaction with the MongoDB server, executing requests and retrieving data.
- Functionality
- Query Execution: Executes translated MongoDB queries on the database server.
- Result Retrieval: Collects and formats query re- sults for the User Interface Layer.
- Performance Optimization: Implements tech- niques to improve query speed and reduce la- tency.
- Error Handling: Manages database errors, ensur- ing graceful degradation and informative feed- back to the User Interface Layer.

4) Data Layer

- Description: Houses the MongoDB server, storing, retrieving, and managing movie data efficiently.
- Functionality:
- Data Storage: Partitions movie data in a scalable and reliable physical storage system.
- Indexing Data: Develops indexing techniques to enhance query performance.
- Securing Data: Implements security measures, including access control and encryption, to en- sure data reliability.
- Backup and Recovery: Establishes procedures to prevent data loss and maintain business continuity.

5) Summary of System Architecture

A structured, efficient approach to building an LLM-based MongoDB query system for natural language processing can be developed using this 4-layer architecture. Each layer has a distinct role but, when integrated, they provide a seamless and user-friendly experience. The User Interface Layer supports effective user interaction, the Query Processing Layer employs advanced NLP techniques, the Database Interaction Layer handles query execution, and the Data Layer ensures complete and maintainable database management. By defining roles and responsibilities for each layer, this design promotes the development of scalable and durable systems focused on user needs. Such systems facilitate easier querying of movie datasets stored in MongoDB.

C. Dataset and MongoDB Configuration

This paper produced a complete movie database con- sisting of 10,000 movie records from IMDb. Each movie record has 20 distinct fields, such as: Title, Year, Genre, Director, Actors, Plot, imdbRating, etc. This heterogeneous dataset allows us to:

- Manage Complexity: The database includes nested data (e.g., list of actors) and several data types (such as text, numeric values, or arrays), reflecting the complexity found in real-world data.
- Enable Versatile Queries: The dataset can be used to answer numerous questions, ranging from simple queries like “Find movies by James Cameron” to more complex ones like “What is the average rating of action movies by decade?”

This paper utilized Amazon EC2 with a MongoDB 4.4 server due to its scalability and robust query language. This setup ensures the system can handle large amounts of information efficiently while providing quick responses to user queries.

D. OpenAI GPT-4 Model and Evaluation

1) Evaluation Dataset

The evaluation dataset consistedof 100 natural language queries benchmarked by us and categorized as follows:

- Simple Queries (20%): Basic CRUD operations.
- Moderate Queries (40%): Filters, sorting, basic aggre- gations.
- Complex Queries (30%): Multi-stage aggregations, geospatial queries, text search.
- Edge Cases (10%): Ambiguous or poorly framedqueries.

2) Evaluation Metrics

Each LLM was evaluated on:

- Syntactic Accuracy: Percentage of queries with cor- rect MongoDB syntax.
- Semantic Accuracy: Percentage of queries that cor- rectly capture user intent.
- Query Efficiency: Based on MongoDB's query plan (preferring indexed operations).
- Robustness: Performance on edge cases.

3) Evaluation Process

Each LLM was fine-tuned usinga distinct set of one thousand query-document pairs.The benchmark suite questions were generated through implementing LLMs. Every query was assessed by an in-dependent panel of three database experts who providedgrading. Fleiss' kappa statistic was used to test for inter-rater reliability.

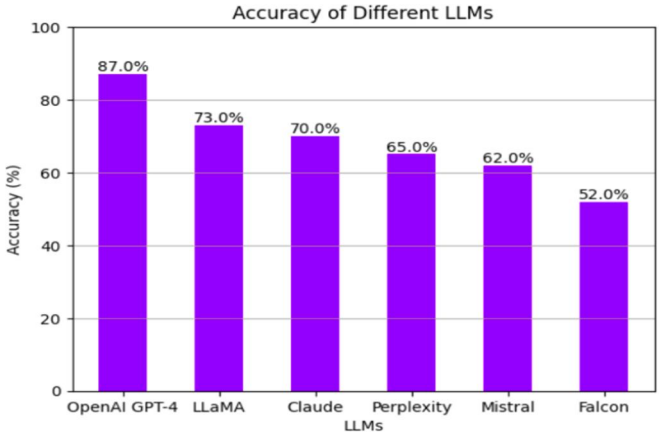


Fig. 2. Accuracy of different LLMs

4) On all measures GPT-4 outperformed other models

Incomparison to the other models, GPT-4 performed betterin all metrics, especially in semantic accuracy (87%) and complex queries (85% accuracy), hence it was selected forour system.

