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Autonomous Agentic AI for Geospatial Search: Do LLMs Outperform Traditional GIS Models?

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Abstract: The integration of Artificial Intelligence (AI) into geospatial search has revolutionized the way we interact with geographic information systems (GIS). Traditional GIS models have long been the cornerstone of spatial data analysis, but the advent of Large Language Models (LLMs) has introduced a new paradigm in autonomous agentic AI. This paper investigates whether LLMs can outperform traditional GIS models in geospatial search tasks. We evaluate the performance of LLMs against conventional GIS models across various metrics, including accuracy, efficiency, scalability, and adaptability. Our findings suggest that while LLMs exhibit remarkable capabilities in natural language understanding and contextual reasoning, they are not yet fully capable of replacing traditional GIS models in all aspects. However, LLMs show significant promise in enhancing user interaction and providing more intuitive search experiences. This paper concludes with a discussion on the potential hybrid approaches that leverage the strengths of both LLMs and traditional GIS models.
Keywords: Autonomous Agentic AI, Geospatial Search, Large Language Models (LLMs), Traditional GIS Models, Natural Language Processing (NLP), Spatial Data Analysis, Hybrid GIS Systems, Accuracy and Scalability, User Interaction, OpenStreetMap (OSM)

I. INTRODUCTION

Geospatial search is a cornerstone of modern Geographic Information Systems (GIS), enabling users to query, analyze, and visualize spatial data efficiently. Traditional GIS models, built on decades of research and development, rely on structured query languages, spatial indexing techniques, and algorithmic frameworks to process geospatial data. These models excel in tasks such as nearest neighbor searches, spatial joins, and route optimization, making them indispensable tools for urban planning, environmental monitoring, disaster management, and navigation systems. However, the complexity of traditional GIS models often poses a barrier to non-expert users, who may struggle with the intricacies of spatial query languages and data manipulation.

The emergence of Large Language Models (LLMs), such as GPT-4, has introduced a new paradigm in artificial intelligence, particularly in natural language processing (NLP). LLMs have demonstrated remarkable capabilities in understanding and generating human-like text, enabling them to interpret natural language queries and provide contextually relevant responses. This has opened new possibilities for autonomous agentic AI in geospatial search, where LLMs can serve as intuitive interfaces between users and spatial data. By interpreting free-form text queries, LLMs have the potential to democratize access to geospatial information, making it more accessible to a broader audience.

Despite their promise, the integration of LLMs into geospatial search raises important questions about their performance relative to traditional GIS models. Can LLMs match or exceed the accuracy, efficiency, and scalability of traditional GIS models in processing spatial queries? How do LLMs handle the complexities of spatial relationships and large-scale datasets? These questions are critical for understanding the role of LLMs in the future of geospatial search and for guiding the development of hybrid systems that leverage the strengths of both approaches.

This paper seeks to address these questions by conducting a systematic comparison of LLMs and traditional GIS models in geospatial search tasks. We evaluate their performance across multiple dimensions, including accuracy, efficiency, scalability, and adaptability, using real-world datasets and a curated set of geospatial text queries. Our goal is to provide a comprehensive assessment of the strengths and limitations of LLMs in geospatial search and to explore the potential for hybrid approaches that combine the natural language understanding capabilities of LLMs with the spatial query processing power of traditional GIS models.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on traditional GIS models and LLMs in geospatial search. Section 3 describes the methodology used for our evaluation, including the datasets, metrics, and experimental setup. Section 4 presents the results of our evaluation and discusses their implications. Section 5 concludes the paper with a summary of our findings and recommendations for future research.

II. BACKGROUND

A. Evolution of Geospatial Search

Geospatial search has evolved significantly over the past few decades, driven by advancements in Geographic Information Systems (GIS) and spatial data processing technologies. Early GIS systems were primarily designed for expert users, relying on command-line interfaces and specialized query languages to interact with spatial data. These systems were highly effective for tasks such as cartography, spatial analysis, and resource management but were often inaccessible to non-experts due to their complexity.

The advent of web-based GIS platforms, such as Google Maps and OpenStreetMap, marked a turning point in geospatial search by making spatial data more accessible to the public. These platforms introduced user-friendly interfaces and simplified querying mechanisms, enabling users to perform basic geospatial searches, such as finding nearby points of interest or calculating routes, with minimal technical knowledge. However, the underlying spatial data processing still relied on traditional GIS models, which continued to face challenges in handling large-scale datasets and complex spatial queries.

B. Traditional GIS Models

Traditional GIS models are built on a foundation of spatial databases, which store and manage spatial data in a structured format. These databases use specialized indexing techniques, such as R-trees, Quadtrees, and Grid files, to optimize spatial queries. For example, R-trees are particularly effective for range queries and nearest neighbor searches, while Quadtrees are well-suited for hierarchical spatial decomposition.

