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Review of Semantic Importance and Role of using Ontologies in Web Information Retrieval Techniques

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Abstract—**The Web contains an enormous amount of information, which is managed to accumulate, researched, and regularly used by many users. The nature of the Web is multilingual and growing very fast with its diverse nature of data including unstructured or semi-structured data such as Websites, texts, journals, and files. Obtaining critical relevant data from such vast data with its diverse nature has been a monotonous and challenging task. Simple key phrase data gathering systems rely heavily on statistics, resulting in a word incompatibility problem related to a specific word's inescapable semantic and situation variants. As a result, there is an urgent need to arrange such colossal data systematically to find out the relevant information that can be quickly analyzed and fulfill the users' needs in the relevant context. Over the years ontologies are widely used in the semantic Web to contain unorganized information systematic and structured manner. Still, they have also significantly enhanced the efficiency of various information recovery approaches. Ontological information gathering systems recover files focused on the semantic relation of the search request and the searchable information. This paper examines contemporary ontology-based information extraction techniques for texts, interactive media, and multilingual data types. Moreover, the study tried to compare and classify the most significant developments utilized in the search and retrieval techniques and their major disadvantages and benefits.**

Keywords-component; Web Information Retrieval; Ontology; Semantics; Multimedia Information Retrieval

I. INTRODUCTION

Humans have been attempting to design an effective means of storing, browsing, and extracting information since the beginning of written languages. The notion of information extraction was initially restricted to the academic libraries' sciences. Researchers proposed that machine-based information extraction initiatives would become commonplace shortly worldwide [23]. People began utilizing devices for prompt information extraction in the early 1970s. However, those devices were primarily created for specific groups such as doctors, educational establishments, and government entities. Users began sharing enormous amounts of information in the textual form, visuals, sound recording, and multimedia as innovative technology and social-media usage such as LinkedIn, Facebook, Instagram, Twitter, Snapchat, WhatsApp, and Tok-Tok were created and regarded as "multimedia data." Due to the upsurge of communications technology users and devices, data in many domains such as eGovernment, eLearning, eBusiness, eCommerce began to grow rapidly. Thus, a programmable information gathering system was required instead of several specific processes initially designed for a specific group [22]. Information retrieval has become a tedious and time-consuming challenge due to the large volume of data and its diverse nature.

Numerous multipurpose search engines were established to tackle the domain mentioned above particular issues, and several generic purpose search engines were initiated that allured multiple users [46]. However, they were not proficient in contextually perceiving the add custom users' query and providing the most relevant response. Search engines mainly handled the concerns and recovered comparable solutions, frequently returning a slew of irrelevant web browsers to the subscriber [41]. A query can be a statement or a hashtag that the user enters, and browsers like Google respond with a positioned set of essential documents. Due to the complexity of the natural languages, it is difficult for the users to express their comprehensive data necessities. Most keywords used among consumers differ from those used among indexed files in the dataset. For instance, a user may inquire about what diabetes preventative measures practitioners recommend. In this scenario, the most pertinent answer can be found primarily on files that have the specific term practitioner or a synonym for it, including such qualified physician; therefore, to trace like these documents, it must be determined that both professionals and doctors are part of the same construct. To address this issue, several methods have been developed over the years to use theoretical knowledge and to help the users in expressing effective queries. The most frequently used approach to content understanding is integrating a dictionary element in IR mechanisms. It symbolizes the semantic correlations between different domain ontologies. A further process is to use content understanding, which is a built-in characteristic of IR systems. Such procedures have emerged as an essential tool in information processing, and the framework of IR has shifted from simple keyword-based initiatives to themes initiatives due to their use. Eventually, the researchers proposed the concept of domain-specific, wherein knowledge is linked to all relevant data in a machine-readable format [48]. Ontologies are used to incorporate this machine-understandable semantic information. RDF, OWL, RDFS, SPARQL, and other semantic languages are used in the semantic Web. The envisaged ontology-based approach demonstrated that theoretical modeling of data, like ontologies, was extremely helpful in retrieving the most pertinent information [42].

