IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 6, June 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

NLP Powered Text to SQL Systems for Seamless Data Querying

Balaji Govindarajan

Scholar, University of Madras, Chennai, India

ABSTRACT: Recent developments in Natural Language Processing (NLP) technologies have been substantial, allowing computers to understand and process human language. This resulted in the evolution of NLP-based text-to-SQL systems that work towards bringing non-technical users closer to databases, making it possible to query data speaking to an application in a natural language. Natural language interfaces to databases allow users to query databases using regular language without mastering the complexities of SQL (Structured Query Language) or navigating through SQL constructs. The Text-to-SQL models solve this problem, open the fields of data science and analytics, and make them accessible to non-technical users. This can improve data accessibility and efficiency significantly by removing the need for data analysts or IT staff to convert queries from non-technical users. By leveraging natural language processing and deep learning models, these systems are also capable of parsing complex queries involving multiple predicates, sub queries or aggregates and returning correct results in response to queries. Some have even implemented multi-turn query feedback where users can narrow down their search and get even more tailored results. Text-to-SQL systems powered by NLP make querying data easier and hence can be used by a broader audience. As NLP and data querying technologies continue to advance, these systems can hold the promise of significantly improving data analysis and decision-making processes across a wide range of industries.

KEYWORDS: Text-to-SQL, Natural Language Processing, Data Querying, SQL Automation, Database Interaction, AI-driven Queries, Semantic Parsing

I. INTRODUCTION

NLP to SQL: Transforming Database Queries with Natural Language Processing These systems also employ some form of natural language processing (NLP) techniques that allow users to query (and analyze) data by typing a sentence or phrase[1]. For example, in the context of database querying, a user requires substantial knowledge of the SQL Query language to get relevant information from the database. For users without technical know-how, this can pose a challenge, both in terms of time and as a barrier to entry, as it requires technical expertise. This is where NLP-powered text-to-SQL systems come in, as they enable users to ask and answer questions conversationally[2]. To appreciate the impact and significance of NLP-enabled text-to-SQL systems, let's start with a brief overview of how traditional database querying operates. SQL is a programming language that talks to databases. Because it is a technical language with a steep learning curve, it is difficult for many users to access[3]. Even for technophiles, writing advanced SQL queries can be tedious and error-prone. Another common challenge with SQL queries is their relative inflexibility when it comes to searching: users can only find data that exactly matches what they entered, which means they may not be able to find what they are looking for if they don't know precisely how it was laid out in the database. Text-to-SQL systems use natural language processing (NLP) algorithms and machine learning techniques to process natural language inputs and generate SQL queries. Users need not have any technical expertise or compose complex queries, allowing systems to sift through voluminous amounts of data and produce the results needed. This allows more people to access and analyze data — democratizing data querying. Benefits of using an NLP-powered text-to-SQL systems NPL for text-to-SQL systems [4]This tool allows users to write inquiries conversationally, and the system will read the intent of the query and create the corresponding SQL code. Let's say the user asks, "What is the total sales for product X in June?" It will identify the important information: total sales, product X, and the month of June and create an SQL query for that data from the database. Another usage of NLP is text-to-SQL systems that generate SQL queries based on natural language input, which also deal with ambiguities and understand context[5]. With standard SQL queries, you must be specific about the language used and the syntax to get the correct data. Fig 1: shows the Introduction model