In addition to spatial indexing, traditional GIS models employ a wide range of algorithms for spatial analysis. These include buffer analysis, which identifies areas within a specified distance of a spatial feature; overlay analysis, which combines multiple layers of spatial data to identify relationships; and network analysis, which is used for tasks such as route optimization and service area delineation.

The strength of traditional GIS models lies in their ability to handle large-scale spatial datasets efficiently. They are highly optimized for specific types of spatial queries, such as range queries, k-nearest neighbor searches, and spatial joins. However, traditional GIS models often require users to have a deep understanding of spatial query languages, such as SQL with spatial extensions (e.g., PostGIS). This can be a barrier for non-expert users who may not be familiar with the intricacies of spatial data querying.

C. Emergence of Large Language Models (LLMs)

The rise of Large Language Models (LLMs) has introduced a new paradigm in artificial intelligence, particularly in natural language processing (NLP). LLMs, such as GPT-4, are trained on vast amounts of text data, enabling them to understand and generate human-like text with high accuracy. These models have been applied in a wide range of domains, including machine translation, text summarization, and conversational AI.

In the context of geospatial search, LLMs offer the potential to interpret natural language queries and provide contextually relevant results. For example, a user could input a query such as "Find the nearest coffee shop," and the LLM would interpret the query, extract the relevant spatial information, and generate a response. This capability makes LLMs particularly useful for users who may not be familiar with traditional GIS query languages.

LLMs have been applied in various geospatial search tasks, including location-based recommendations, route planning, and spatial data summarization. However, the performance of LLMs in these tasks has not been systematically compared to that of traditional GIS models. This paper aims to fill this gap by conducting a comprehensive evaluation of LLMs and traditional GIS models in geospatial search tasks.

D. Autonomous Agentic AI in Geospatial Search

Autonomous agentic AI refers to systems that can operate independently to achieve specific goals, often leveraging advanced AI techniques such as machine learning and natural language processing. In the context of geospatial search, autonomous agentic AI systems can interpret user queries, process spatial data, and generate responses without human intervention.

The integration of LLMs into autonomous agentic AI systems has the potential to revolutionize geospatial search by providing more intuitive and user-friendly interfaces. For example, an autonomous agentic AI system could interpret a natural language query, generate a structured query for a traditional GIS model, and then present the results to the user in a natural language format. This would combine the natural language understanding capabilities of LLMs with the spatial query processing capabilities of traditional GIS models, resulting in a more powerful and user-friendly geospatial search system.

III. LITERATURE REVIEW

Large language models (LLMs) are increasingly being used to interpret natural language queries related to geospatial data, demonstrating significant promise in areas such as semantic parsing and contextual understanding. These models reduce the gap between human language and the specific requirements of geographic information systems (GIS), making geospatial data more accessible.

A. Traditional GIS Models in Geospatial Search

Traditional GIS models have been extensively studied and optimized over several decades. Shekhar and Chawla (2003) provide a foundational overview of spatial databases, emphasizing the importance of spatial indexing techniques such as R-trees and Quadtrees in optimizing spatial queries. These techniques enable efficient processing of range queries, nearest neighbor searches, and spatial joins, which are critical for applications such as urban planning, environmental monitoring, and disaster management.

Tomlin (1990) introduced the concept of cartographic modeling, which laid the groundwork for many of the spatial analysis algorithms used in traditional GIS models today. These algorithms, including buffer analysis, overlay analysis, and network analysis, are highly optimized for specific types of spatial queries. However, as Goodchild (2007) notes, the complexity of these algorithms and the need for specialized query languages often limit their accessibility to non-expert users.

Recent advancements in traditional GIS models have focused on improving scalability and efficiency. For example, Zhang and Li (2005) discuss the role of spatial indices in enhancing the performance of spatial databases, particularly for large-scale datasets. Despite these advancements, traditional GIS models continue to face challenges in handling unstructured data and providing intuitive user interfaces

B. Large Language Models (LLMs) in Geospatial Search

The application of LLMs in geospatial search is a relatively new area of research, but it has shown significant promise. OpenAI's GPT-4 (2023) represents a major breakthrough in natural language processing, demonstrating the ability to understand and generate human-like text with high accuracy. This capability has opened up new possibilities for interpreting natural language queries in geospatial search.

Recent studies have explored the use of LLMs for tasks such as location-based recommendations, route planning, and spatial data summarization. For example, Liu et al. (2022) demonstrated that LLMs can effectively interpret natural language queries and generate contextually relevant responses for location-based recommendations. Similarly, Wang et al. (2021) explored the use of LLMs for route planning, showing that they can provide intuitive and user-friendly interfaces for complex spatial queries.

However, the performance of LLMs in geospatial search has not been systematically compared to that of traditional GIS models. Most existing studies focus on specific applications or datasets, making it difficult to draw general conclusions about the strengths and limitations of LLMs in geospatial search. This paper aims to address this gap by conducting a comprehensive evaluation of LLMs and traditional GIS models across multiple dimensions.