I have addressed state-of-the-art and current ontology-based conceptual information gathering methods and techniques such as “Text-based IR,” “Multimedia IR,” and “Cross-lingual IR”. In this paper, the author tries to do the comparison and classified the utmost contemporary various methods used to perform the aforementioned ontology-based information retrieval tasks. The importance of the Semantic Web in the realm of natural language evolution and its efficiency in information processing are briefly described in the first segment. I also went over contemporary knowledge interpretation models like conceptual maps and conceptual frameworks used to improve semantically associated information retrieval effectiveness. After that, the study provides an outline of the various methods recommended in the context of scriptural information extraction, preceded by interactive media and cross-lingual processing. The effectiveness of several suggested techniques in written text, interactive media, and cross-lingual pattern recognition is then compared. Subsequently, I had discussed future directions for annotation information extraction in the final stage of the study.

II. Semantic Importance in Information Retrieval

Speech recognition processing's ultimate goal is to comprehend and transfer facts and evidence expressed in a specific language. The semantics of information is critical to manipulating enormous amounts of information more efficaciously in substantial contexts. Data semantics is not just to reveal the actual content of the message but also to determine the framework of words used in the subject matter. It is found that adding suitable semantic and syntactic classification systems to the questions significantly improved question classification efficiency [10,38]. The researchers used various information sources to calculate “semantic-relatedness” between words [38]. The other researchers also looked at different WordNet-based conceptual similarity metrics and their implementations in the realm of web-based information extraction [18].

Due to the rapid growth of text information, word mismatches are occurring [5]. Due to the ambiguity issues of the language, a single word may indicate similar concepts [3, 12]. Due to these reasons, the information contained has proven to be an essential element in information retrieval because it is comprehensively used in the frame of reference of the matching process, which significantly improves the search results. Semantic data feature extraction can extend the semantic content of a user's preference to make it more impactful. By enhancing the predefined query with additional semantic features, semantic augmentation enhances the effectiveness of a system query in aspects of information gain. Semantic data restoration is constantly advancing and has become a catchphrase akin to "think outside the box" for all researchers and specialists. It goes faraway simple data and information extraction by employing information semantic meaning to aid data processing.

The researchers' work today is highly viewed as major revolutionary works toward the “semantic-based” information extraction field [49]. They fostered a Semantic Information Retrieval (SIR) framework that was tasked with responding to questions expressed in a dense type of English. SIR was written in the Speech impediment computer program and could comprehend semantic information. This program's capability was based on an underlying structure that connected parsed components demonstrated in a particular communicative statement using word associations and property lists. Semantic information was retrieved from input inquiries using a configuration function. After that, the system evaluated the inquiries to assess their forms and processed them appropriately. If a selected sentence was a declarative inquiry, the structure used to populate the model with the most pertinent information. Conversely, assuming that the provided sentence was a question, the framework either returned the response to answer or ascertained why this was not found in the model parameters. SIR could resolve semantic uncertainties in the search request and alter the model's framework to conserve computer memory.

Semantic analysis has transformed IR and is widely found in different fields such as the semantic Web. Ontologies, the cornerstone of semantics, is built using semantic features. Several researchers have developed semantic contexts of the semantic Web. The researchers used the semantic Web to retrieve information [9]. They created a prototype that enabled people to annotate their queries with semantic information from existing conceptual frameworks. Utilizing annotated semantic features increased precision over simple regular text retrieval techniques. In [20], the author used semantic Web for biological and medical patent extracting knowledge and information extraction. The researchers aimed to use web applications to bring the current semantic data to individual and custom information extraction [50]. The researchers try to automate the process of semantic annotation which is intended to observe semantics in the semantic Web [36]. Unmonitored information processing was used to create seed documents by [13,14]. They made the Sem-Tag System that automatically classifies massive corpora with semantic information [14]. Also, studies are being done working on developing deep learning ontologies [9, 21,40].

