

A Detailed Study on Aggregation Methods used in Natural Language Interface to Databases (NLIDB)

Ashlesha Kolarkar¹, Sandeep Kumar²

¹Computer Science and Engineering
Koneru Lakshmaiah Education Foundation Vaddeswaram,
Vijayawada.

ashlesha.pandhare@gmail.com

²Computer Science and Engineering
Koneru Lakshmaiah Education Foundation Vaddeswaram,
Vijayawada,
er.sandeepsahratia@kluniversity.in

Abstract—Historically, databases have been the most crucial issue in the study of information systems, and they constitute an essential part of all information management systems. Since, it complicated due to restricting the number of potential users, particularly non-expert database users who must comprehend the database structure to submit such queries. Natural language interface (NLI), the simplest method to retrieve information, is one possibility for interacting with the database. The transformation of a natural language query into a Structured Query (SQL) in a database is known as a "Natural Language Interface to Database" (NLIDB). This study uses NLIDB to handle the works performed under various aggregations with aggregation functions, a grouping phrase, and a possessing clause. This study carefully examines the numerous systematic aggregation approaches utilized in the NLIDB. This review provides extensive information about the many methods, including query-based, pattern-based, general, keyword-based NLIDB, and grammar-based systems, to extract data for a dissertation from a generic module for use in such systems that support query execution utilizing aggregations.

Keywords-Structured Query Language (SQL), Pattern Based Aggregation, Query Based Aggregation, Natural Language Interface (NLI), and Natural Language Interfaces to Databases (NLIDB).

I. INTRODUCTION

Databases are becoming increasingly crucial in many applications that use private and public information systems [1]. Databases simplify the procedures associated with data management in information systems for data storage, processing, and retrieval [2, 3]. Due to the development and sophisticated usage of computer technologies, the web has a wide range of applications. A query must be so that the computer will comprehend and produce the required output to retrieve data from a relational database. Almost all languages for relational database systems adhere to the Structured Query Language (SQL) standards [4]. The interpretation of the queries in Boolean terms determines how the SQL rules can be applied.

On the other hand [5, 6], some user needs might be addressed by something different than a standard querying system. For example, traditional query languages cannot adequately represent the requirements' attributes. Effective user-database interactions [7] are required by many next-generation database systems, which involve intelligent information management. As opposed to working on attribute values, non-expert users increasingly request the ability to query relational databases using more natural language that includes linguistic variables

and phrases [8]. A data management system that can handle enormous volumes of persistent data and infer additional data and information using various methods of reasoning is a feature of an Indexed Database System (IDBS). It includes approaches to knowledge representation, inference methods, and intelligent user interfaces (UIs) that extend the capabilities of conventional query languages [9]. The following techniques are critical for enhancing database systems [10]:

Inference techniques let users reason about data to extract more data and information.

Knowledge representation techniques help users better characterize the semantics of application domains in databases.

Intelligent user interfaces allow users to make requests and receive results.

In current years, there has been a growth in the demand for non-expert users to query relational databases in a more conversational style that incorporates linguistic terms and phrases instead of focusing on attribute values [11-13]. A potential tactic is to provide a clever interface for database systems that enables users to carry out dynamic querying in databases. Natural language interfaces have been a hot area of

study for a very long time. An attempt is made to "understand" requests made in English or any other natural language by a natural language interface to a database system. Natural Language Interfaces to Databases (NLIDBs) [14, 15] translate statements made in natural language into database queries.

NLIDB bridges the communication gap by acting as an intermediary layer between the RDBMS and the end user. With the aid of many other components, the end-natural user's language query is converted to SQL using some programming methods [16-18]. The architecture of an NLIDB system describes the interconnected and sequential behavior of all the components. In this area, researchers are attempting to increase the effectiveness and performance of NLIDB systems.

