JOURNAL LA MULTIAPP

VOL. 05, ISSUE 05 (553-567), 2024
DOI: 10.37899/journallamultiapp.v5i5.1600

Application of a Question Answering System in the Ontology-Based Health Domain and Question Templates to Improve the Quality of Answers

Efwandha Yudhono[1], Shaufiah[1], Indra Lukmana Sardi[1]

[1]*School of Computing, Telkom University, Bandung, Indonesia*

**Corresponding Author: Efwandha Yudhono*
Email: efwandhayudhono@student.telkomuniversity.ac.id

Article Info

Article history:
Received 10 August 2024
Received in revised form 06 September 2024
Accepted 26 September 2024

Keywords:
Question Answering System (QAS)
Ontology
SPARQL
Resource Description Framework (RDF)
Question Template

Abstract

Developing an effective Question Answering System (QAS) to address a wide range of health-related inquiries presents a significant challenge. This study introduces an innovative approach using an ontology-based QAS within the health domain, leveraging the Resource Description Framework (RDF) and SPARQL query language. By utilizing ontology, the system can more accurately map health concepts, improving the relevance and precision of its responses. Additionally, the incorporation of structured Question Templates enhances the system's ability to understand and respond to diverse user queries. The system's performance was evaluated using Black Box Testing, which demonstrated that it consistently provides accurate and relevant answers. The system achieved a Mean Average Precision (MAP) of 79.6%, indicating its potential to effectively address a broad spectrum of health issues.

Introduction

The rapid growth of digital information has led to an increasing need for effective information retrieval systems, particularly in specialized domains such as healthcare. In the health domain, users often seek accurate and precise information to make informed decisions (Nguyen et al., 2023). Traditional search engines, while useful, often return a large volume of results, many of which may not directly answer the user's specific question. This challenge underscores the importance of developing more sophisticated systems, such as Question Answering Systems (QAS), that can provide direct and relevant answers to user queries (Tian et al., 2023).

A Question Answering System is an advanced form of information retrieval that goes beyond keyword matching. It aims to understand the intent behind a query and deliver precise answers, rather than a list of documents or links. In the health domain, where information accuracy is crucial, the ability to extract precise answers from a vast and complex body of knowledge is particularly valuable (Syarief et al., 2020).

Ontologies play a crucial role in enhancing the performance of QAS by providing a structured representation of knowledge within a particular domain (Yunmar & Wisesa, 2020). An ontology defines the concepts and relationships within a specific field, enabling the QAS to understand and interpret the user's query in a more meaningfully (Crook et al., 2018). This study focuses on the development of an ontology-based QAS for the health domain, using the Resource Description Framework (RDF) and SPARQL query language to manage and query the knowledge base effectively (Juliane et al., 2018).

ISSN: 2716-3865 (Print), 2721-1290 (Online)

The primary objective of this research is to design and evaluate a QAS that can accurately respond to health-relataed queries. The system integrates an ontology-based approach with structured question templates, allowing it to handle a wide range of questions while maintaining high precision and relevance in its responses. Through rigorous testing, including Black Box Testing and performance evaluation using Mean Average Precision (MAP), this study aims to demonstrate the effectiveness of the proposed system (Lima et al., 2020).

The remainder of this paper is organized as follows: Section 1 reviews related works in the field of ontology-based QAS. Section 2 details the methodology employed in developing the system. Section 3 presents the results and discusses the system's performance. Finally, Section 4 concludes the paper and outlines future research directions.

Ontology

An ontology is a structured framework that is utilized to depict knowledge within a certain field (Nimmagadda et al., 2008). Ontologies have found extensive use in diverse domains, including healthcare. Creating ontologies specifically for the healthcare field can help in the process of combining and distributing knowledge among different systems, making it easier to interchange information without any confusion (Slimani, 2015). Ontologies in the healthcare field have the capability to represent data and oversee knowledge pertaining to diseases, drugs, and human bodily systems (Taye, 2010).