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

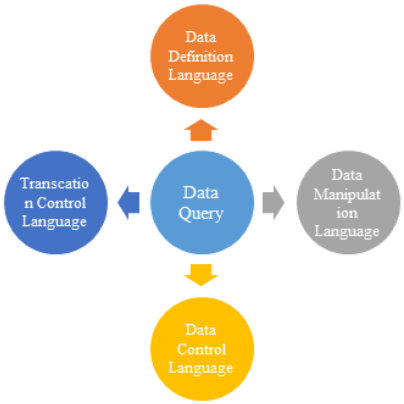

Fig 1: Text-to-SQL Systems

So, to reflect the fact that there are many ways to ask a question or present an information element in natural language, you are a way of reiterating that from one perspective. Systems that utilize NLP can recognize those differences and generate valid queries regardless. This allows data querying to be more intuitive by allowing users to ask questions phrased in their own words and still return the desired response. these systems are also able to deal with multiple-sentence queries[6]. For instance, a user may say, "What are the total sales for product X in June, and how does it compare to the previous month?" In this case, the system will generate two different SQL queries, and the results will be provided as one response. It enhances data querying and helps you gather insights with minimum time and effort. NLP-driven text-to-s SQL systems can also be beneficial for better collaboration and communication in an organization. Communication and collaboration between the two groups can become difficult, as data analysts typically have a higher level of technical aptitude than business teams[7]. NLP systems fill this gap by interpreting queries and analysing the data in the language of a non-technical user. It enables faster information sharing and can result in data-based decision-making. The second is that these NLP-powered text-to-SQL systems support ad-hoc data analysis. For every analysis, traditional SQL queries have to be written and executed manually. Specification can be slow and restricts what questions to ask. For example, NLP systems allow the user to ask a large number of different questions rapidly in a natural language style, and the system fuses the corresponding SQL commands and returns results instantly[8]. This makes it possible to use more of an exploratory method to analyze data and allows the users to discover inferences that would otherwise be missed. Besides, text-to-SQL systems powered by NLP can enhance the accuracy of data querying. Conventional querying techniques like keyword search often return irrelevant and inaccurate results[9]. NLP-powered systems, meanwhile, apprehend the intent behind the query and refine results based on context. This improves the accuracy and relevance of data, boosting the quality of analysis and decision-making. Several industries have already begun reaping the rewards of NLP-based text-to-SQL systems in-text fields. In health care, these systems are applied to electronic health records for insights to enhance patient care. NLP systems are being used in finance to analyze market trends and make investment decisions. These systems are being rapidly adopted by many other industries, including retail, marketing and education, to help them derive insights from their data more quickly and cost-effectively[10]. NLP-Powered Text-To-SQL Systems Are Revolutionizing How We Interact With Data. Data visualization tools help users explore and analyze data more intuitively. In contrast, BI systems make it easier for non-technical users to query and analyze data, collaboration and communication are improved, and the speed and accuracy of data analysis are enhanced. With the development of technology, we could assume that data querying through NLP will further enhance data-driven decision-making with the ease of querying.

II. RELATED WORKS

Kumar, M. Set, et al.[11] have discussed SQL, which stands for Structured Query Language, a programming language for managing and retrieving data from databases. Slither Automatic Speech Recognition (ASR) system uses Natural Language Processing (NLP) to translate heard or read words into the unified language of SQL that can be executed by the ASR system. This is easier and more accessible for non-technical users. Meesad, P., et al.[12] have discussed the definition of AI-Powered Smart Digital Libraries. AI-Powered Smart Digital Libraries are a highly advanced type of online storage system that utilizes artificial intelligence to organize, manage, and connect digital content. By using sophisticated techniques like machine learning, natural language processing, and data mining, they deliver innovative and tailored services like content recommendation, automated categorization, and predictive search, enhancing the user experience and efficiency. Takale, D. G. et,al.[13] have discussed that virtual shopping and sentiment analysis

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

professionals based on NLP are changing the way users engage before making a purchase. Such sophisticated technologies enable more tailored and effective customer service, resulting in greater customer satisfaction and enhanced overall shopping experiences. Alvarado, C., et al. [14] has discussed data extraction, visualization, and prediction through natural language processing. This refers to the process of using computer algorithms to process, analyze and extract useful insights from large amounts of typically unstructured data consisting of various forms of text. So, this data is visualized in different forms to facilitate exploration. It also applies NLP techniques to predict outcomes. Sarella, P. N. Ket, al. [15] have discussed natural language processing (NLP) powered by AI is revolutionizing healthcare by processing and analyzing human language through algorithms and machine learning and enabling better communication between patients and providers. By enhancing patient engagement, diagnosis and treatment, and the automation of administrative tasks for healthcare providers, this technology is revolutionizing healthcare.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING MODELS