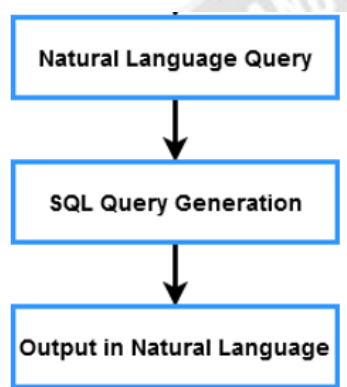


Fig 1. General framework of NLP query processing system

Classic NLP, ontology-based prediction, pattern matching, knowledge extraction, graph-based, hidden Markov chain analysis, and machine learning are some of the different NLIDB implementation methodologies discussed in this article. The major aim of the research is to conduct a detailed analysis on the different types of aggregation techniques used in the natural language processing systems.

This paper is structured into the followings: Section 2 reviews the different types of aggregation methodologies used in NLIDB. Also, it investigates the problems and challenges associated to the methodologies. Section 3 consists of the comparative analysis of the present methods with its accuracy, drawbacks and challenges. Then, the overall summary of the paper is presented in Section 4 with its implications and future scope.

II. AGGREGATION METHODOLOGIES

Here, a systematic study is conducted to achieve our goal using the method presented below. This literature review considers four different aggregation methodologies in Natural Language Inquiry (NLI) into a structured query (SQL) in a NLIDB.

A. Query based Aggregation

Hreberd, *et al* [19] developed a Contextual Multiple Classification Ripple Down Rules (C-MCRDR) system for facilitating NLIDB. The speech-enabled chatbot is incorporated with an Automatic Speech Recognition (ASR) system in this framework. The RDR knowledge engineering method makes it easier to maintain the live system's KB than other programmed or syntactically challenging systems. They employed a pedagogical domain to assess this system, which uses a production database to produce offline course-related articles. Baik, *et al* [20] developed a new TEMPLER model for improving the performance of conventional NLIDBs with the help of SQL query logs. Also, the query fragment graph is used to increase top-1 accuracy in current NLIDBs by 138% by leveraging SQL query log data, proving the effectiveness of the technology. Lalwani, *et al* [21] implemented a chatbot system using advanced Artificial Intelligence (AI) and NLP models. Typically, a class of bots known as chatbots have been present in chat networks. The user can communicate with them using

GUI or widgets. This study aims to investigate the different types of user queries for analyzing the users' messages. In this framework, the personal query response system is developed to validate users' authenticity based on their identity and password. The other modules of this framework are Artificial Intelligence Modeling Language (AIML), query analysis and response system. Moreover, the processes such as lemmatization, POS tagging, semantic sentence similarity, and log file maintenance are performed. The key benefits of this application system are reduced time and cost with better accessibility.

Sangeetha, *et al* [22] used an advanced deep learning technique to develop an intelligent automatic query generator framework. The article covers how SQL is built on translating spoken natural language queries into words. They provided a basic architecture for creating a database interface for intelligent devices connecting to any database. The innovative interface uses speech recognition techniques to translate audio input into text. Then, a semantic matching strategy is used to translate natural language queries into SQL. The development of precise queries and the speed at which relevant components in a document are identified and improved with the use of natural language techniques. Sowah, *et al* [23] developed a Cooperative Query Processing (CQA) model for enabling information search and retrieval in databases. The purpose of this work was to incorporate NLP with CQA model for the prediction of user queries. Anilkumar, *et al* [24] presented a new method for providing NLP with the use of AI mechanism. The suggested query processing system provides the search interface for accessing online applications, numerous databases and search engines.