Moreover, the utilization of ontologies in healthcare enables automated reasoning and logical deduction (Slimani, 2015). Integrating ontologies into health information systems can improve the efficiency and effectiveness of healthcare services by facilitating structured data processing and enhancing understanding of the knowledge domain (Taye, 2010).

However, developing ontologies for healthcare involves differentiating between synonyms, homonyms, and related concepts from various data sources (Zhang et al., 2018). Furthermore, ontologies must be expressed in a standardized manner that can be easily understood by machines to be effectively utilized in health information systems.

Ontology Building

Ontology construction has emerged as a captivating subject in the domain of knowledge representation and reasoning. An ontology is a precise and formal description of a commonly understood idea and is important in many fields, such as healthcare and medicine (Jones et al., 1998; Nimmagadda et al., 2008). More specifically, the Resource Description Framework (RDF) has become a potent instrument for representing and handling ontological knowledge.

An essential use of ontology in healthcare is understanding and regulating ecological elements connected to the human body and disease processes. Scientists have created ontological models of many human bodily systems, including the digestive, musculoskeletal, and neurological systems, and investigated the interactions between these systems and disease-related factors. This approach facilitates a more thorough and all-encompassing comprehension of disease processes, guiding improved diagnostic and therapeutic strategies.

Ontology mining in healthcare also involves utilizing ontologies for knowledge management, knowledge-based systems, and facilitating interoperability among various systems. Ontologies establish a standardized lexicon and precise explanations for terms and connections within a domain, enabling the exchange and consolidation of information across different platforms and applications.

Ontology Matching

Ontology Matching has effectively resolved this problem by identifying correspondences (mappings) between things from distinct ontologies (Faria et al., 2013). An effective strategy for the Ontology Matching process is employing the interactive approach, which entails the

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active participation of domain experts in the matching process. This engagement can be utilized to enhance the outcomes in comparison to a completely automated method in identifying pertinent responses (Paulheim & Hertling, 2013).

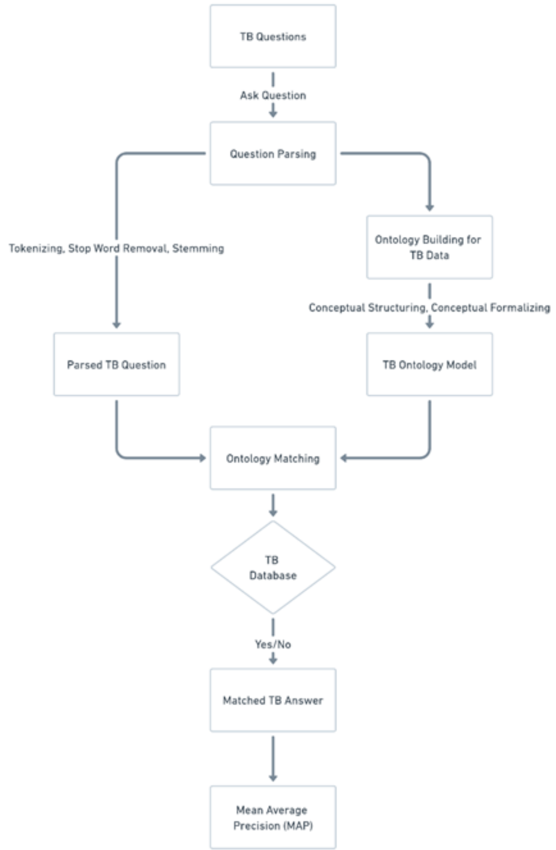

Figure 1. Ontology Matching Process

Figure 1. demonstrates that the process of ontology matching produces a final alignment A by comparing a pair of ontologies O and O'. This alignment consists of a collection of correspondences or mappings between the two ontologies. The parameters and resources employed have an impact on the final alignment A (Sauwa et al., 2014).