Semantic systems or waypoints are the most prevalent ways of representing knowledge for complex information [11]. Semantic networks use visualizing to show concepts and their relationships in vertices and edges. The devices in the report show the ideas are there, and the contours show how they are related to each other in terms of semantics. They have already been used a lot in semantic-based information extraction.

The researchers published an in-depth article on the theme map displays information gathering [30]. They emphasized that semantic channels and maps compress a plethora of information into a relatively small space and reveal associations between semantic information, familiar concepts, and documents. In [34,47], authors developed the "Grant System" to facilitate the identification of funding mechanisms through resource constraints disseminating activation. They discovered a significant increase in user engagement and a significant increase in prediction accuracy values compared to convolutional neural network (CNN) systems. The author proposed a fragmented mentoring inference engine based on a participant network. In their neural framework, they distributed file indices across the system based on the semantics of the papers as determined by latent semantic archiving (LSA) [47]. One such reduced search costs because all semantically similar indices were located in the exact location in this network.

Similarly, the author evaluated self-generating semantic maps [28]. They used Kohonen's identity map process to optimize a semantic layout and implemented it in a collection of documents. Map data facilitated the browsing and handling of bibliometrics. Thus, the various efforts on “semantic memory and maps” demonstrate that semantic-based retrieval outperforms key phrase document retrieval by a wide margin.

III. Role of ONTOLOGIES in Information Retrieval

Ontologies represent hierarchical structures of machine-readable, comprehensible, and processable data [43]. A supercomputing ontology is made from highly heterogeneous grouping or categories formed by domain precise terms, character traits, and entanglements. Ontology could be used for sentiment analysis information retrieval to improve retrieval, term annotation, text categorization, and IR framework. Following is a brief discussion of ontology's role in semantic information extraction:

A. Query Expansion

The semantic information similar to statements observed in the underlying domain particular ontology is used to broaden the user request [7].

B. Resolution of Term Disambiguation

Interpretive paradigms relating to the same notion are resolved [37].

C. Document Classification

Using ontological concepts to categorize documents and aid in query expansion [16].

D. Enhanced IR Model

Incorporating ontology into an established IR model to obtain a customized and improved data retrieval model due to semantic classification effects [1, 17, 33]. Ontology was used in various information search projects for a multitude of reasons, which are explained below:

- Semantic Digital Library (SDL): As a body of knowledge, SDL has used ontology. The subject matter and metadata including all files are inserted into the ontology to enable fast information retrieval.
- Crime News Retrieval (CNR): For the aim of fostering semantic-based retrieval of information, CNR has modeled named entity recognition [32].
- Multi-Modality Ontology-Based Image Retrieval (MMOBIR): MMOBIR had also postulated several ontologies, including text-based ontology, graphic ontology, and website ontology, to characterize images in aspects of textual, video, and context embedding. MMOBIR also demonstrates how these ontologies could be ingrained in DBpedia (an open-sourced experience and understanding database) to aid the deep investigation.

Insignificant contexts, ontology offers a strong and formulaic depiction of data for making it processable, easy to share, and recyclable [3,4]. For example, the researchers used an ontology model to generate aural media information. They outperformed trifling keyword-based information extraction proposals significantly [44]. Similarly, in [52] author used an ontology like an information provider of topic knowledge to enhance the impact of a single recognition system. Furthermore, the author used ontology to boost the effectiveness of a constitutional search engine [51]. They revealed that ontology benefits users greatly by implying pro version words. The researchers have utilized ontology in the semantic IR process to help classify web content on the fly [19].

