ADVANCED INFORMATION RETRIEVAL SYSTEM

THEORETICAL AND EXPERIMENTAL PERSPECTIVE

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Advanced Information Retrieval System: Theoretical and Experimental Perspective

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Advanced Information Retrieval System: Theoretical and Experimental Perspective

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FOREWORD

Information Retrieval is considered a remarkable AI-driven system due to its outstanding progress and continuous assessment. Information retrieval is applied in computer science, medical data analysis, statistics, as well as in blogs and newspapers, due to its interdisciplinary nature. Theoretical aspects of IR form the basis of any scientific discipline. The initial four to five chapters of the proposed book provide a theoretical understanding and comprehensive review of IR techniques. The subsequent chapters will then transition to more advanced techniques, such as AI, deep learning, and data mining, for applicability in real-life chapters. Theory without experimental results is incomplete, so the authors have added a significant portion to support the experimental perspective.

This book encompasses both theoretical and practical approaches in relation to real-world applications. The book will cover the latest methods in AI, big data, data mining, multimedia retrieval, and personalization. What makes this book different is its systematic presentation, including foundational areas like indexing, ranking algorithms, query processing, relevance feedback, and evaluation metrics, as well as newer topics like semantic retrieval, integration of machine learning techniques, and user behavior modeling. Not only does it foster learning, but it also encourages innovation, which has served as a great foundation for academic research and system development.

The book will be valuable for students, academicians, and researchers, presenting the integration of the latest technologies for building more efficient and effective IR systems. The authors are certain that the proposed book will make a significant contribution to the field of information retrieval.

It will work as a good reference book for graduate and post-graduate students, containing a wide range of topics from basic concepts to advanced experiments. This book also provides a detailed discussion on experimental design, data collection, and evaluation metrics, assisting researchers in designing robust and reliable IR experiments. Identification of emerging trends helps researchers identify new opportunities for their problem statements. For academicians, it acts as a valuable resource for a structured and detailed course on both theoretical and experimental perspectives in the field.

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PREFACE

Nowadays, servers contain a lot of information, but extracting or retrieving the meaningful information is a challenging and complex task. Information retrieval is required in multidisciplinary fields, including medical, computer science, media, linguistics, blogs, statistics, encyclopedias, and many more. Technological advancements in computer vision, artificial intelligence, and data mining have significantly influenced IR systems. These days, users' expectations are very high, which has influenced the traditional IR systems into fast, precise, and relevant search results. Various information sources, such as multimedia, internet sources, books, newspapers, social media, and big data, have presented new issues and prospects in IR.

The theoretical aspect will provide a comprehensive understanding of the primary theories and methods that support IR systems, but the experimental methods will support theoretical models in real-life applications. The latest developments will be reviewed and discussed in this book, such as NLP, data mining, AI techniques, web search, and contextual search. The IR system will be evaluated on parameters, such as recall, precision, accuracy, reliability, used requirement, security, and many more. The issues with the IR system will be identified along with future directions for researchers and academicians. This book will serve as a comprehensive resource for students, researchers, and academicians.

ACKNOWLEDGEMENTS

The journey of writing "Advanced Information Retrieval System: Theoretical and Experimental Perspective" has been both intellectually inspiring and immensely rewarding. This book would not have been possible without the support, guidance, and encouragement of many individuals and institutions.

First and foremost, I express my heartfelt gratitude to my mentors, colleagues, and peers, whose valuable insights and constructive feedback have significantly contributed to the depth and quality of this work. Their expertise has been instrumental in refining the theoretical concepts and experimental approaches presented in this book.

I am also deeply thankful to my institution and the research community for providing a conducive academic environment and access to essential resources that facilitated my exploration of advanced information retrieval systems.