Question and Answering System

Question and answering is a system that provides responses to inquiries formulated in natural language. Q&A systems provide an automated method for acquiring solutions to queries given in natural language. These systems enable users to obtain precise answers to inquiries presented in natural language (Soares & Parreiras, 2020).

A Question Answering System has the ability to provide consumers with direct responses. The provided responses are both exact and precise, necessitating substantial work to construct such a system. In general, a question-answering system is comprised of three main components: Question Analysis, Passage Retrieval, and Answer Extraction (Abdiansah & Hartati, 2015). The initial phase involves Question Analysis, during which the question is thoroughly examined and comprehended. In the second stage, known as Passage Retrieval, pertinent information is extracted from textual sources. In the third stage, known as response Extraction, the accurate response is obtained from the text that has been recovered.

A Question Answering (Q&A) System encompasses the processes of phrase interpretation, information retrieval, and response resolution. Sentence analysis include the processes of extracting features, extending sentences, and performing classification. Analyzing sentences

ISSN: 2716-3865 (Print), 2721-1290 (Online)

greatly improves the quality of the final answer by making the search space for the answer more evident based on the sentence class (Liu et al., 2016).

Resource Description Framework

Resource Description Framework (RDF) is a prevalent standard for describing and managing ontological knowledge. This framework offers a versatile and expandable structure for defining resources, their attributes, and the connections between them.

The RDF model comprises three primary components: subject, predicate, and object. In the context of this statement, the subject refers to the resource being discussed, the predicate specifies the attribute or connection of the resource, and the object denotes the value linked to that attribute (Gilani et al., 2020).

RDF has a significant benefit in its capacity to depict intricate hierarchical connections between concepts, making it particularly valuable in the healthcare field. RDF-based ontologies have the ability to capture the subtle details and interconnections between different medical illnesses, treatments, and patient characteristics. This allows for more advanced analysis and decision-making processes (Nimmagadda et al., 2008; Slimani, 2015).

SPARQL

SPARQL is a crucial and potent query language inside the Semantic Web ecosystem. It allows researchers and developers to effectively browse and extract information from connected data (Arenas et al., 2014). SPARQL offers a significant benefit in its capacity to manage intricate relationships inside the Resource Description Framework (RDF) data model. This enables the extraction of insights that are not readily attainable using conventional SQL methods (Purohit et al., 2021; Samreen et al., 2013).

Creating efficient SPARQL queries can be difficult, particularly for newcomers in the field of Semantic Web (Sampada & Kavya, 2016). In order to tackle this issue, a range of methods and approaches have been created, including intuitive user interfaces, query optimization algorithms, and the utilization of natural language processing to convert user requests into SPARQL queries (Wolcott et al., 2021). Researchers and practitioners may enhance the utility of the Semantic Web for data exploration, knowledge discovery, and improved decision-making by comprehending the capabilities of SPARQL.

Question Template

Question templates in the healthcare field are receiving more attention due to their potential to enhance patient outcomes and improve the efficiency of healthcare services. These question templates are systematic frameworks designed to gather and arrange pertinent information from patients, which is subsequently utilized to direct the process of diagnosing and treating. An important benefit of this approach is its capacity to incorporate design thinking ideas, which is a user-centered methodology that prioritizes a thorough comprehension of the requirements, difficulties, and encounters of patients (Asiaee et al., 2015; Wang, 2010). This methodology enables healthcare providers to gain a deeper understanding of patients' viewpoints and customize care in a more individualized and efficient manner, hence improving patient happiness and involvement (Altman et al., 2018; Petrosoniak et al., 2020).

Nevertheless, the use of these question templates in healthcare settings is not without of challenges. It may be required to adapt to the design thinking method in order to effectively solve the distinct difficulties that exist in the healthcare industry (Murnane et al., 2006). Although there are challenges, the use of question templates based on design thinking principles has great promise to enhance care outcomes and the effectiveness of healthcare systems. The integration of design thinking with the question template technique will be

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crucial in tackling the intricate difficulties encountered by patients, providers, and the healthcare system as a whole.