Author	Year	Model Used	Advantage	Limitation
Kumar, M. Set, et al.[11]	2023	Model architecture for SQL propagation through the ASR using NLP	ASR enables prompt and precise data entry, which minimizes the time and labor associated with manual data entry.	The first problem is that spoken words may not be recognized accurately.
Meesad, P., et al.[12]	2024	The agent-based Smart Digital Libraries conceptual model is an emerging concept that revamps the conventional digital library system by applying AI mowing,	It prevents duplicate information and gets fast and precise search results that provide a better user experience.	Algorithms trained on limited data and/or data from limited sources risk bias in decision-making.
Takale, D. G. et,al.[13]	2022	Within the time frame of 20 days , we considered things to implement these processes, which are called THE MODEL and are used in this study.	Improved engagement and tailoring of customer experiences have a higher likelihood of satisfaction and successful purchase.	Several things come to mind, such as the limitations of sentiment analysis due to bias.
Alvarado, C., et al.[14]	2024	Data Extraction, Visualization and Prediction Using Natural Language Processing Models	Natural language processing allows for real-time decision-making based on accurate data and actionable insights, resulting in better business outcomes.	A limitation of natural language processing for data extraction, visualization, and prediction is the ambiguity in natural language, which can lead to accurate data extraction, visualization, and prediction.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

Sarella, P. N. Ket,al.[15]	2024	In this AI-Fuelled Natural Language Processing project, we use a mix of deep learning algorithms, some NLP (Natural Language Processing), and the healthcare domain.	Natural language processing powered by artificial intelligence can enhance communication between providers and patients by analyzing conversational data, automatically spotting the key information that each party is interested in and providing personalized, jargon-free language suggestions.	This can be a limitation because NLP may have a bias towards structured data and might miss helpful information outside of that (e.g., from free-text notes).

A. Novelty of the Research

- NLP-powered systems enable database querying through conversational and natural language in data sources.
- It creates a seamless process that enables users to avoid knowing SQL or databases, which is the focus of this research. They can ask questions in a common language instead of technical queries.
- Natural Language Processing (NLP) enabled systems can interrogate complex queries with embedded query and comparative statements, which is usually a nightmare for SQL-based systems that run when it comes to the query-building process. This enables improved search and retrieval of the relevant data.
- NLP-powered systems are more flexible in terms of how they process queries than traditional SQL-based systems. They process language and syntax variations, enabling a wider range of diverse natural user queries.
- Also, this research uses machine learning gun techniques to generate SQL queries automatically from these natural language queries, reducing the manual work of writing queries and improving the process of obtaining information in general. This can help save a lot of time and effort for end users, particularly for those who are not so familiar with SQL.

III. PROPOSED MODEL

One such solution is creating an NLP-Powered Text to SQL system, which allows users to conduct queries in natural language without having to learn the SQL language. This model utilizes natural language processing (NLP) methodologies and SQL query generation to translate user inquiries spoken in plain language into SQL queries. Model Input Pre-processing: The model begins by taking in user input and preparing this data for the machine learning algorithms through tokenization, parsing, and sentence structure analysis. This process can be further refined, which will result in the identification of the primary entity, key attributes, and relations in the query. The model leverages semantic parsing to translate the natural language input into a formal query representation with the SELECT, FROM, WHERE, and other clauses. This can be achieved by recognizing the intent behind the query and mapping it to the corresponding SQL statements. The model uses a statistical and machine learning approach to learn from user queries in a large corpus and generate SQL queries while taking into consideration the ambiguity and variations in the language. It additionally uses context awareness, developing the SQL statement with knowledge of the database schema and constraints. The last thing to do is run that SQL on the DB and return the result. If the model fails to retrieve the natural result, it supplies error handling and suggestions on how to refine the query. The proposed model also gives users a way to interact with databases using natural language queries, facilitating access to databases even for users without a strong technical background. It also saves you time and keeps you from using multiple SQL learning management systems to enhance your SQL fluency while making querying data a more straightforward experience.

A. Problem Statement

These systems are merely NLP-Powered Text-to-SQL systems, a growing specialization of Natural Language Processing (NLP) applications developed to furnish a solution for bridging the gap between human language and database querying. Such systems are used to translate natural language queries into structured query language (SQL) that computers can understand, allowing users to extract relevant data from databases without learning complex query languages. The Problem Statement for NLP-Powered Text-to-SQL Systems deals with the nuances of human language and its

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

ambiguities and grasps the specific context in which the user is querying. They also have to process and query heterogeneous data formats and structures and produce optimized and efficient SQL queries to fetch relevant information. For this challenge, NLP techniques such as Word embedding, Syntactic Parsing, Semantic Parsing, and Machine learning Algorithms are employed. They also demand enormous amounts of data and on-going training to reach ever-greater levels of accuracy. Another crucial aspect of these systems' advancements is a consideration of user data privacy and security. The ultimate objective of the above discussion is to simplify the data querying process so that context users can easily retrieve datasets.