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CHAPTER 1

Evaluating Traditional and Modern Information Retrieval Techniques

Abstract: The vast data sources use Information Retrieval (IR) methods for accessing the required information. The classical methods of IR, like Boolean retrieval and vector space, are fundamental for search strategies. The integration of these techniques with artificial intelligence will improve the accuracy of information retrieval. The research work compares the working of both the classical and modern information retrieval techniques. The comparison provides the merits and demerits of both methods so that information retrieval can be made more intelligent. The classical methods include Boolean retrieval and Term Frequency - Inverse Document Frequency (TF-IDF), while the modern method is Bidirectional Encoder Representations from Transformers (BERT). The authors have used the MS MARCO dataset for training and testing purposes. The authors have calculated precision, recall, and F1 score to evaluate the research work. From the simulation of work, it has been noticed that modern information retrieval methods can reduce the computational cost and enhance the accuracy of retrieval.

Keywords: BERT, Information Retrieval (IR), Modern IR techniques, Traditional IR techniques.

INTRODUCTION

IR methods are used to find the relevant information from the huge data store. We all know that due to the digital era, information is growing very fast, so advanced IR methods are required to retrieve the required information. The IR methods find the issues in user queries and huge datasets, and also confirm that the retrieved information is accurate. The IR methods easily process the unstructured data that is present in multiple formats containing text, images, audio, video, PDF, and many more. The property of handling diverse types of information enables IR methods to fulfill the information needs in various domains such as digital libraries, search engines, and web searches.

The classical techniques of IR, like Boolean retrieval and TF-IDF, depend only on keyword matching and statistical techniques to assess the documents. Because of

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the simplicity of these techniques, they provide fast results but lack in capturing deeper semantic meanings behind the words. The new techniques enable the intent of the contextual meaning of search, resulting in improved results and user experience [1].

Fig. (**1**) shows the process of information retrieval in detail. Both classical and modern types of techniques are analyzed in the research work. For the implementation of the research work, the MS MARCO dataset has been utilized. The dataset is divided into training and testing to validate the experimental results. The performance metrics are calculated for the analysis of the work. The research work is divided into 5 main sections, and each section validates the work based on some common parameters. Graphs and tables are used to analyze the research work.

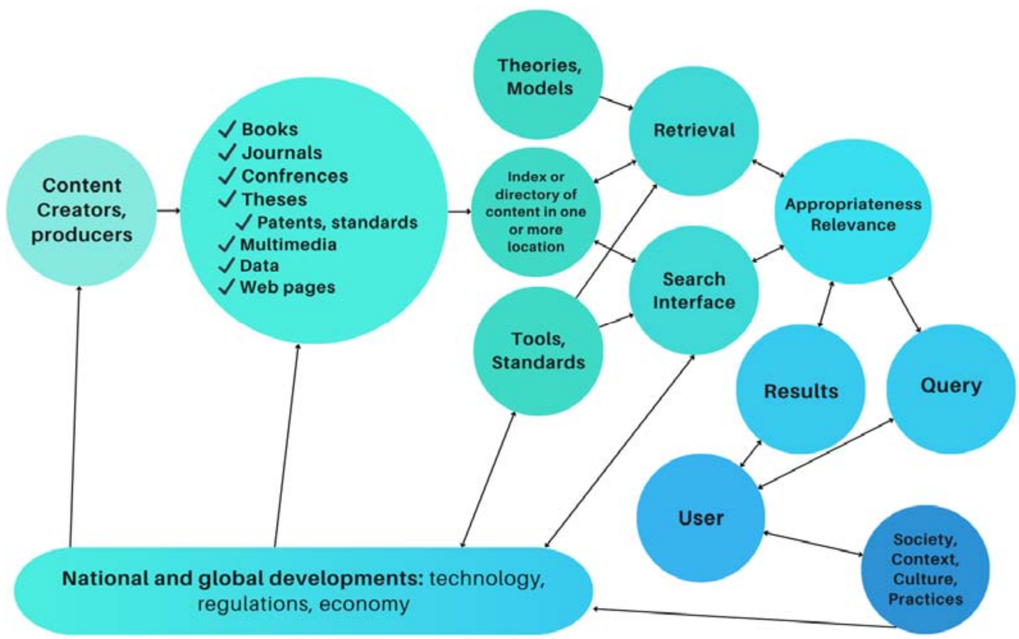

Fig. (1). Information retrieval system.