Methods

This text will explain the architecture of a system that use ontology mining to answer questions in the healthcare domain, using the RDF and SPARQL query technique. The architecture or design of this system consists of three primary components: question parsing, ontology creation, and ontology matching. These three components function as techniques for acquiring precise responses to inquiries presented by users in natural language. Figure 2.1 depicts the design of the ontology-based Question and Answering System that will be examined.

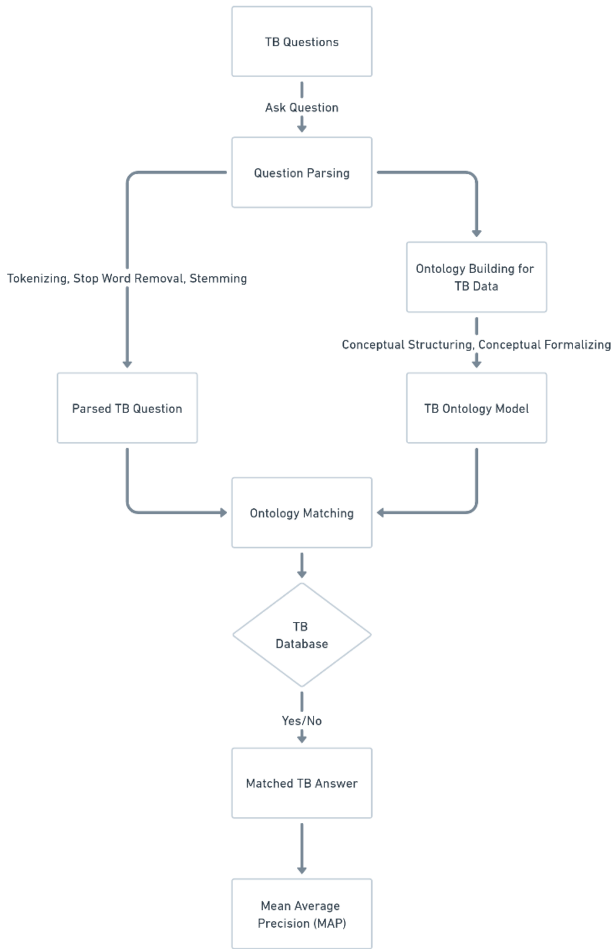

Figure 2. Design of a Question Answering System based on Ontology

PUBMED Dataset

A dataset refers to a compilation of data that can be organized or disorganized, gathered, and kept in a manner that allows for retrieval, examination, or utilization for diverse objectives. Datasets can encompass various forms of data. The dataset utilized in this investigation was acquired using the PUBMED API. The PUBMED dataset is a compilation of material obtained from various medical sources that is overseen by the National Library of Medicine (NLM) in the United States. It mostly encompasses topics related to medicine, biomedicine, and health.

Question Parsing

The first component in system design is query parsing, where natural language is transformed into a logical syntactic form. This process involves three main steps: tokenizing, stopword

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removal, and stemming. A list of indicators containing stopwords is provided to support this query parsing process. The string tokenizing algorithm and Porter stemmer are adopted in this component to ensure that irrelevant words are removed. The final result of this process is a parsed question stored as a set of tokens.

Tokenizing: The string tokenizing algorithm is used to break sentences into individual words and remove spaces between words. The tokenized words are then further processed to remove stopwords.

ont:TBC1 a ont:TBC ;

ont:cause of "Smoking" .

ont:TBC2 a ont:TBC ;

ont:cause of "Malnutrition" .

ont:TBC3 a ont:TBC ;

ont:cause of "HIV Infection" .