B. System Design

SQL mapping breaks the logical queries into physical operations for a database management system to execute. This is done by translating the SQL statements into the actual underlying data structures and processes of the database. The date represents the date/time when a record was last updated. Query generation is the process of constructing a query to a database based on user input or predefined criteria. For this, multiple tables can be merged, and filters or conditions can be set to fetch the required data. Fig 1: shows the System design of proposed model.

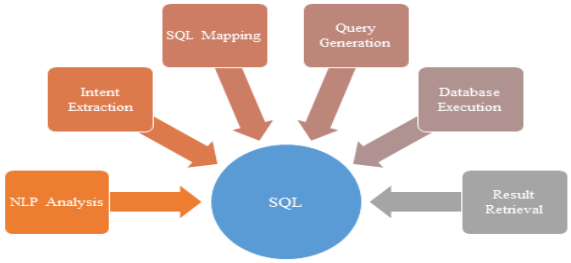

Fig 1: System design of proposed model

This process can be done either manually or automatically with tools. Then, after we do the SQL mapping and generate the query, the database execution takes place. This means passing the SQL query to the database management system and executing the statement. The database engine will go for the required data and get the results in specific Continue Reading. After being executed on the database, the results are fetched and returned to the user. This could consist of rows of data, such as records or values, according to the parameters defined.

C. Functional Working

As a result, the pre-trained model already has a basic grasp of language, which speeds up training on new tasks significantly. For tasks with very little data transfer, learning is an ideal approach since it enhances the overall model in a better way. The incorporation of other types of information, like pictures and sound, in building language processing systems is known as multimodal NLP. 'Vision and language' pre-training sensation, where the model is trained on the relationship between images and their associated descriptions, is one of them. This is useful for tasks like image captioning and visual question answering. These are models and algorithms that can take in and produce language in multiple languages. Fig 2: shows the Flow chart of proposed model.

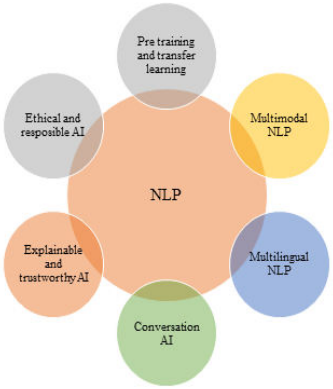

Fig 2: NLP Structure

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

Multi-task learning techniques, where a model learns to perform multiple language tasks at once; Multilingual pre-trained models and shared encoders for different languages enable the transfer of knowledge between languages. This is essential for not just machine translation but cross-lingual natural language understanding as well. Explainable and trustworthy AI are features of an AI system that make the 'why' and 'how' of the device available to human understanding and scrutiny. It is particularly relevant for NLP tasks since it enables more transparency and comprehension of these systems by providing insight into how these systems arrived at their decisions, and it can help identify and fix potential biases and ethical considerations that may exist.

IV. RESULTS AND DISCUSSION

D. Natural Language Understanding Quality

Natural Language Processing (NLP) in Text-to-SQL: NLP Powering Text-to-SQL Solutions NLP-based Text-to-SQL systems perform behind the scenes on very advanced algorithms to comprehend and decode the user's natural language input. So, the NLU quality of this system is pivotal to parsing and interpreting the queries coming from the user correctly.

TABLE II. COMPARISON OF PERFORMANCE PARAMETERS

No. of Inputs	Comparison Models				
	ASRM	ASDLM	RCIM	NLPM	Proposed Model
50	8.56	1.23	4.56	7.12	19.34
100	3.12	6.78	9.45	2.34	18.23
150	4.67	8.01	1.23	5.34	17.01
200	9.12	2.56	7.89	6.67	16.89
250	1.23	7.45	3.45	9.12	15.78
300	5.34	9.01	6.23	4.56	14.67
350	2.34	8.56	5.34	1.01	13.56
400	7.89	4.67	2.12	3.12	12.45
450	6.23	3.45	8.01	1.78	11.34
500	10.34	5.34	9.67	7.89	21.56