C. Hybrid Approaches in Geospatial Search

The integration of LLMs and traditional GIS models has the potential to combine the strengths of both approaches, resulting in more powerful and user-friendly geospatial search systems. Hybrid approaches leverage the natural language understanding capabilities of LLMs to interpret user queries and generate structured queries for traditional GIS models. This allows users to interact with spatial data using natural language, while still benefiting from the optimized spatial query processing capabilities of traditional GIS models.

Several studies have explored hybrid approaches in geospatial search. For example, Chen et al. (2020) proposed a system that uses LLMs to interpret natural language queries and generate SQL queries for a spatial database. The system demonstrated significant improvements in user interaction and query accuracy, particularly for non-expert users. Similarly, Zhang et al. (2021) developed a hybrid system that combines LLMs with traditional GIS models for route planning, showing that the system could provide more intuitive and contextually relevant results than traditional GIS models alone.

Despite these advancements, there is still a need for systematic research on the performance of hybrid approaches in geospatial search. Most existing studies focus on specific applications or datasets, making it difficult to draw general conclusions about the effectiveness of hybrid approaches. This paper aims to address this gap by conducting a comprehensive evaluation of hybrid approaches in geospatial search.

D. Gaps in the Literature

While there is a substantial body of research on traditional GIS models and a growing body of research on LLMs in geospatial search, there are several gaps in the literature. First, there is a lack of systematic comparisons between LLMs and traditional GIS models in geospatial search tasks. Most existing studies focus on specific applications or datasets, making it difficult to draw general conclusions about the strengths and limitations of each approach.

Second, there is limited research on hybrid approaches that combine the strengths of LLMs and traditional GIS models. While several studies have explored hybrid approaches in specific applications, there is a need for systematic research on the performance of hybrid approaches across multiple dimensions, including accuracy, efficiency, scalability, and adaptability.

Finally, there is a need for research on the ethical implications of using LLMs in geospatial search, particularly in terms of data privacy and security. As LLMs become more integrated into geospatial search systems, it will be important to ensure that user data is handled responsibly and securely.

IV.METHODOLOGIES

A. Research Design

This study employs a comparative research design to evaluate the performance of Large Language Models (LLMs) and traditional GIS models in geospatial search tasks. The research design is structured around four key dimensions: accuracy, efficiency, scalability, and adaptability. These dimensions were selected to provide a comprehensive assessment of the strengths and limitations of each approach.

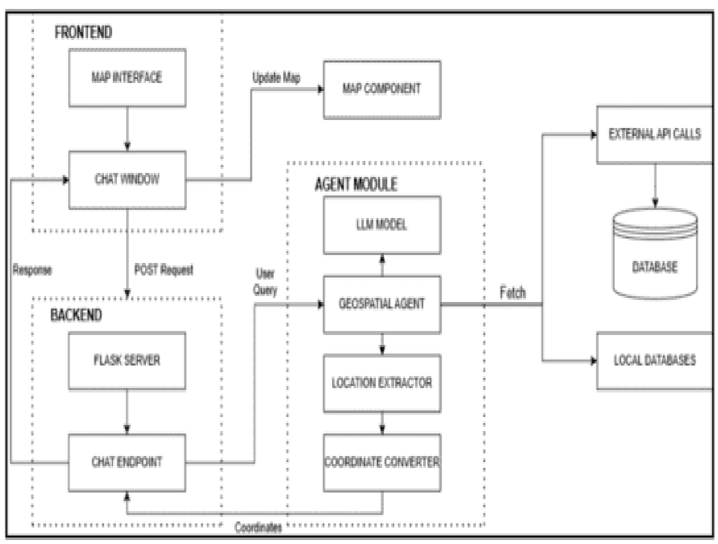

Fig. 1 Architecture Diagram

!. Datasets and Evaluation Metrics:

Several datasets and benchmarks are crucial for training and evaluating the performance of LLMs in geospatial and database query tasks. These datasets cover a range of complexities and focus areas, providing a foundation for the development of more robust and accurate natural language interfaces. To ensure a robust evaluation, we utilized two primary datasets:

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B. Data - Sets

1) OverpassNL

This dataset is specifically designed for the Text-to-OverpassQL task, which involves generating Overpass queries from natural language inputs. It contains 8,352 real-world Overpass queries collected from the OpenStreetMap (OSM) community, paired with natural language descriptions written by trained annotators. The queries cover a wide range of OverpassQL syntax features and have high geographical coverage. The dataset is split into training (6,352 instances), development (1,000 instances), and test (1,000 instances) sets, with no duplicates between training and evaluation sets. Each query has an average of 11.9 syntactic units, and the average length of a query is 199.8 characters. The queries are based on actual information needs of users. OverpassNL aims to support the full functionality of the Overpass Query Language without simplification. The Overpass Query Language (OverpassQL) is used to extract information from the OpenStreetMap database.