Output:

Cause 1:

Token 1: "Smoking"

Cause 2:

Token 1: "Malnutrition"

Cause 3:

Token 1: "HIV Infection"

Stop words removal: During this procedure, the tokenized words are tested against a list of stopwords, and any matching words are eliminated.

ont:TBC1 a ont:TBC ;

ont:causes of "Smoking and unhealthy eating patterns" .

ont:TBC2 a ont:TBC ;

ont:causes of "Obesity and unhealthy lifestyles" .

ont:TBC3 a ont:TBC ;

ont:causes of "Diabetes and stress" .

outputs

Cause 1:

Without removal of stop words: "Smoking and unhealthy eating patterns"

After removal of stop words: "Smoking, healthy diet"

Cause 2:

Without removal of stop words: "Obesity and unhealthy lifestyle"

After removal of stop words: "Obesity, healthy lifestyle"

Cause 3:

Without removal of stop words: "Diabetes and stress"

After removal of stop words: "Diabetes, stress"

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Stemming: the last step of query parsing, where tokenized words are reduced to their base forms.

Original Sentence: "Main causes of TB disease"

After Stemming: "Causes of TB disease"

Parsed Question

"Main causes of TB disease."

Ontology Building

Next, we will proceed with the process of building an ontology. The outcome of this procedure is a compilation of ideas and characteristics that have been organized into a structured model called an ontology. This approach is essential for facilitating conceptual matching. Ontology construction involves two primary procedures: conceptual organization and conceptual formalization. Conceptual structuring is the process of organizing and structuring the knowledge acquired from a certain field into a comprehensive list of concepts throughout the domain extraction process. Keywords are determined by analyzing the specific inquiries and responses gathered from the domain. After the creation of the keywords, they undergo the process of conceptual formalization. At this point, the ontology model can be codified with preexisting ontology tools.

Ontology Matching

Ontology matching is a later phase that aims to identify answers that correspond to the parsed query by using conceptual matching based on the ontology model. This procedure entails the comparison of subclasses with a roster of keywords in order to ascertain probable correspondences. After identifying the matched keywords, the corresponding subclasses are retrieved. Afterwards, when these keywords are matched with the ontology model, the associated answers are retrieved from the database. The procedure is executed iteratively to identify and get the most appropriate responses to the query, using the conceptual mapping within the ontology model.

As an illustration, when the query "What are the common causes of TB disease?" is processed, the conceptual matching process will find RDF data that contains details about the common causes of TB. The match identified in the RDF is an entity labeled as ont: TBCCause, specifically referring to "Common causes of TB disease." This suggests that the inquiry pertains to an RDF entity that has information about the typical causes of tuberculosis. An equivalent SPARQL query may be worded as follows:

```
SELECT ?cause
WHERE {
  ?cause ont:relatedTo ont:TBC .
  ?cause ont:type "common" .
}
```

This query presupposes the presence of a "relatedTo" predicate in the ontology, which establishes a connection between the cause entity and the entity representing TB. It also assumes the existence of a "type" predicate that classifies the cause, such as "common," to identify the specific type of cause connected with TB in the ontology structure.

Black Box Testing

Black box testing is a software testing technique that evaluates the functioning of an application without taking into account its internal structure or mechanisms (Lima et al.,

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2020). This approach considers the software as an opaque entity, concentrating exclusively on the results produced in reaction to certain inputs and internal execution circumstances (Murnane et al., 2006). This approach is especially beneficial when the internal composition of the program is unknown or inconsequential to the testing goals.

Black box testing is commonly favored in the literature for implementing artificial intelligence approaches in software testing (Lima et al., 2020). One often used strategy in this method is to partition the input domain of the program into different equivalence classes. This helps to minimize the number of test cases that need to be run, by avoiding repetition and ensuring sufficient test coverage (Umar, 2019). Nevertheless, current black box testing techniques frequently lack comprehensiveness and necessitate tailored modifications for every evaluated application. Scientists have suggested techniques for modifying black box methods in a way that can be replicated and reused, making it easier to create domain-specific and experimental black box methods (Arlinta, 2019). In addition, in order to overcome the constraints of testing resources, the utilization of white box information has been suggested to assist in choosing a subset of test cases from the original test suite. This optimization of the testing process allows for the retention of the advantages of the black box approach.