Similarly, user queries may contain terms from multiple domains, making it difficult for the search strategy to select an accurate domain ontology. In [15], the researchers recommended a filter feature selection methodology in response to this problem. The semantic terms discovered by combining numerous semantically similar ontologies were added to every user query [1]. When no semantic classification could be found, the WordNet ontology would supplement the user request with semantic aspects [3,5].

IV. Types of multilingual information retrieval

A. Text-based Information Retrieval

The necessary semantic relatedness between query words or terms and corpus has made ontology-based content retrieval difficult for researchers. The vector space model, alternatively referred to as the vector representation, is one in which notions of records and inquiries are depicted as vectors. Their resemblance is estimated using the trigonometric measure. The similarity score measure identifies the extent of resemblance between one vector of text document and a search vector. Likewise, other well-known clustering methods such as TF-IDF vectors and BM25 are being used in vector spatially IR, but have not been applied to the Ontological-IR system. Additionally, ontologies are critical for extracting constructs from files and enquires.

The researchers proposed an ontology-based IR procedure that extracts concepts from queries [39]. Their model hypothesizes key aspects for a query were already visible in established ontologies like WordNet. Using ontology, a collection of conceptual frameworks for each file was extracted. The retrieved ideas were then contrasted to the request concepts, and a scoring system was estimated to rank the files. They utilized 1239 MEDLINE documents with the keyword Cystic Fibrosis to analyze the best system's integrity.

The authors added semantic customization to the annotation IR system [9]. They adopted an ontology-based collection structure and classified each domain principle with a user personalized score. Using the above method, the reference model between search terms and file concepts was acquired, and afterward, the user interest score (individualized score) was added. Each file was given a good score and statistically analyzed. They also offered a means to switch the extent of personalization automatically. They utilized 145,316 docs from CNN's webpage to evaluate their design protocol.

In [24], the author introduced a similar strategy for Arabic context-learning. They compared query and file similarity using a cosine similarity metric. It has used a conceptual framework to score records and semantic connections to enable assumptions across all requested documentation. For the semantic information of the document, researchers suggested a generic vector space model combining entities (NEs) and search terms [8]. They used NE's signifiers, identifiers, and categories. All propositional media's static or semantic data for communication in Wh-queries was represented using entity classes. They used TREC data to experiment. A domain-linked ontological concept was created first from the query's semantics. They used ontology to expand query semantics. The entire collection was classified with ontological constructs to find documents that were semantically connected to the user's query. The user was then straightened and returned. The suggested model surpassed other key phrase approaches in their tests. The author proposed ontology-based IR. Their approach relies on a foundation taxonomy generated from Contextual Information or a lexical data system [33]. They added an ontological stack mapping component to the core taxonomy. They developed a weighting scheme for the vector space. That way, they could avoid vocabulary mismatches and minimize vector dimensions in IR.

B. Retrieval of Multimedia Information

It is a general procedure to explore, index, store, and audio and video pictures, video content, audio, 3d animation, or their combinations in the present era. Data in the shape of voice, video, and pictures are deposited in desktop computers and on the World wide web. With the increasing use of social media networks such as Facebook and Twitter, the collection rate of data sets such as images, electronica, and video files has multiplied. Multimedia is regarded as the most straightforward method of disseminating information. To illustrate, consider WhatsApp, which allows for text messenger. People happily share voice messages and text pictures over simple text messages because they've found more comfortable visual features. As a result, the use of such multimedia services is growing at the same rate as faster than light, making media retrieval an essential task in IR. However, the challenge of characterizing visual features and using them more effectively for content examination and retrieval arises. To address these concerns, multimedia recovery techniques were designed, in which descriptive characteristics from pictures and audio information were retrieved and traced to high-level query functionalities. However, the steady expansion of web content has made the computation and development of project amounts of multimedia content time-consuming. According to a study, there were nearly eight terabytes of web data in 1999, and the size of Internet traffic doubled every two years [35]. Approximately 7.7 zetas visualized in the figure were revealed on the internet at the outset of 2016, and it is predicted to hit roughly 40 zeta bytes by 2020.