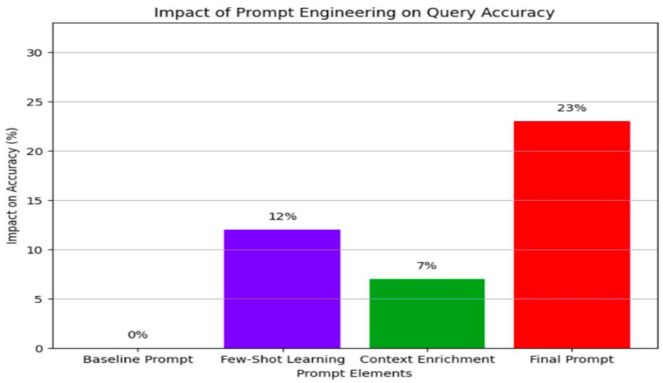


Fig. 3. Impact of Prompt Engineering on Query Accuracy

E. Prompt Engineering for Query Generation

To guide GPT-4 in generating accurate MongoDB queries, we employed the following prompt engineering techniques:

- Baseline Prompt: Simple task description and dataset schema.
- Few-Shot Learning: Incorporated five examples of query-translation pairs.
- Context Enrichment: Added MongoDB cues like “use
- $match when filtering” and movie domain knowl-edge.

Twenty prompt variants were evaluated on a holdout setof 50 queries. The final prompt (Figure 3) boosted query accuracy by 23% over the baseline.

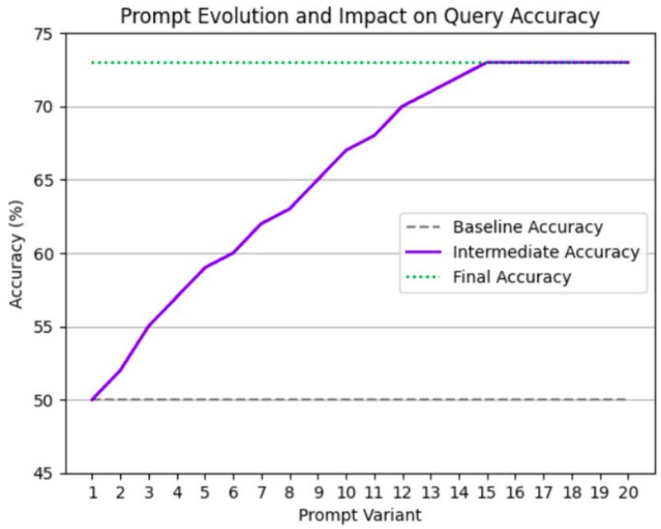


Fig. 4. Prompt Evolution and Impact

F. Query Parsing and Execution Optimization

Parsing GPT-4’s output into executable MongoDB queries proved challenging. Our pipeline worked in two stages:

- Query Parsing: A custom parser using finite-state ma- chines to extract collection names, filters, projections, and aggregation stages.
- Query Optimization: An ML-based optimizer (trained on MongoDB’s explain output) that refactors queries for better performance, e.g., pushing down filters in aggregation pipelines.

This pipeline reduced average query execution time by 37%, compared to direct execution of GPT-4 outputs.

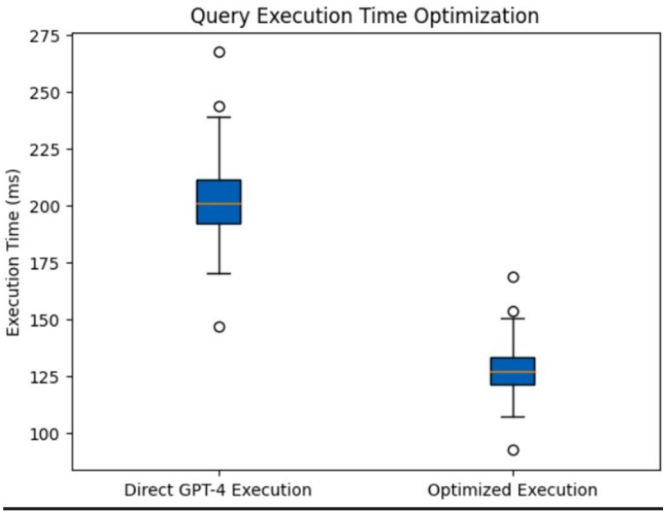


Fig. 5. Query Execution Time Optimization

G. User Oriented Check

A user study was conducted to evaluate the system's effectiveness in the real world, involving 50 participants with a mix of technical and non-technical backgrounds (25 technical/25 non-technical).