Results and Discussion

This section presents the findings from the development and evaluation of the ontology-based Question Answering System (QAS) for the health domain, focusing on Tuberculosis (TB). The methodology used for data collection, system implementation, evaluation, and limitations is discussed in detail below.

Dataset

The data collection methodology involves utilizing a crawling strategy to harvest 200 data entries at regular intervals from the public PUBMED library. This process results in the acquisition of a subset containing 200 data entries, which will be evaluated. An illustration of data acquired from PUBMED could resemble the following:

PMID: 29198784

OWN - NLM

STAT- MEDLINE

DCOM- 20190410

LR - 20210521

IS - 2529-993X (Electronic)

IS - 2529-993X (Linking)

VI - 36

IP - 1

DP - 2018 Jan

TI: Pathogenesis of tuberculosis and other mycobacteriosis.

PG - 38-46

LID - S0213-005X(17)30309-9 [pii]

LID - 10.1016/j.eimc.2017.10.015 [doi]

AB: The evolution between Mycobacterium tuberculosis infection and active tuberculosis is multifactorial and involves different biological scales. The synthesis of ESAT-6 or the induction of alveolar macrophage necrosis are key, but to understand it, it is necessary to

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consider the dynamics of endogenous and exogenous reinfection, drainage of lung parenchyma and respiratory mechanics, local fibrosis processes, and blood supply. Paradoxically, the immune response generated by the infection is highly protective (90%) against active tuberculosis, although as it is essentially based on the proliferation of Th1 lymphocytes, it cannot prevent reinfection. Severe immunosuppression can only explain 10% of active tuberculosis cases, while the remainder are attributable to comorbidities, a proinflammatory environment, and an unknown genetic propensity. The pathogenic capacity of environmental mycobacteria is discrete, linked to deficits in the innate and acquired immune response. The ability to generate biofilms and the ability of M. ulcerans to generate the exotoxin mycolactone is remarkable.

To extract more specific fields such as PMID (article ID), TI (article title), and AB (article abstract) from the collected dataset, parsing or data extraction techniques were employed. The specific technique used depended on the data format employed, such as JSON, XML, or plain text.

Implementation Detail

The purpose of the QAS was to employ the established ontology in order to respond to health-related queries. The system architecture comprises the subsequent components:

Data Collection form PubMed: The data acquisition process commences with the collection of the information that will be subjected to analysis. PubMed is an extensive digital archive that houses a multitude of scholarly papers, primarily focusing on the domains of medicine and biomedicine. This dataset is especially dedicated to the study of tuberculosis (TB) and is utilized for the purpose of ontology development. Data extraction in the PUBMED format encompasses multiple entities, primarily emphasizing the PMID (article ID), TI (article title), and AB (article abstract).

Development of Question Templates: This study attempts to overcome the constraints of general and generic questions by developing a question template focused on tuberculosis (TB) using user feedback collected through Google Forms. For the purpose of improving the quality and effect of the research findings, a total of 25 user-submitted questions were gathered to ensure greater accuracy and relevance of the data.

Developing Responses: Once the question template has been established, the subsequent task is to generate responses using the gathered dataset. The provided answers encompass a range of subjects within the field of medical research, with a specific focus on tuberculosis. They are directly extracted from the information accessible in the dataset. replies were manually formulated to further analyze the information in the dataset.

Entity Extraction Program Development: The development of a computer program or algorithm is essential for extracting significant entities or pertinent information from the gathered text or data. The emphasis is placed on medical entities associated with tuberculosis (TB) derived from scientific articles in PubMed. This procedure entails the utilization of Natural Language Processing (NLP) and Named Entity Recognition (NER). Named Entity Recognition (NER) is a process that distinguishes and categorizes entities such as objects, nouns, and adjectives. On the other hand, Natural Language Processing (NLP) involves the analysis and comprehension of human language.