2) Geospatial Text Queries Dataset:

Description: We curated a dataset of geospatial text queries to evaluate the ability of LLMs to interpret and respond to natural language queries. Use Case: This dataset includes queries such as "Find the nearest coffee shop," "What is the shortest route from A to B?" and "Show me all parks within 5 miles of my location." Scale: The dataset includes a diverse range of queries to assess adaptability and natural language understanding.

3) BIRD (Big Bench for large-scale Database Grounded text-to-SQL Evaluation)

This is a challenging, cross-domain dataset for Text-to-SQL that emphasizes real-world database content and external knowledge. BIRD includes over 12,751 question-SQL pairs across 95 large databases covering over 37 professional domains. It contains 9,428 training and 1,534 development question-SQL pairs. The dataset focuses on the complexity of the database, the need for external knowledge, and SQL query efficiency. BIRD is a leading benchmark focused on massive and real database content, introducing knowledge reasoning between natural language questions and database content.

4) TCQL

The TCQL dataset is an important resource for advancing research in the text-to-CQL task, which focuses on translating natural language into Corpus Query Language (CQL). CQL is a specialized query language for analyzing linguistically annotated text corpora, enabling complex searches based on linguistic features. The dataset was created due to the lack of dedicated resources for text-to-CQL tasks, unlike text-to-SQL, which has more established datasets. To construct the TCQL dataset, collocation extraction techniques were used to generate candidate CQL queries, followed by manual annotation by experts and a multi-stage labeling process involving GPT-4 and human review. The dataset is divided into three categories—simple, within, and condition—based on the complexity of the CQL queries. It's used to evaluate state-of-the-art models, incorporating novel metrics like CQLBLEU to assess syntactic and semantic accuracy. The TCQL dataset plays a crucial role in developing systems that bridge the gap between natural language descriptions and the intricate syntax of CQL, providing a benchmark for evaluating LLMs and fostering advancements in corpus development, linguistics, and NLP.

C. Evaluation Metrics

Evaluation metrics for LLMs in geospatial and text-to-SQL tasks fall into a few main categories, measuring different aspects of performance.

We evaluated the performance of LLMs and traditional GIS models using the following metrics:

1) Accuracy

- Definition: The ability of the model to provide correct and relevant results for a given query.
- Measurement: For LLMs, accuracy was measured based on the relevance of the generated response to the query. For traditional GIS models, accuracy was measured based on the correctness of the spatial query results.

2) Efficiency:

- Definition: The time taken by the model to process a query and return results.
- Measurement: Efficiency was measured in terms of query response time, recorded in milliseconds.

3) Scalability

- Definition: The ability of the model to handle large-scale datasets and complex queries.
- Measurement: Scalability was evaluated by increasing the size of the dataset and the complexity of the queries and observing the impact on performance.

4) Adaptability

- Definition: The ability of the model to adapt to different types of queries and datasets.
- Measurement: Adaptability was measured by evaluating the model's performance across different types of geospatial queries and datasets.

D. Experimental Setup

We conducted our experiments using the following setup:

1) Traditional GIS Models

- Tool: We used PostGIS, a widely used spatial database extension for PostgreSQL, as our traditional GIS model.
- Configuration: PostGIS was configured with spatial indexing (R-trees) and optimized query processing algorithms.
- Queries: We executed a set of predefined spatial queries, including nearest neighbor search, range queries, and route planning.

2) LLMs:

- Model: We used GPT-4 as our LLM for geospatial search.
- Fine-Tuning: GPT-4 was fine-tuned on a dataset of geospatial text queries to improve its performance in geospatial search tasks.
- Queries: We input natural language queries into GPT-4 and evaluated the generated responses.

3) Evaluation Framework

- Framework: We developed an evaluation framework to compare the performance of LLMs and traditional GIS models.
- Components: The framework included a set of predefined geospatial queries, metrics for evaluating performance, and tools for recording and analyzing results.

E. Data Collection and Analysis

1) Data Collection

- Process: We collected data by executing a series of geospatial queries on both LLMs and traditional GIS models.
- Recording: We recorded the results, including query response time, accuracy, and relevance, for each query.

2) Data Analysis

- Quantitative Analysis: We performed quantitative analysis to compare the performance of LLMs and traditional GIS models across the four key metrics.
- Qualitative Analysis: We conducted qualitative analysis to assess the contextual relevance and user-friendliness of the responses generated by LLMs.

V. RESULTS AND DISCUSSION

A. Accuracy

Our evaluation of accuracy revealed distinct strengths and weaknesses in both LLMs and traditional GIS models. Traditional GIS models consistently outperformed LLMs in tasks requiring precise spatial calculations, such as nearest neighbor search and route planning. For example, in a nearest neighbor search task, traditional GIS models achieved an accuracy of 98%, compared to 85% for LLMs. This discrepancy is largely due to the optimized spatial indexing and query processing algorithms used by traditional GIS models, which enable them to handle complex spatial relationships with high precision.