Here, the word pair mining technique was used to update the spelling mistakes in the user input. Moreover, the suggested system enables the users to update the database with the insertion or deletion of values. Also, it accepts the statement provided by the user as input and performs tokenization by eliminating irrelevant words. In this work, they have put forth a technique that enables users to look for internet resources, including databases, search engines, and applications. The system responds to the user's various queries with precise and effective results. Even if the user input contains spelling mistakes, the spelling is autocorrected. There are two ways to correct spelling; the first uses a dictionary, and the second does not. They use a word pair mining strategy to address spelling errors in user input. The system proposed in this study includes auto-correction features for misspelt words and a user-computer interface in the form of a database query language. Bai, et al [11] developed an advanced natural language interface for an efficient retrieval of web information. This paper proposed an enhanced neural model based on an current framework IRNet for NL database query. Also, a representation of a Gated Graph Neural Network (GGNN) is used to translate database entities and relations to mitigate limitations in web information services. The earlier efforts have led to further advances in the subject, but it still needs more attention to address issues that still need to be addressed. The NLIDB systems are expanded to offer distributed ways by fusing the basic architecture with other system development tools or coding languages. Additionally, it is necessary to automate the system for persons with disabilities with an API version that is used in other apps based on related concepts. It should also come with a voice interface to help uneducated people.

Bais, et al [25] utilized a graph theory models for developing an Arabic natural interface for an effective information extraction. Generally, the natural language queries have the disadvantage of not providing guidance on accessing the requested data. This paper describes a NLIDB model which removes the need for consumers to comprehend the database structure by allowing users to access data from a database using Arabic. As it gains experience, it may also work self-reliantly of the database industry and enlarge its knowledge base. Veerappa, et al [26] developed a new approach, named as, Syntax Table Aware Semantic Parser (STAMP) for effectively accessing and managing information from the database. This problem is resolved using the research's technique, which considers both the SQL syntax and table structure. The quality of the produced SQL query is greatly improved by learning how to imitate material from column names, cells, or SQL keywords and by improving the where clause's development by using the column-cell relationship. The investigations are focused on WikiSQL, a recently disclosed dataset that contains the most query SQL sets.

B. Pattern based Aggregation

Chakraoui, et al [27] presented a review of various techniques to develop an effective recommender system. In the present work, a running example of an enhanced interface for bibliographic information retrieval was presented, allowing different types of researchers to identify their needs utilizing natural language comprehension and some critical criteria. Text- and language-based approaches like tokenization, syntactic and semantic analysis used for analyzing natural language questions. Yaghmazadeh, et al [28] presented a novel technique for constructing SQL queries automatically from natural language(NL).The fundamental part of this technology is a revolutionary NL-based method of program synthesis that associates type-directed program synthesis, automatic program repair, and semantic parsing tools from the NLP community. This system converts natural language sentences into SQL queries. Users need not be familiar with database structure to use this solution, which is fully automated and can be applied to any database without any customization. Wang, et al [29] presented a general-purpose transfer-learnable NLI to learn a single model that is used as an NLI for any relational database. They consider the peculiarities and difficulty of natural language while adhering to the data management philosophy of dissociating data from its structure. They also offer an automatic annotation method that isolates the schema from the data and incorporates natural language understanding into the schema. They also provided a modified sequence model to translate annotated natural language queries into SQL statements.

Seipel, et al [30] implemented a conversational interface architecture for the Microsoft HoloLens device. By addressing some of the drawbacks of AR technology, this study hopes to enhance the exploration process. Many natural language processing (NLP) elements, such as intent recognition and natural language generation, are frequently needed to create the conversational interface. In this design, conversational elements are merged with AR-based software visualization. In this article, the system uses changed visuals and speech-based

outcomes based on different user utterances to provide information on the component-based software architecture that is still being investigated. Moller [31] developed a test chatbot that added predictive capabilities to the Manufacturing Execution System (MES) and provided real-time production updates in plain language. By showcasing a factory-based human-AI cooperation system, the research contributes to industrial information systems. In light of this research, MES-based technical help systems are developed to facilitate speedy information retrieval. Single, et al [32] used a natural language processing methods to retrieve the information from a database of chemical accidents. Techniques for web scraping are used to supplement pharmacological information. The collected data is

then automatically incorporated into an established ontology framework. The ontology-based chemical accident database, which human specialists or computer systems may access, offers additional accident exploration capabilities. The ontology helps identify causal accident relations because it specifies the semantic context of accident information. Salgado, et al [33] applied a subtractive mountain clustering technique to the problem of natural language processing to construct a chatbot that replies to user enquiries. After identifying the most appropriate word for each cluster and placing it at the center, all the other words are combined according to a specified measure tailored to the language processing domain. The algorithm processes both the queries and the pertinent previously stored data. The proper processing of the text is necessary for the chatbot to provide responses that are pertinent to the questions that have been asked. They created equivalent questions and used the drug's package insert as the readily available information to validate the method.