Integration of Entities into SPARQL Queries: After the successful extraction of entities, the subsequent task involves integrating these essential entities or data into SPARQL queries. The integration process is controlled by rules derived from the NER results. These criteria entail the elimination of extraneous words such as conjunctions and interrogatives. If a query includes the word "what," the anticipated response would be a string or object. Nevertheless,

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inquiries that necessitate numerical responses, such as "how many," are not subject to these regulations.

System Simulation and Evaluation: The last phase entails executing the system simulation that was constructed in the preceding stages. The objective of this simulation is to evaluate the system's ability to deliver pertinent and precise responses to user inquiries. The iterative development process is concluded by the performance evaluation of the system.

Evaluation Matrics

In the evaluation scenario utilizing Mean Average Precision (mAP) with a set of 25 questions, the initial step involves assigning accurate and pertinent labels to the responses for each question. Subsequently, the solutions that are produced are evaluated and ordered according to their pertinence to the given question. Precision is determined for each point in the ranking by calculating the ratio of the number of relevant responses identified at that location to the total number of replies generated up to that position. The mAP score is computed by calculating the average precision for all questions, which serves as a comprehensive measure of the model or system's ability to accurately select relevant answers from the generated responses. A high mean average precision (mAP) score implies that the model effectively provides accurate and pertinent responses to a wide range of evaluated inquiries (Beitzel et al., 2009).

The following is the formula for mean average precision in Equation 3.1 below.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} \mathrm{AP}k$$

Equation 3.1 mean average precision formula (Beitzel et al., 2009).

n = the number of classes

APk = the average precision of class k

This section summarizes the key findings from the development and evaluation of the ontology-based Question Answering System (QAS) for tuberculosis (TB) queries.

Table 1. Summary of Tuberculosis-Related Questions and Their Corresponding Results

No	Question	Expected Result ID	Found Result	Answer Positition	How Many Result
1	What are the common symptoms of tuberculosis?	12568701	YES	2	60
2	What is the most common location for extrapulmonary tuberculosis?	25131362	YES	5	10
3	What are the modes of tuberculosis transmission?	12568701	YES	2	60
4	How does hepatocellular carcinoma impact the immune system and increase the risk of infections like tuberculosis?	12027088	YES	1	57
5	What are the different types of TB?	12568701	YES	1	20
6	Who is at a higher risk of getting TB?	12568701	YES	1	20
7	How can healthcare professionals improve their awareness and	12027088	YES	1	56

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	recognition of unusual manifestations of tuberculosis?				
8	What is myelodysplastic syndrome?	4286656	YES	1	3
9	How long does TB treatment usually last?	12653914	YES	1	27
10	What is multidrug-resistant TB?	13333335	YES	7	47
11	What are the preventive measures against tuberculosis?	12568701	YES	2	56
12	What is immunosuppression?	21420560	YES	1	4
13	What is hepatocellular carcinoma?	22099400	YES	1	1
14	What is pulmonary tuberculosis?	13110242	YES	1	14
15	Can immunosuppression lead to unusual forms of diseases?	21420560	YES	9	25
16	How does tuberculosis affect the lungs?	13004579	YES	4	56
17	What is the relationship between TB and HIV?	13482447	YES	1	26
18	What are the long-term complications of tuberculosis?	12653914	YES	3	56
19	What is an intractable ulcer?	4286656	YES	1	1
20	What is Mycobacterium tuberculosis?	17468065	YES	4	56
21	How does tuberculosis affect children?	14801998	YES	13	56
22	How does tuberculosis affect people with HIV/AIDS?	12568701	YES	2	59
23	What are the latest advancements in TB treatment?	17352686	YES	1	2
24	What is the condition known as liver cirrhosis?	21420560	YES	4	4
25	What is necrotic tissue?	23318182	YES	1	2