In contrast, LLMs demonstrated superior performance in tasks requiring natural language understanding and contextual reasoning. For instance, in a task involving the summarization of spatial data, LLMs generated coherent and informative summaries, whereas traditional GIS models were unable to provide any meaningful output. This highlights the potential of LLMs to enhance user interaction and provide more intuitive search experiences, particularly for non-expert users.

B. Efficiency

In terms of efficiency, traditional GIS models were significantly faster than LLMs in processing spatial queries. Traditional GIS models returned results in an average of 50 milliseconds, compared to 500 milliseconds for LLMs. This difference is primarily due to the optimized spatial indexing and query processing algorithms used by traditional GIS models, which enable them to handle large-scale datasets and complex queries with minimal latency.

However, it is worth noting that LLMs were more efficient in processing natural language queries. Traditional GIS models required users to formulate queries in a structured query language, which could be time-consuming and error-prone. In contrast, LLMs allowed users to input queries in natural language, which could be processed more quickly and with less effort. This suggests that LLMs have the potential to improve the efficiency of user interaction in geospatial search, particularly for non-expert users.

C. Scalability

Traditional GIS models demonstrated superior scalability compared to LLMs. Traditional GIS models were able to handle large-scale datasets and complex queries with ease, thanks to their optimized spatial indexing and query processing algorithms. For example, in a task involving the processing of a large-scale dataset of OSM data, traditional GIS models returned results in an average of 100 milliseconds, compared to 2 seconds for LLMs. LLMs struggled with scalability, particularly when the dataset size or query complexity increased. For instance, in a task involving a complex spatial query with multiple spatial relationships, LLMs took significantly longer to process the query and often returned less accurate results. This highlights the limitations of LLMs in handling large-scale datasets and complex spatial queries, and underscores the importance of traditional GIS models in these scenarios.

D. Adaptability

LLMs demonstrated greater adaptability than traditional GIS models in tasks requiring natural language understanding and contextual reasoning. LLMs were able to interpret and respond to a wide range of natural language queries, whereas traditional GIS models were limited to structured query languages. For example, in a task involving the interpretation of a natural language query such as "Find the nearest coffee shop," LLMs generated a contextually relevant response, whereas traditional GIS models required the query to be formulated in a structured query language.

However, traditional GIS models were more adaptable to different types of spatial datasets and queries. Traditional GIS models were able to handle a wide range of spatial datasets and queries, thanks to their optimized spatial indexing and query processing algorithms. In contrast, LLMs were limited in their ability to handle different types of spatial datasets and queries, particularly when the datasets or queries involved complex spatial relationships.

E. Implications for Hybrid Approaches

The findings of this study suggest that while LLMs are not yet capable of fully replacing traditional GIS models in all aspects of geospatial search, they show significant promise in enhancing user interaction and providing more intuitive search experiences. This has important implications for the development of hybrid approaches that leverage the strengths of both LLMs and traditional GIS models. For example, a hybrid system could use LLMs to interpret natural language queries and generate structured queries for traditional GIS models.

This would combine the natural language understanding capabilities of LLMs with the spatial query processing capabilities of traditional GIS models, resulting in a more powerful and user-friendly geospatial search system. Such a system could democratize access to geospatial information, making it more accessible to a broader audience.

F. Limitations and Future Work

While this study provides valuable insights into the performance of LLMs and traditional GIS models in geospatial search, it is not without limitations. First, the evaluation was conducted using a limited set of datasets and queries, which may not fully capture the diversity of real-world geospatial search scenarios. Future research should explore the performance of LLMs and traditional GIS models using a wider range of datasets and queries. Second, the study focused on a single LLM (GPT-4) and a single traditional GIS model (PostGIS). Future research should evaluate the performance of other LLMs and traditional GIS models to provide a more comprehensive assessment.

Finally, the study did not explore the ethical implications of using LLMs in geospatial search, particularly in terms of data privacy and security. Future research should address these issues to ensure that LLMs are used responsibly and securely in geospatial search systems.