III. Comparative Analysis

By paying attention to one another, this backbone creates better word representations and can be used to encode the query and the database structure more efficiently. The system's

functionality for multilingual processes needs to be improved because complex multi-turn problems are expected to be stretched, necessitating a lot of knowledge to train the algorithm. It is more difficult and nearer to real-world use situations to serve as a testing ground for new methods. Both are necessary to examine the effects of SQL query log and to enhance current deep learning-based NLIDB systems using SQL log data. The "group by" and "order by" clauses have received the minimum attention because there aren't enough datasets with training examples. Therefore, improving these clauses can result in overall accuracy closer to being used in actual. Table 1 presents the detailed comparative analysis among the existing techniques.

A. Existing work

1. There are already systems like ELIZA, a model of a Rogerian psychotherapist.
2. Terry Winograd created the early natural language understanding computer software SHRDLU at MIT between 1968 and 1970.
3. One of the earliest effective database NLP systems was LIFER/LADDER (Hendrix, 1978). Also, a natural

Table 1. Comparative Analysis

References	Approach/ Technique	Dataset	Accuracy	Drawbacks & Challenges
Aibo Guo et al [1]	Neural Network	Wiki SQL, TableQA	88%	<ul style="list-style-type: none"> • The column contents they employed might be more effective if they are used on a smaller scale. • Measures the similarity of two texts from a semantic, rather than a string, standpoint. • To broaden the scope of the research to address new issues Expanding for text to SQL in the context of a table rather than a knowledge network.
Ellery Smith et al [2]	Linguistics & learning based extraction models	CaRB	-	<ul style="list-style-type: none"> • It requires incorporating more OIE (Open Information Extraction) extractors with a learning-based approach. It uses standard knowledge bases to handle entity disambiguation.
Fadi H. Hazboun et al [3]	OLAP Hypercube	OLAP DATASE T	-	Use standard knowledge bases to handle entity disambiguation to facilitate massive data consumption, switching from 4-D cubes to infinite-dimensional n-D cubes.
Bouchra El Idrissi et al. [4]	Basic Graph Pattern (BGP)	RDF/OWL	-	<ul style="list-style-type: none"> • Evaluation of sophisticated queries using SPARQL constructs and custom rule inference Take into account SPARQL update, logic checking, and consistency validation
Sandeep Varma et al. [5]	Semantic parsing algorithm	SPARQL	-	<ul style="list-style-type: none"> • A single model can respond to queries from various documents and tables, structured to unstructured data must be converted.
Tae-Young Kim et al. [6]	CNN-LSTM neural networks	TPC-E benchmark	93%	<ul style="list-style-type: none"> • Deep learning model optimization requires the development of superior alternatives to improve efficiency.
Hao Wu et al. [7]	Deep learning-algorithm	ChineseQ CI-TS	96.5%	<ul style="list-style-type: none"> • Examine the usage of pre-training models like BERT, ELMO, and others for encoding keywords.