Furthermore, MIR is a disparate domain with a diverse set of research concerns, methods, and substantiated data types such as sound, visuals, pictures, motion graphics, video files, rich text, HTML tags, and an amalgamation of each of these [2,25]. The rack percentage of data sets such as images, songs, and video content has skyrocketed over time. As a result, there is a growing demand for productive audio-visual search and retrieval methodologies for web users.

To continue making the MIR framework more human-centered, the system's response must be precise to satisfy the user. In pursuit of various multimedia assets, many consumers use distinct MIR processes such as Google for video and image search, Altavista to search for audio files, and several others. Furthermore, there are numerous MIR seminars and conferences, including ACM and SIGMM. MIR programs are generally used to meet two primary user needs: i) exploring and (ii) surfing the Web with media summaries [18]. There are primarily two types of techniques to meet these two requirements: feature-based and classification. In recent years, classification methods have gained popularity due to their ability to assert media semantic information, a valuable aspect of IR.

Researchers have shifted toward information strategies and technology is advancing at a breakneck pace [3,6,26,27, 45]. Furthermore, non-textual information has become more prevalent than textual data, so it will soon become a common method of sharing data. Given these patterns, a thorough examination of all state-of-the-art recovery strategies for non-textual, audio-visual data is required. Information extraction systems, such as internet search engines, are well common and highly available, whereas interactive media IR systems are not well developed and are less widely available.

C. Text-based Image Retrieval (TBIR)

TBIR processes are most often used in web applications for picture retrieval [32]. This method employs text connected with the image, such as a data file, web address, or annotation. This text often explains what the image contains. When one customer uses a textual inquiry, numerous strategies are used to rectify the polysemy issue before extracting key phrases from it. The query is then tagged using these keywords. The dataset includes searchable or labeled images compared to annotated queries, with the most matching images returned as a result.

Fig. 1 depicts the architecture of text-based image feature extraction.

It is suggested that an ontology-based IR framework with a soccer context application [29]. They primarily concentrated on three challenges in information retrieval: expandability, recovery performance, and functionality. They enhanced retrieval performance by employing inference, rules, and an URL information applicator. They suggested a framework for semantic archiving based on Apache Lucene to improve the capability of keyword-based search by offering retrieved and implied information using ontology. They have used a searchable model to solve the functional ambiguity problem. Because of the productive semantic archiving model, this method achieves the most facets of the metadata. Fig. 2 depicts the architecture of content-based image feature extraction.

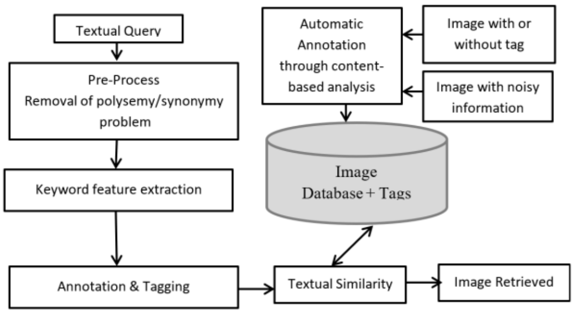

Figure 1. The architecture of text-based image retrieval feature extraction

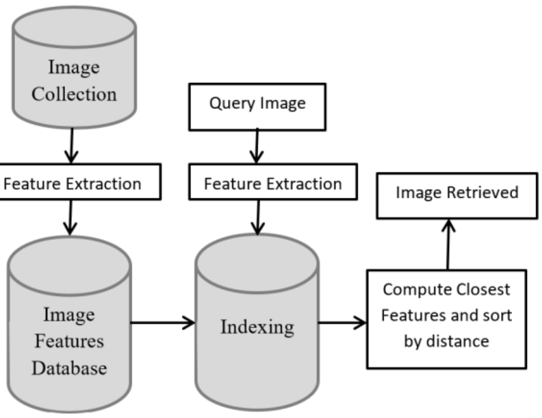

Figure 2. The architecture of content-based image retrieval feature extraction

D. *Video Retrieval*

Digital information is rapidly expanding due to the phenomenal advances in digital devices to encapsulate it. Documents, pictures, audio, and video files are all examples of digital data. As it includes all other electronic pictures, audio, and words, visual is an essential digital media that holds a wealth of information. A video search algorithm is the retention of information from a video dataset based on the user's needs. To handle such a vast database, effective data recovery methods are required.