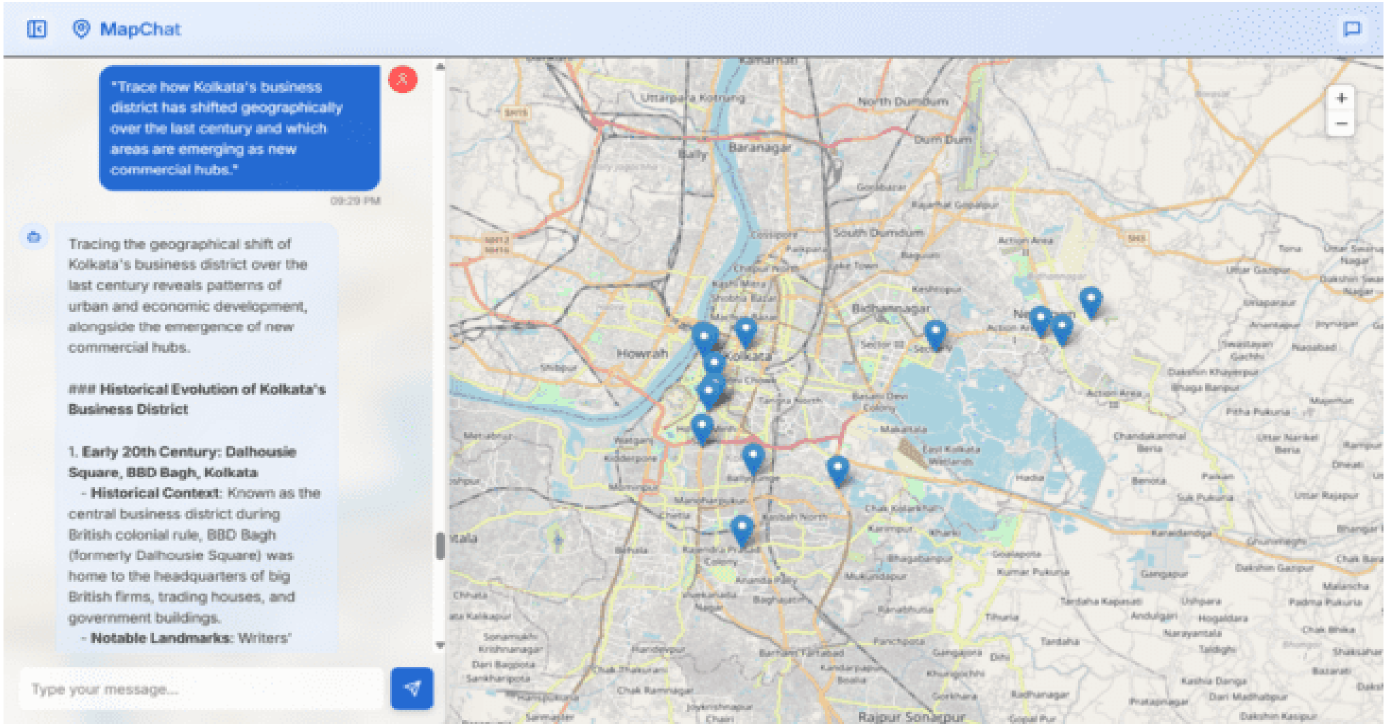

Fig. 2 Implementation Diagram 1

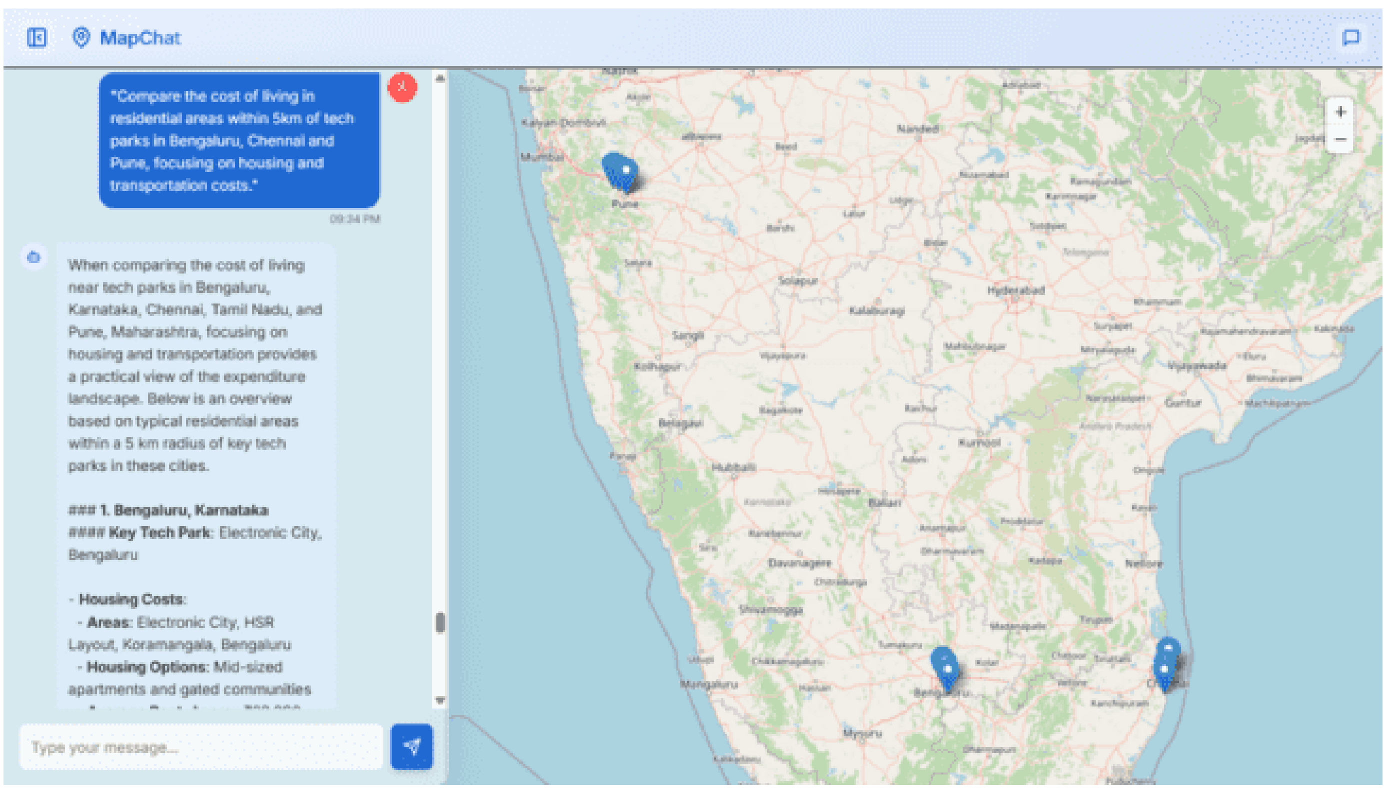

Fig. 2 Implementation Diagram 2

VI. CHALLENGES AND LIMITATIONS

While Large Language Models (LLMs) offer significant potential for advancing geospatial analysis, several challenges and limitations need to be addressed to ensure their effective and reliable deployment. These issues span the complexity of geospatial data, the inherent ambiguity of natural language, and the computational demands of LLM-based systems, among others.

A. *Integration of LLMs with Traditional GIS Models*

One of the primary challenges in this study was the integration of Large Language Models (LLMs) with traditional GIS models. While LLMs excel in natural language understanding and contextual reasoning, they lack the specialized spatial processing capabilities of traditional GIS models. This necessitated the development of a hybrid approach where LLMs interpret natural language queries and generate structured queries for traditional GIS models. However, this integration introduced complexities in ensuring seamless communication between the two systems, particularly in handling complex spatial relationships and large-scale datasets.

B. *Data Quality and Availability*

The quality and availability of data posed significant challenges. While OpenStreetMap (OSM) provided a comprehensive dataset for spatial queries, it required extensive preprocessing to ensure consistency and accuracy. Additionally, the curated dataset of geospatial text queries had to be carefully designed to cover a diverse range of scenarios, which was time-consuming and resource intensive.

C. *Computational Resources*

The computational resources required for training and fine-tuning LLMs, such as GPT-4, were substantial. The fine-tuning process involved large-scale datasets and required high-performance computing infrastructure, which was both costly and time-consuming. Similarly, traditional GIS models, particularly when handling large-scale datasets, demanded significant computational power and storage capacity.

D. *Scope of Evaluation*