Zhi Chen ¹ et al [8]	Graph Projection Neural Network (GPNN)	Spider	72.3%	<ul style="list-style-type: none"> Using flexible pre-trained models, assess the proposed ShadowGNN.
Sen Yang et al. [9]	Pipeline and deep learning method	-	-	<ul style="list-style-type: none"> With adaptive pre-trained models, evaluate the proposed ShadowGNN.
Akshar Prasad et al. [10]	Machine Learning Techniques	IMDb, Company sales	91.7%, 94 %	<ul style="list-style-type: none"> -
Tian Bai et al [11]	Graph neural network (GNN)	SPIDER	70.8%	<ul style="list-style-type: none"> More research is into creating TTS models and algorithms with improved performance using NL models in conjunction with application domain knowledge or semantics.
Botao Zhong et al [12]	Deep Learning	Squad	80%	<ul style="list-style-type: none"> The training and testing datasets size may impact how well the suggested strategy performs. An integrated retrieval module will be supported by ontology and semantic technology.
Xiaoyu Zhang et al [14]	Neural network	TableQA	90%	<ul style="list-style-type: none"> Concatenate on database columns and contents to increase the variance of column expressions Whether a particular database can provide an answer to the query.
Addi Ait-Mlouk et al [15]	Machine Learning Algorithm	Facebook	-	<ul style="list-style-type: none"> Incorporating third-party services, expanding the system to other knowledge bases and languages, privacy protection, and generating replies based on those sources.
Srdja Bjeladinovic et al [16]	-	HybridDB, oracle, MongoDB	-	<ul style="list-style-type: none"> They performed integration and enhancement of consistent use of several databases, mainly when they served as parts of hybrid databases.
Mohammad Halim Deedar et al [17]	Fuzzy System	Employee	-	<ul style="list-style-type: none"> They developed a system for grouping users who spend a lot of time finding records and updating their profiles.
Herbert et al [19]	MCRDR	-	-	<ul style="list-style-type: none"> Cover scenarios that must be correctly categorized, integrated and adapted in other domains.
Baik et al [20]	TEMPLAR	YELP	85%	<ul style="list-style-type: none"> Accuracy has significantly improved when TEMPLAR is used to enhance pipeline NLDBs with log data.
Lalwani et al [21]	Path Similarity and Wu-Palmer (WUP) Similarity	-	-	<ul style="list-style-type: none"> Here, various algorithms are used in an AIML-based bot. Accessible quickly and also saves time and money.
Sangeetha et al [22]	Intelligent query generator framework	-	80%	<ul style="list-style-type: none"> It can be enhanced to put the suggested dispersed technique into practice. The use of distributed computing techniques can speed up and improve interface training.
Sowah et al [23]	NLP	-	-	<ul style="list-style-type: none"> It shows how users can utilize natural language to query database and acquire additional information.
Anil Kumar et al [24]	Natural Language Processing.	-	-	<ul style="list-style-type: none"> Must provide a voice interface to assist those with disabilities and those who are illiterate, Additionally, the system ought to have an API version. Such keywords are simpler to find in the input sentence that is provided.
Bais et al [25]	Natural language interface for databases	-	-	<ul style="list-style-type: none"> Databases only accept structurally formed logical combinations for search queries. Users don't need to comprehend the database structure because the interface allows them to extract data from databases using Arabic.
Veerappa et al [26]	The table structure and SQL syntax	WikiSQL	60%	<ul style="list-style-type: none"> The high degree of computational complexity during clause development SQL query substantially, as well as encouraging the where clause's development by utilizing the column-cell relationship

Chakraoui et al [27]	NLI and enhanced by Apriori and spanning trees algorithm.	-	-	<ul style="list-style-type: none"> The syntactic similarity is used to identify the content of a given item. Utilize the operating system's built-in speech recognition capability to enhance our recommender system.
Yaghmazadeh et al [28]	NL-based program synthesis methodology .	MAS,YE LP,IMDB	90%	<ul style="list-style-type: none"> Proves domain-specific heuristics are essential and effective.
Wang et al [29]	NLP	WiqiSQL	82.2%	<ul style="list-style-type: none"> It primarily separates the metadata from the data itself, learning, transferring, and accumulating domain-specific knowledge independently. The correctness of the original model is partially connected with transferability.
Seipel et al [30]	AR-based software visualization.	-	-	<ul style="list-style-type: none"> It is required to perfectly implement the Virtual assistants that can have interesting discussions about the current exploring assignment. It must be required to adapt an ISLANDVIZ visualization to work with component models other than OSGi.
Møller, C et al [31]	Manufacturing execution systems	-	-	<ul style="list-style-type: none"> MES chatbot interface benefits shop floor employees and makes information extraction simple compared to conventional search methods. Intended to increase the complexity of the suggested design to evaluate its advantages
Single et al [32]	NLP	-	-	<ul style="list-style-type: none"> Process of creating ontologies more accessible and easier to maintain. It covered enormous knowledge fields with numerous ontology-based accident databases.