The text-based video retrieval method obtains videos based on text existing in videos, such as text-based subtitles, titles of performers, and position of events, among other things [31]. Textual portions such as characters, phrases, phrases, and frames of text data are assessed within video sequence in text-based extracting features. These keyframes must be labeled based on the text-based data contained within them. Optical Character Recognition (OCR) devices are typically used to retrieve text data from videos. Categories are being used to extract data, which can be used as search terms for indexing. Fig. 3 depicts the architecture of a content-based video information retrieval.

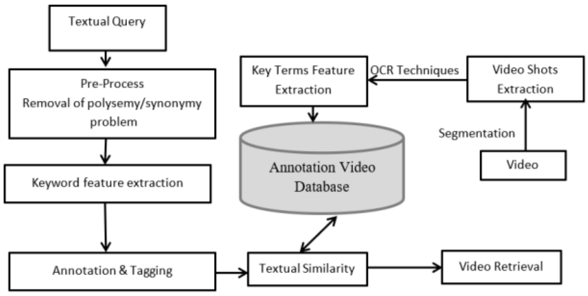

Figure 3. The architecture of content-based video information retrieval

Ontological text-based video retrieval methods are essential for searching an artist's album, an art form of songs, and event occurrences depending on the geographic locations discussed in videos. These strategies are also valuable for library resources of educational videos for online educational applications. The choice of the best OCR platform is a limitation for such techniques, and all these methods do not assess the videos semantically. As a result, investigators' emphasis has changed to video rather than just text. Fig. 4 depicts the architecture of content-based video retrieval.

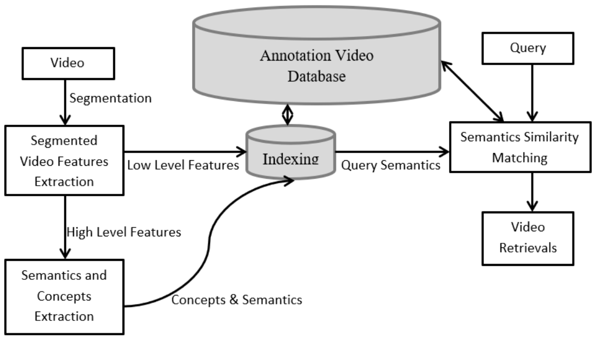

Figure 4. The architecture of content-based video retrieval

V. DISCUSSION

This section highlights and compares the performance of various frameworks presented in the search for written text, multilingual, and interactive media retrieval concerning the field of expertise and evaluation methods. The outcomes among several available texts, videos, and inter-lingual information retrieval methods. In [7], authors developed a scheme for text-based information extraction that uses context-based semantic retrieval effectiveness based on themes similarity to enhance the accuracy of search engine results.

RDF frequent patterns are being used to contain source information, and query ideas are paired against established RDF triples rather than keywords. This allows the browse structure to concentrate on the concept combined effect and the resemblance of their relationships simultaneously. Before transferring it to the Semantic matcher, the user search is augmented with semantic area and synonym. Then, triple browsing and semantic similarity are carried out. Eventually, all outcomes are ranked based on their relevance to the user's request. They compare the correlation between recall and precision in indexing and retrieval specific keywords, simple semantics, and semantic neighborhoods. They review that a keyphrase information system achieves minimum and maximum values of 0.74 and 0.16, respectively, particularly in comparison to 0.83 and 0.37 for a basic semantic-based search engine.