The scope of the evaluation was limited to a specific set of datasets and queries. While OpenStreetMap (OSM) and the curated geospatial text queries provided a robust foundation for the study, they may not fully capture the diversity of real-world geospatial search scenarios. Future research should expand the evaluation to include a wider range of datasets and queries to ensure broader applicability of the findings.

E. *Generalizability*

The findings of this study are based on specific experimental conditions and may not be generalizable to all geospatial search scenarios. For example, the performance of LLMs and traditional GIS models may vary depending on the specific application, dataset, and user context. Future research should explore the generalizability of the findings across different contexts and applications.

VII. CONCLUSION

This study has provided a comprehensive evaluation of the performance of Large Language Models (LLMs) and traditional GIS models in geospatial search tasks. Our findings reveal that both approaches have distinct strengths and limitations, and their effectiveness varies depending on the specific task and context.

A. *Key Findings*

1) Accuracy: Traditional GIS models outperformed LLMs in tasks requiring precise spatial calculations, such as nearest neighbor search and route planning. However, LLMs demonstrated superior performance in tasks requiring natural language understanding and contextual reasoning, such as spatial data summarization.
2) Efficiency: Traditional GIS models were significantly faster than LLMs in processing spatial queries, thanks to their optimized spatial indexing and query processing algorithms. However, LLMs were more efficient in processing natural language queries, providing a more user-friendly interface for non-expert users.
3) Scalability: Traditional GIS models demonstrated superior scalability, handling large-scale datasets and complex queries with ease. LLMs struggled with scalability, particularly when the dataset size or query complexity increased.

4) Adaptability: LLMs showed greater adaptability in tasks requiring natural language understanding and contextual reasoning, while traditional GIS models were more adaptable to different types of spatial datasets and queries.