- language user interface is created for the US Navy's ship-related data database.
- Since then, several developments in NLP have been made, including using CFG and NLDBI (Natural Language Database Interface) (Context-free grammar). These systems have already been implemented, and we suggest a fresh approach to using NLP to query database systems.

B. Proposed Work

The amount of data being generated nowadays is continually growing. We can store a lot of data thanks to the emerging new database tools and emerging technologies. Still, the issue is that

many people need to become more familiar with the interfaces and technology that process data and present it in the way the user requests. It implies that a large number of people need more database management skills. Therefore, we are implementing a technology that will help users get precise data from databases without prior database knowledge by converting natural language questions into SQL queries. Consequently, there are various stages to how our existing system operates. Fig 2 and Fig 3 presents the comparative analysis among the existing models [33] based on the parameters of accuracy and query matching accuracy. DL provides increased accuracy up to 96.5% and the syntax tree based query modeling provides an increased matching accuracy up to 66.6%.

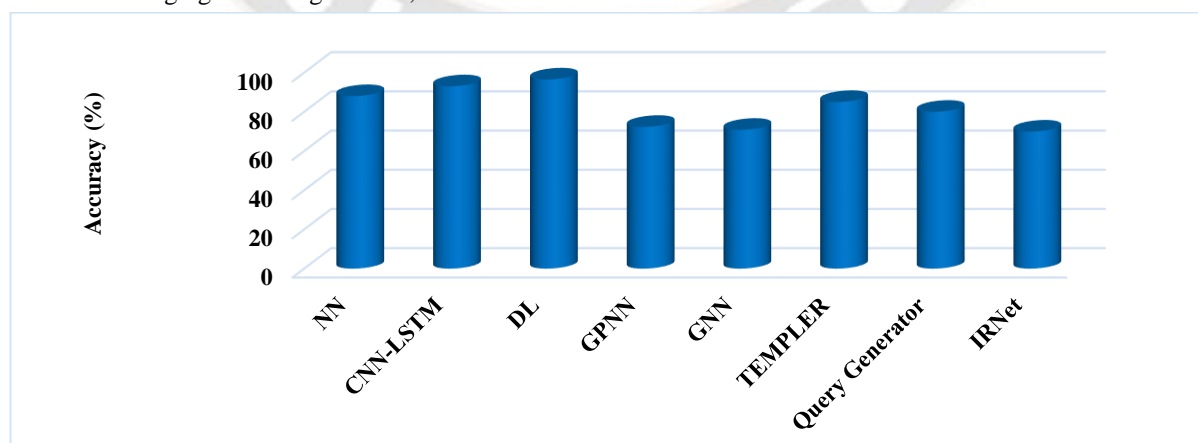


Fig 2. Comparative analysis based on accuracy

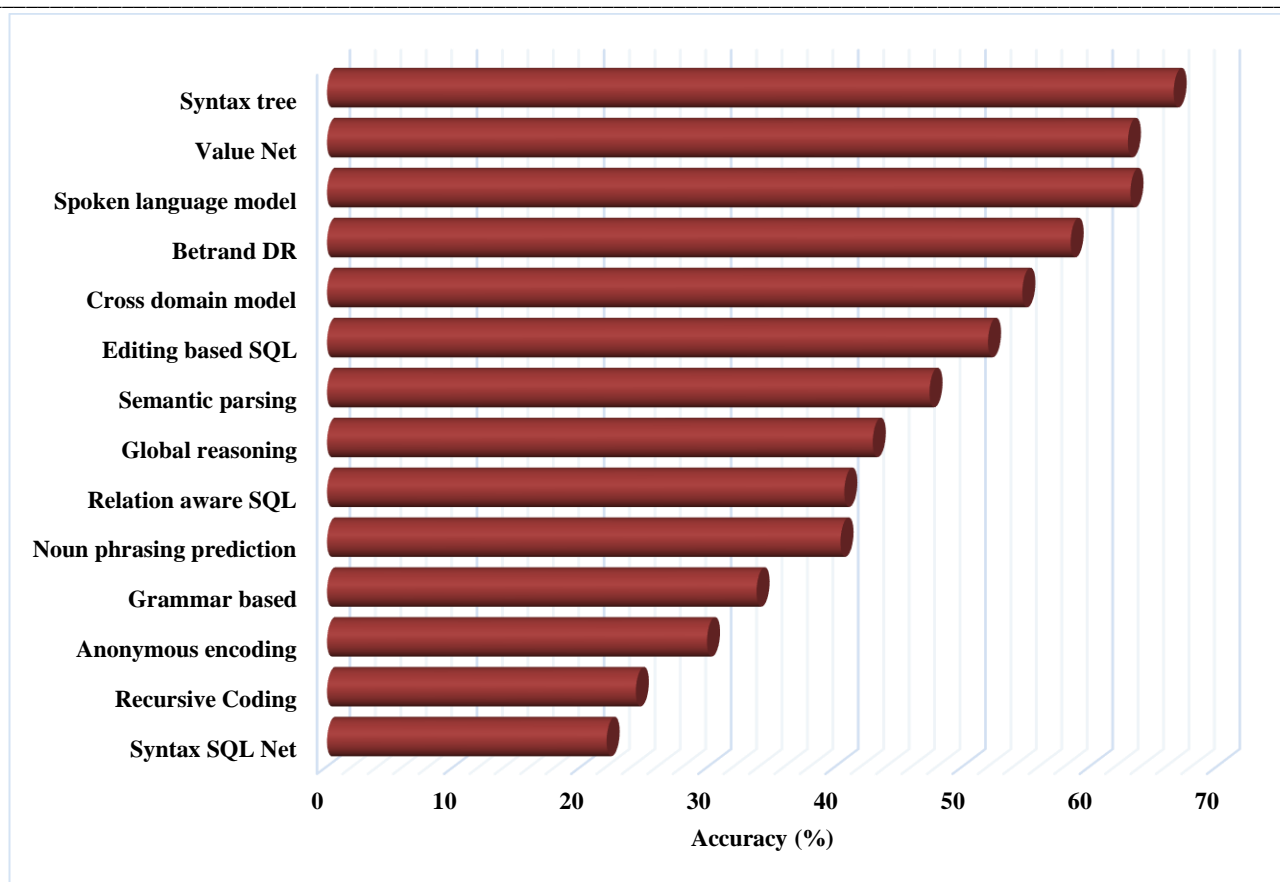


Fig 3. Comparative analysis based on query matching accuracy

IV. CONCLUSION

This paper presents the detailed survey on various aggregation methods used in NLIDBs. In this study, aggregation functions, a grouping phrase, and a possessing clause are used to manage the works produced under various aggregations. The multiple systematic aggregation techniques used in the NLIDB are thoroughly examined in this paper. This paper gives in-depth information on the many ways to extract data for a dissertation from a generic module for use in systems that support query execution using aggregations, including query-based, pattern-based, general, keyword-based NLIDB, and grammar-based systems. This framework pays attention to one another, resulting in better word representations that can encapsulate the query and the database structure. Increasing the Xsystem's capabilities for multilingual processes is necessary since complex multi-turn problems are anticipated to be extended and require extensive knowledge to train the algorithm. Serving as a testing ground for new techniques is more challenging and close to scenarios encountered in real-world applications.

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