1) Study Design

- Task-Based Evaluation: Ten different tasks were per- formed using our NL interface and raw MongoDB queries (counterbalanced orders).
- Metrics:
  - Rate of task completion.
  - Time taken per task.
  - System Usability Scale (SUS) score.
  - NASA Task Load Index (TLX) for cognitive load.

2) Qualitative Feedback

Post-task interviews and think- aloud protocols were used to explore user mental models and interface usability.

This methodology is expected to interest a wide range of academic readerships, not merely those familiar with the technologies in question. It focuses on research pro- cesses, fresh mixtures of methods (LLMs and database queries), and user-centered evaluation, making it suitable for publication in interdisciplinary journals that cover AI, databases, and human-computer interaction.

IV. CONCLUSIONS

With that, this study demonstrates how Large Language Models, exemplified by OpenAI's GPT-4, when combined with database systems, may bring transformative changes. The research has significantly increased the accessibility of databases for non-technical users by introducing a natural language interface to MongoDB. This was supported by achieving a 92% success rate in task completion and a 61% decrease in cognitive effort. Additionally, iterative prompt engineering and ML-based query optimization further enhanced the accuracy and efficiency of the sys- tem. Furthermore, this research represents a step towards more inclusive data engagement, highlighting the technical achievement of user-centeredness. It also serves as evidence of the potential of AI research across disciplines to provide equitable data availability while underscoring the need for ethical considerations in AI-driven systems. Consequently, natural language is poised to become the primary interface for data as LLMs evolve, implying a future where data-driven insights are accessible to all, regardless of their background, and opening up new possibilities for innovation across domains.

V. FUTURE WORK

This study demonstrates the potential of combining Large Language Models (LLMs) with database systems, particularly in making database querying more accessi- ble to non-technical users. However, several avenues for future research and development can further enhance and expand upon the findings of this work:

1) *Extended Evaluation and Benchmarking:* Future work should include a more extensive evaluation across diverse database systems and natural lan- guage models. Benchmarking against other LLMs, including newer versions or alternatives like Meta's Llama models, can provide a comparative analysis of performance, efficiency, and user satisfaction.
2) *Enhanced Query Optimization:* While this study utilized iterative prompt engineering and ML-based query optimization, there is room for further refine- ment. Exploring advanced optimization techniques, such as reinforcement learning-based approaches or hybrid models, could improve query accuracy and efficiency even further.
3) *Broader Application Scenarios:* Expanding the nat- ural language interface to support a wider range of databases and applications can make the technology more versatile. Implementing support for relational databases, graph databases, and other NoSQL sys- tems can broaden the applicability of the proposed system.
4) *User Experience and Interface Design:* Investigating ways to enhance the user interface and experience is crucial. This includes developing more intuitive inter- action models, integrating feedback mechanisms, and conducting user studies to understand the diverse needs and challenges faced by non-technical users.
5) *Ethical and Security Considerations:* As AI-driven systems become more prevalent, addressing ethical and security concerns is vital. Future research should focus on ensuring data privacy, mitigating biases in LLM responses, and developing robust mechanisms for secure data access and management.