Notwithstanding, semantic IR with the conceptual neighborhood has correlation statistics of 0.81 and 0.48, suggesting a significant relationship between recall and precision. Furthermore, researchers proposed an ontological indexing approach that considers the background of query phrases to discover accurate results from a database regarding a relatively insignificant text base search that extracts results specific keyword match [34]. In [20], the author suggested ontology-based IR, which significantly improves the efficacy of IR. They incorporate a fuzzy ontology generated automatically from documents. They evaluate the efficacy of TF-IDF-based IR, TFIDF-based IR utilizing searching (WordNet), and IR to use a variety of ontologies. They assess the top 1000 extracted feature documents from all existing techniques. They conclude that IR efficiency increases by 2-6 percent in average accuracy and 1-7 percent in mean average accuracy. TFIDF, TFIDF with search queries, and ontology-based IR generate mean exact average figures of 53.11 percent, 48.31 percent, and 54.69 percent, respectively. In [19], the author recommended a three-layer semantic-based archiving approach with an accuracy of 73.1 percent, which is 12.2 percent greater than regular index-based IR.

Similarly, it is suggested that an ontology-based IR technique enhances file retrieval [43]. They tested their proposed methodology on data sets and found that it surpassed the standard approach on all of them. On one of the test datasets, the ontology-based IR strategy shows the highest F-score of 77 percent, compared to 70 percent for the benchmark strategy. Furthermore, it is posited that a semantic query growth technique uses patterns, conceptual frameworks, and IR methods to boost the effectiveness of results pages [44]. The proposed approach outperformed all three scenarios, notably SLIPPER, metadata advancement with conceptual frameworks, and shows many resemblances and semantic query growth without ontologies, with an F-score of 12.70% compared to 9.20% on TREC5 data. Furthermore, in terms of top 20 ranks (P@20), their approach achieves an estimate of 21.01 percent, compared to 16.02 percent for other strategies. They have presented a dynamic data gathering method that combines choppy ontology with easily verified alliance search techniques to boost efficiency.

Furthermore, envisioned a key-phrase semantic retrieval conceptual model that improves performance through semantic archiving, ontology-based information retrieval, and deductive reasoning [47]. They slithered 10 UEFA contests for experimenting, obtaining 1180 commentaries and 901 events. They created an index using the extraction of information and implied knowledge to assess over ten soccer-related concerns. Over six queries, this indicator achieves an overall accuracy of much more than 97 percent. In [33], the author introduced an ontology-based semantic information augmented platform that aids in discovering cloud computing suits the needs of various users. Their proposed framework generates an archive accompanying cloud storage to enable the quest for consumer infrastructure. The system is tested using an ICT ontology of 500 web services and five distinct academic queries published for ten predetermined digital services. The proposed method achieves an ordinary F-score of 0.81 and 0.82 for single and multi-topic queries.

VI. CONCLUSION

Semantic-based data retrieval is afflicted by a slew of issues, including the scarcity of semantic forms of knowledge, assessment milestones, data sources, efficient IR techniques, and the inevitable development of the domain. Similarly, multimedia content retrieval has yet to tackle the obstacles of the semantic disparity between subscriber query keywords and interactive media resource attributes. Another significant restriction in interactive media IR is the scarcity of large datasets indexing classifiers required for highly directional multimedia features. On the other hand, cross-lingual information extraction lacks substantial resources, including such corpora, ontologies, and idiomatic expressions for several well-known languages (e.g., Arabic). Furthermore, cross-lingual feature extraction has yet to resolve the knowledge discovery challenges, which has proven to be a significant barrier for many scholars and practitioners. To exceed expectations in the field of information extraction, satisfactory research in translation software, instantaneous ontology acquiring knowledge from unstructured information, and semantic data interpretation and extraction are required.

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