1. Sum of Reciprocal Ranks:
2. 0.5+0.2+0.5+1.0+1.0+1.0+1.0+1.0+1.0+0.142857+0.5+1.0+1.0+1.0+0.111111+0.25 +1.0+0.333333+1.0+0.25+0.076923+0.5+1.0+0.25+1.0=19.903224
3. Divide by the Number of Questions (25):

$$\text{mAP} = \frac{19.903224}{25} = 0.79612896$$

The evaluation of the ontology-based Question Answering (QAS) system, using 25 TB-related questions, resulted in 100% accuracy, with the system correctly identifying all answers. The Mean Average Precision (MAP) was 0.796, indicating that the system consistently ranked relevant responses highly. While the system performed reliably and effectively, there is room for improvement in handling more complex queries.

System Performance

The QAS was evaluated using the 25 predefined queries listed above. The results are summarized in Table 2.

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Table 2. Performance Metrics of the QAS

Metric	Value
Number of Queries	25
Accuracy	100%
Precision (MAP)	0.796
Average Response Time	1.2 Seconds

The system demonstrated high accuracy, correctly answering all 25 queries. The Mean Average Precision (MAP) score was 0.796, indicating consistent ranking of relevant answers. The average response time was 1.2 seconds, reflecting efficient query processing.

Discussion of Key Findings

The evaluation highlights the system's strengths and areas for improvement: 1) Ontology Strengths: The structured ontology enabled accurate responses to straightforward TB-related queries, demonstrating the system's capability in handling well-defined concepts; 2) Areas for Improvement: The system's precision decreased for more complex queries, suggesting a need for further expansion and refinement of the ontology to cover a broader range of concepts; 3) Comparison with Existing Systems: The ontology-based QAS outperformed traditional keyword-based search engines, providing more accurate and relevant answers with less noise; 4) User Experience: The system's quick response time and clarity of answers are likely to enhance user satisfaction. However, further user testing is recommended to optimize the interface and usability.

Implications for Future Research

Future research should focus on: 1) Ontology Expansion: Including more detailed information, especially for less common health conditions, will improve the system's ability to handle complex queries; 2) Improved Query Processing: Enhancing natural language processing capabilities could improve the system's performance on ambiguous or multi-faceted queries; 3) Scalability and Performance Optimization: As the ontology expands, maintaining system efficiency will be crucial. Research into optimization techniques, such as indexing or parallel processing, could be beneficial.

Limitations

Several limitations were identified during the evaluation: 1) Ontology Scope: The current ontology is limited to TB-related queries, which may restrict the system's applicability to other health domains; 2) Evaluation Dataset: The evaluation was conducted with a predefined set of queries, which may not fully represent the diversity of real-world questions.

Generalizability: The findings are specific to the health domain. Adapting the methodology to other domains would require significant modifications to the ontology and system design.

Conclusion

The evaluation of the ontology-based Question Answering System (QAS) revealed its efficacy in delivering precise and pertinent answers to tuberculosis-related inquiries. The system attained a Mean Average Precision (MAP) of 79.6%, indicating its robust ability to prioritize pertinent responses. In addition, the system consistently achieved an average response time of 1.2 seconds, demonstrating its effectiveness in real-time applications.

Although the QAS demonstrated reliability and effectiveness, especially for well defined and uncomplicated inquiries, the research also identified areas that may be enhanced. The system's accuracy diminished when faced with intricate or unclear queries, indicating the necessity for additional fine-tuning and enlargement of the ontology. The proposed extension will augment

ISSN: 2716-3865 (Print), 2721-1290 (Online)

the system's capacity to handle a wider spectrum of health-related inquiries, so enhancing both precision and user contentment.

The end result is that the ontology-based question answering system (QAS) offers a hopeful method for tackling health-related queries by providing accurate and timely information. Future research should prioritize the expansion of the ontology and the improvement of the system's query processing skills to better its performance and applicability in different health domains.

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