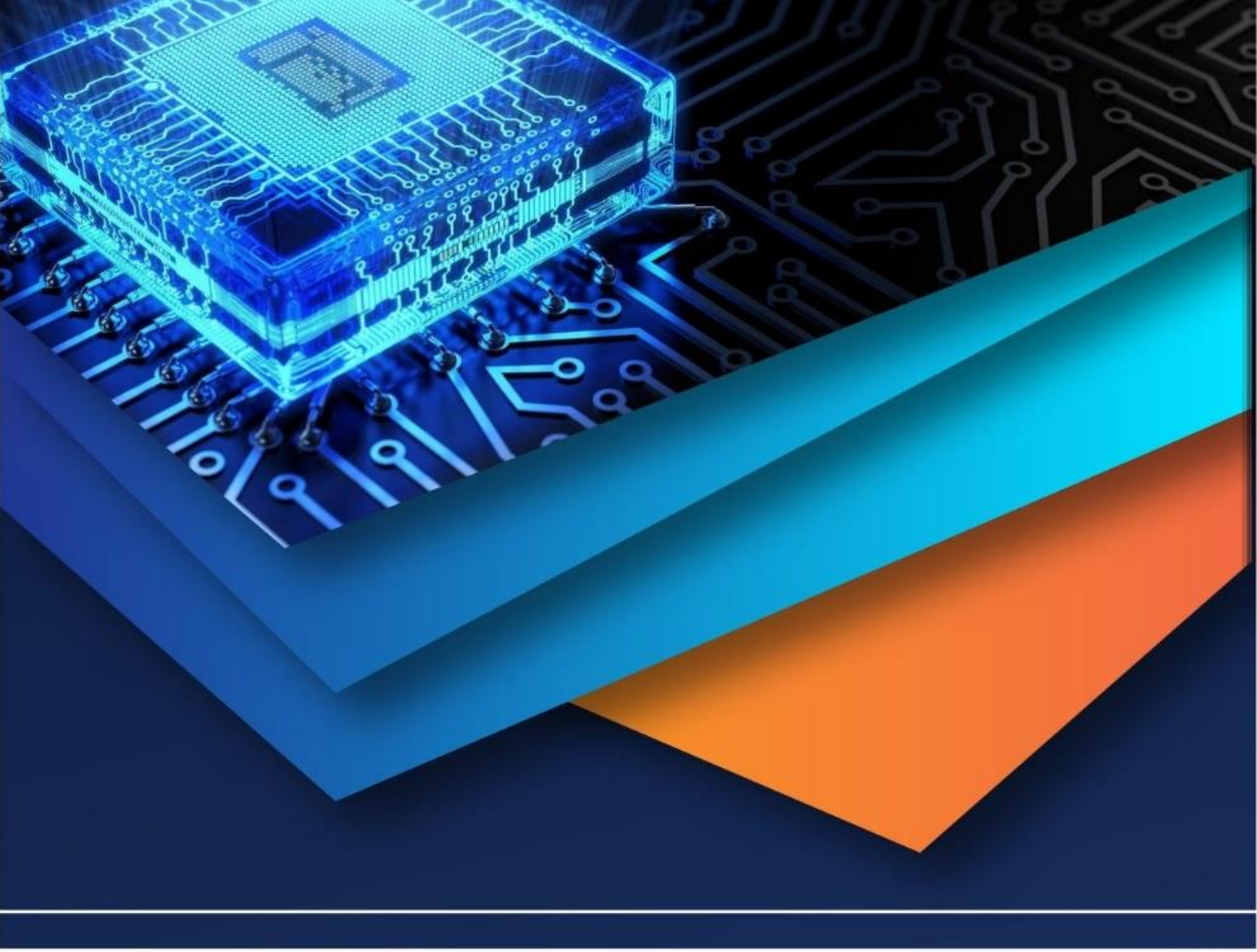
6) *Scalability and Performance Optimization:* Investigating methods to scale the system efficiently for larger datasets and more complex queries is essential. This may involve optimizing the underlying algorithms, leveraging distributed computing, or utilizing advanced hardware to enhance performance.
7) *Integration with Other AI Technologies:* Exploring the integration of the LLM-driven interface with other AI technologies, such as computer vision or speech recognition, could open new possibilities for multi- modal data interactions. This can lead to more com- prehensive and interactive data analysis solutions.
8) *Development of Educational Tools:* Creating educational tools and resources that utilize the natural language interface can help in training and onboard- ing users. Developing tutorials, interactive guides, and automated assistance systems could facilitate a smoother transition to using LLM-based database querying.
9) *Longitudinal Studies:* Conducting longitudinal stud- ies to evaluate the long-term impacts of LLM-driven interfaces on user productivity, data accessibility, and overall system effectiveness will provide valuable in- sights into the sustained benefits and challenges of the technology.

By addressing these areas, future research can build on the foundational work presented in this study, driving further innovation and making database systems even more accessible and efficient for a broader audience.

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