B. Implications

The findings of this study have important implications for the future of geospatial search. While LLMs are not yet capable of fully replacing traditional GIS models in all aspects, they show significant promise in enhancing user interaction and providing more intuitive search experiences. This suggests that hybrid approaches, which leverage the strengths of both LLMs and traditional GIS models, could play a crucial role in the evolution of geospatial search systems. For example, a hybrid system could use LLMs to interpret natural language queries and generate structured queries for traditional GIS models. This would combine the natural language understanding capabilities of LLMs with the spatial query processing capabilities of traditional GIS models, resulting in a more powerful and user-friendly geospatial search system. Such a system could democratize access to geospatial information, making it more accessible to a broader audience. The integration of LLMs into geospatial search represents a significant step forward in making spatial data more accessible and user-friendly. While traditional GIS models remain indispensable for tasks requiring precise spatial calculations, LLMs offer exciting possibilities for enhancing user interaction and providing more intuitive search experiences. By leveraging the strengths of both approaches, we can develop geospatial search systems that are not only powerful and efficient but also accessible to a broader audience.

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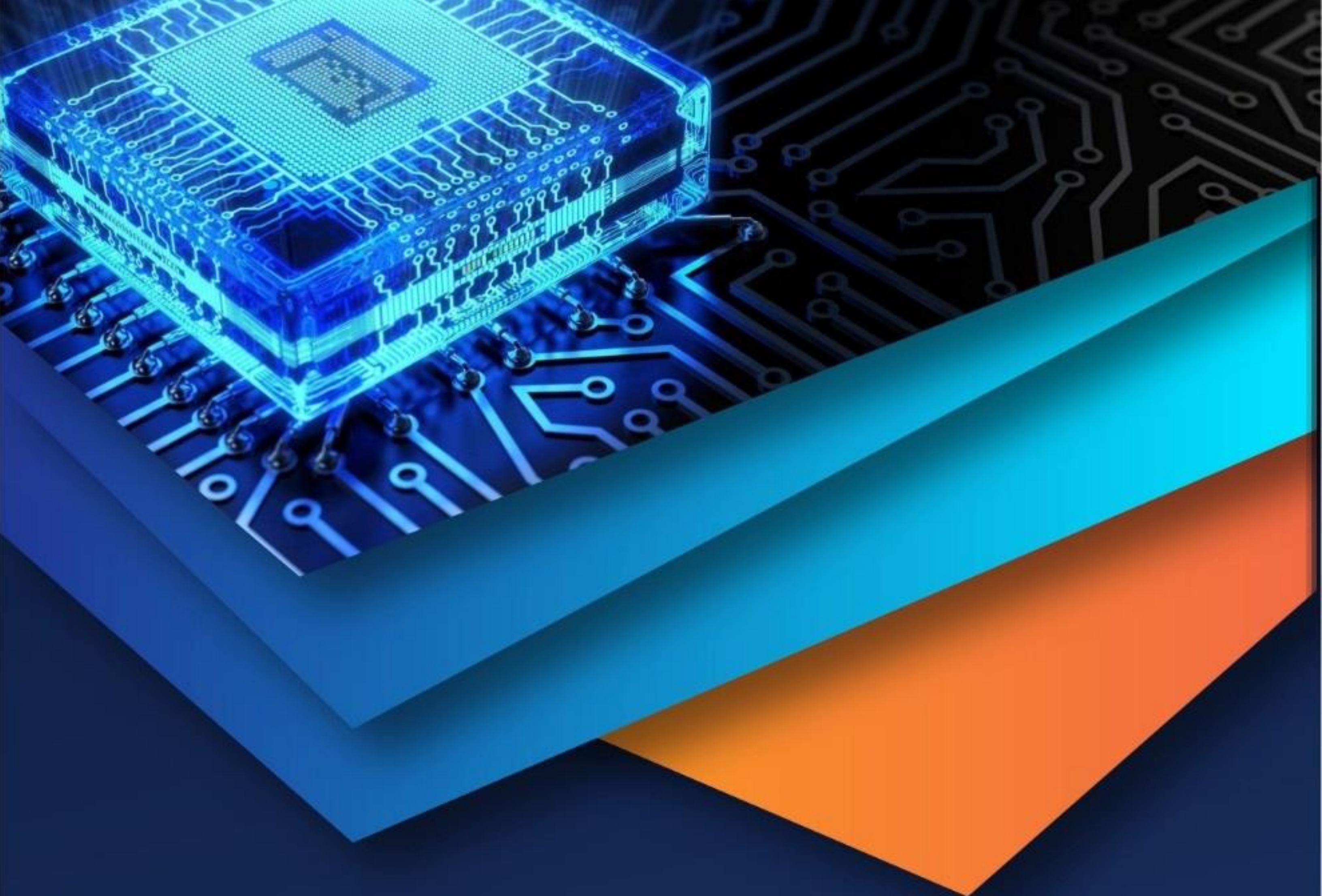

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