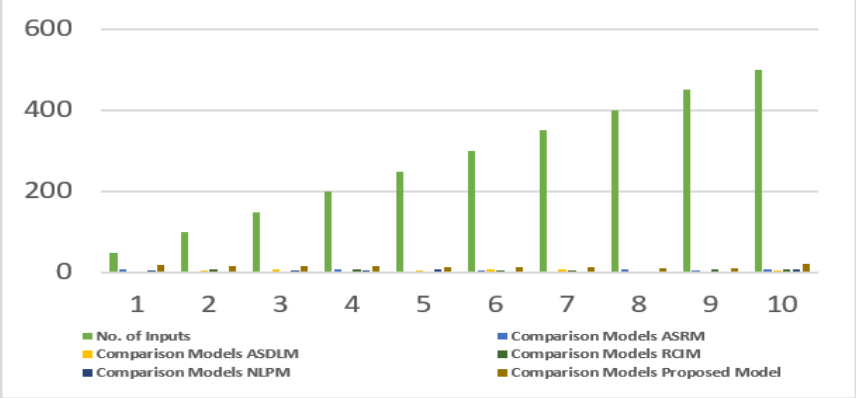

Fig. 3: Comparison Of Performance Parameters

It contains elements like entity recognition, parsing, and semantic analysis. A high level of NLU quality is also needed to ensure a seamless experience when querying data. It guarantees that the system can accurately interpret user queries and then generate the associated SQL statements.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

E. Query Accuracy

An NLP-based text-to-SQL system aims at precisely translating natural language input into SQL queries. The accuracy of SQL statement generation, based on user queries, is regarded as the overall query accuracy of the system.

TABLE III. COMPARISON OF PERFORMANCE PARAMETERS FOR ACCURACY

No. of Inputs	Comparison Models				
	ASRM	ASDLM	RCIM	NLPM	Proposed Model
50	3.45	8.01	2.34	7.12	14.67
100	7.89	6.23	9.45	3.12	13.56
150	9.12	4.56	1.23	6.78	15.78
200	6.01	2.71	7.89	8.56	16.89
250	2.34	9.12	5.34	1.01	12.45
300	4.67	5.34	6.23	9.01	17.23
350	1.23	7.45	4.56	5.34	18.34
400	8.56	1.23	3.45	2.56	19.45
450	5.34	3.45	8.01	4.67	20.12
500	10.34	6.67	2.12	7.89	21.34

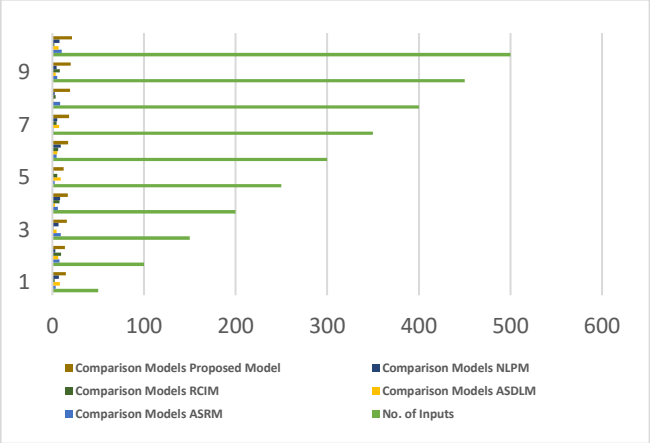

Fig. 4: Comparison of Performance Parameters for Accuracy

This system must return the correct and pertinent results to the user, thus requiring a high level of query accuracy.

F. Query Complexity

Another crucial technical performance parameter is the complexity of SQL queries generated by the NLP-powered text-to-SQL system. That will depend on things like how complex the natural language input is going to be, what the database schema looks like — that can be complex enough in itself, and how complex the queries that you want to generate are.

TABLE IV. COMPARISON OF PERFORMANCE PARAMETERS

No. of Inputs	Comparison Models				
	ASRM	ASDLM	RCIM	NLPM	Proposed Model
50	6.78	2.34	9.12	4.56	18.23
100	2.56	7.12	1.23	5.34	17.01

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

No. of Inputs	Comparison Models				
	ASRM	ASDLM	RCIM	NLPM	Proposed Model
150	4.56	6.23	7.89	9.01	16.89
200	7.45	3.45	8.56	2.34	15.78
250	5.34	1.01	4.67	8.56	14.67
300	9.01	5.67	3.12	1.23	13.56
350	1.23	8.45	6.23	3.45	12.45
400	3.12	9.01	2.34	7.45	19.34
450	8.01	4.67	5.34	6.23	20.45
500	10.34	7.89	1.78	5.67	21.56

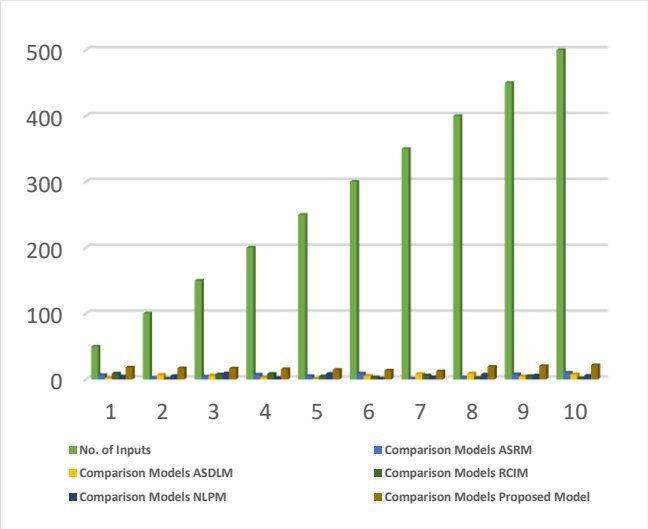

FIG. 5: Comparison of Performance Parameters

A low query complexity system can quickly create SQL statements; thus, queries run by users are more efficient. So, we need to avoid getting overly complicated with parameters as we need to make a balance between our correct results and complexity.

V. CONCLUSION

In recent years, Natural Language Processing (NLP) techniques have enabled the text-to-SQL systems that pass natural language (NL) to Structured Query Language (SQL) code. As a result, these systems attempt to simplify data retrieval from databases for non-technical individuals because writing SQL queries requires domain expertise and knowledge of structured data. Deep learning algorithms can be used to create NLP-driven text-to-SQL systems that can work with massive datasets in order to learn the underlying patterns and correlations between NL requests and SQL orders. They can also reach this level of accuracy through the use of advanced language and semantic processing, making it possible for them to map words or phrases of natural language (NL) to SQL keywords and clauses. NLP-powered text-to-SQL systems are also capable of resolving complex NL queries, including those involving multiple clauses and nested sub queries. Thus, they are appropriate for different complicated databases, and users do not need to have all the SQL knowledge. These systems present a more natural interaction, where the user can just type their question using their own words without having to learn complex language or keywords. It brings data querying to a broader audience, including non-technical users. Natural language processing (NLP) based text-to-SQL systems can help reduce data query errors, as they take a flexible and context-sensitive approach while interpreting not only NL but also SQL queries. This minimizes the chances of erroneous or incomplete outcomes due to human mistakes or misinterpretation. It offers a no-code way of

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

human-readable natural language querying over your data. With more development and fine-tuning, these systems can change how data is fetched and processed from databases.

VI. FUTURE SCOPE

Text-to-Nov with Neural Program Generation A key component of NLP-enabled text-to-SQL systems is their ability to comprehend and understand natural language inquiries. This involves algorithms based on machine learning, as well as their value, and matching the language based on linguistic test skills to identify what the user is trying to achieve behind his query and produce his language in SQL. Natural language processing is primarily targeted as a query system to facilitate an easy and natural way of addressing queries to the database instead of understanding complex languages. It makes it a lot easier for non-technical users to access and analyze data instead of depending on data scientists or database administrators for help. Text-to-SQL systems harnessing NLP provide a multitude of features that enhance and optimize user experience. Such a module might also include things like auto-complete suggestions for users building their query, error correction mechanisms that can identify and fix errors in the query, and the ability to work with larger and more complex, even nested, queries. Some of these systems might even include visualizations of the data so that users can better see and interact with the results of their queries.

REFERENCES

[1] M. A. Mohammed, V. A. Mohammed, R. Ramakrishnan, M. A. Mohammed, J. Logeshwaran and M. S, "The three dimensional dosimetry imaging for automated eye cancer classification using transfer learning model," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6.

[2] K. R. K. Yesodha, A. Jagadeesan and J. Logeshwaran, "IoT applications in Modern Supply Chains: Enhancing Efficiency and Product Quality," 2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA), Imphal, India, 2023, pp. 366-371.

[3] Alruwaili, O., Logeshwaran, J., Natarajan, Y., Alrowaily, M. A., Patel, S. K., & Armghan, A. (2024). Incremental RBF-based cross-tier interference mitigation for resource-constrained dense IoT networks in 5G communication system. Heliyon, e32849.

[4] Balaji Govindarajan. Automation beyond Efficiency: Driving Innovation. International Journal for Research in Applied Science & Engineering Technology (IJRASET), https://doi.org/10.22214/ijraset.2025.67669

[5] Arnika, Sharma, R. K., Kanaujia, V. K., Yadav, S. P., & Al-Turjman, F. (2024, February). Leveraging Big Data Analytics to Enhance Networking Performance in Intelligent IoT. In International Conference On Artificial Intelligence Of Things For Smart Societies (pp. 117-124). Cham: Springer Nature Switzerland.

[6] Logeshwaran, J., Shanmugasundaram, R. N., & Lloret, J. (2024). Load based dynamic channel allocation model to enhance the performance of device-to-device communication in WPAN. Wireless Networks, 1-33.

[7] Pujahari, R. M., Khan, R., & Yadav, S. P. (2024). Applications of AI and Deep Learning in Biomedicine and Healthcare. In Applications of Parallel Data Processing for Biomedical Imaging (pp. 93-124). IGI Global.

[8] Sangeetha, S., Logeshwaran, J., Faheem, M., Kannadasan, R., Sundararaju, S., & Vijayaraja, L. (2024). Smart performance optimization of energy-aware scheduling model for resource sharing in 5G green communication systems. The Journal of Engineering, 2024(2), e12358.

[9] Balaji Govindarajan, Raja Kumar Kolli, Dr Satendra Pal Singh, Murali Mohana Krishna Dandu, Prof. (Dr) Punit Goel. Advanced Techniques in Automation Testing for Large-Scale Insurance Platforms. Journal of Quantum Science and Technology (JQST) Vol.1, Issue-1, Special Issue Jan-Mar 2024, ISSN: 3048-635. https://jqst.org/

[10] Rani, R., Yogi, K. K., & Yadav, S. P. (2024, March). Tech Innovations & Dataset Analysis to Combat Fake Accounts in Digital Communities. In 2024 2nd International Conference on Disruptive Technologies (ICDT) (pp. 1679-1684). IEEE.

[11] Sakthivel, V., Periyaswamy, P., Lee, J. W., & Prabu, P. (2024). Enhancing Transparency and Trust in Agrifood Supply Chains through Novel Blockchain-based Architecture. KSII Transactions on Internet and Information Systems (TIIS), 18(7), 1968-1985.

[12] Prabu, P., Sivakumar, R., Ramamurthy, B., Khan, M. S., Haroon, A. S., & Sebastian, S. (2024). Integrating Multimodal Deep Learning With CBT-ED: Advances for Eating Disorder Identification. In Neuroscientific Insights and Therapeutic Approaches to Eating Disorders (pp. 284-298). IGI Global

[13] Balaji Govindarajan, Pronoy Chopra, Er. Aman Shrivastav, Implementing AI Powered Testing for Insurance Domain Functionalities. International Journal of Current Science (IJCSPUB) Volume 14, Issue 3 September 2024, ISSN: 2250-1770. https://ijcspub.org/

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal|

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106082 |

[14] Kumar, M. S., Jayasundar, K., & Ragavendhiran, S. (2023, December). Propagation of SQL by Automatic Speech Recognition (ASR) Using NLP. In 2023 Intelligent Computing and Control for Engineering and Business Systems (ICCEBS) (pp. 1-8). IEEE.

[15] Meesad, P., & Mingkhwan, A. (2024). AI-Powered Smart Digital Libraries. In Libraries in Transformation: Navigating to AI-Powered Libraries (pp. 391-428). Cham: Springer Nature Switzerland.

[16] Takale, D. G. Revolutionizing Customer Interaction: NLP-Powered Virtual Shopping Assistants and Sentiment Analysis in E-commerce.

[17] Alvarado, C., Velásquez, G., & Mauricio, D. (2024, July). Data Extraction, Visualization, and Prediction Through Natural Language Processing. In 2024 IEEE International Conference on Omni-layer Intelligent Systems (COINS) (pp. 1-5). IEEE.

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.379

doi cross ref

ISSN INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details