RELATED PAPERS

A Comparison of Usability Techniques for Evaluating Information Retrieval System Interfaces (2009)

The paper evaluated the Web of Science interface using two different usability techniques, advocating for a multi-technique approach to comprehensively assess

IR interfaces. The need for integrating usability techniques into IR design is emphasized, highlighting a gap in current research [2].

A Survey on Various Architectures, Models, and Methodologies for Information Retrieval (2013)

The introduction of the paper sets the stage by explaining the fundamental components of the IR process, which include queries, documents, and search results. It highlights that users typically create queries using a small set of keywords to express their information needs [3].

Comparative Study of Information Retrieval Models used in the Search Engine (2014)

The paper focused on IR methods. It analyzes different IR models' performance. Key models include Boolean, vector space, and probabilistic models. The study evaluated the precision and recall of these models. It aimed to identify user queries effectively [4].

A Comparison of Information Retrieval Models (2014)

The design of web search systems often fails to consider user needs, impacting the effectiveness of IR. Understanding user behavior and search techniques is crucial for identifying relevant information tailored to individual users. The paper discussed three mathematical models—Boolean, vector space, and probabilistic models—that represent documents and calculate similarity to user profiles, emphasizing the importance of personalized search processes [5].

Review: Information Retrieval Techniques and Applications (2015)

IR is a subfield of computer science focused on the organization and retrieval of information from large databases, aiming to satisfy user queries. The IR process involves several stages, including indexing, filtering, searching, and matching, ultimately leading to the retrieval of relevant documents. Key measures for evaluating IR systems were precision and recall, which assess the relevance of retrieved documents against user queries [6].

Generating Clarifying Questions for Information Retrieval (2020)

Search queries are often short and ambiguous, complicating the identification of user intents; result list diversification is a common solution, but asking clarifying questions can enhance user interaction, especially in conversational systems. User studies indicate that clarifying questions not only improve functional outcomes but also provide emotional benefits, instilling confidence in users about the search

CHAPTER 2

Comparative Analysis of Different Information Retrieval Methods

Abstract: Information Retrieval (IR) techniques are growing continuously from being keyword-based systems to advanced search. These days, IR techniques utilize Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) for providing more accurate and personalized results. In the proposed research work, the IR techniques are analysed for their merits and demerits. In the work, it has been examined how contemporary research has been transformed into query document matching. This work integrates Term Frequency-Inverse Document Frequency (TF-IDF) into two retrieval metrics—cosine similarity and dot product similarity. Integration aims to provide better results. Cosine similarity is good at capturing vector orientation, while dot product similarity is good for vector magnitude. A combined similarity is weighted at parameter α to enhance the retrieval capacity. From the simulation of work, it has been calculated that the combined method performed well. In the future, authors will incorporate machine learning or deep learning methods to enhance the performance of these IR techniques.

Keywords: Information retrieval, Term frequency-inverse document frequency, Cosine similarity, dot product similarity, Retrieval Augmented Generation (RAG).

INTRODUCTION

As digital information is growing day by day, IR techniques need to be more accurate so that the required information can be retrieved on time. To improve the IR system, the authors analyzed different IR techniques to find the merits and demerits of the existing methods. There is a significant improvement in IR techniques if we consider the growth from traditional techniques to modern techniques. Modern techniques can handle diverse data and retrieve accurate results on time [16]. Due to the exponential growth of digital data, the components of search range from educational content to social media, transport, e-commerce, healthcare, and many more.

The user experience is improved by maintaining scalability and confirming the relevance of the content [17]. Fig. (**1**) represents some measure functions that are

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required to be performed before the process of actual search starts, such as understanding how to formulate the query using some special keywords like OR, AND, NOT, *etc.* [18]. First, we need to understand the classical methods and then apply the modern methods for information retrieval. The data needs to be stored in a structured way for efficient query retrieval. The text pre-processing includes tokenization, stop-word removal, stemming, and much more needs to be done. Users are also required to capture the semantic relationship in data. The dimensions of data are also required to be reduced so that hidden relationships can be captured on time. Fig. (**2**) shows the different components of the IR system.

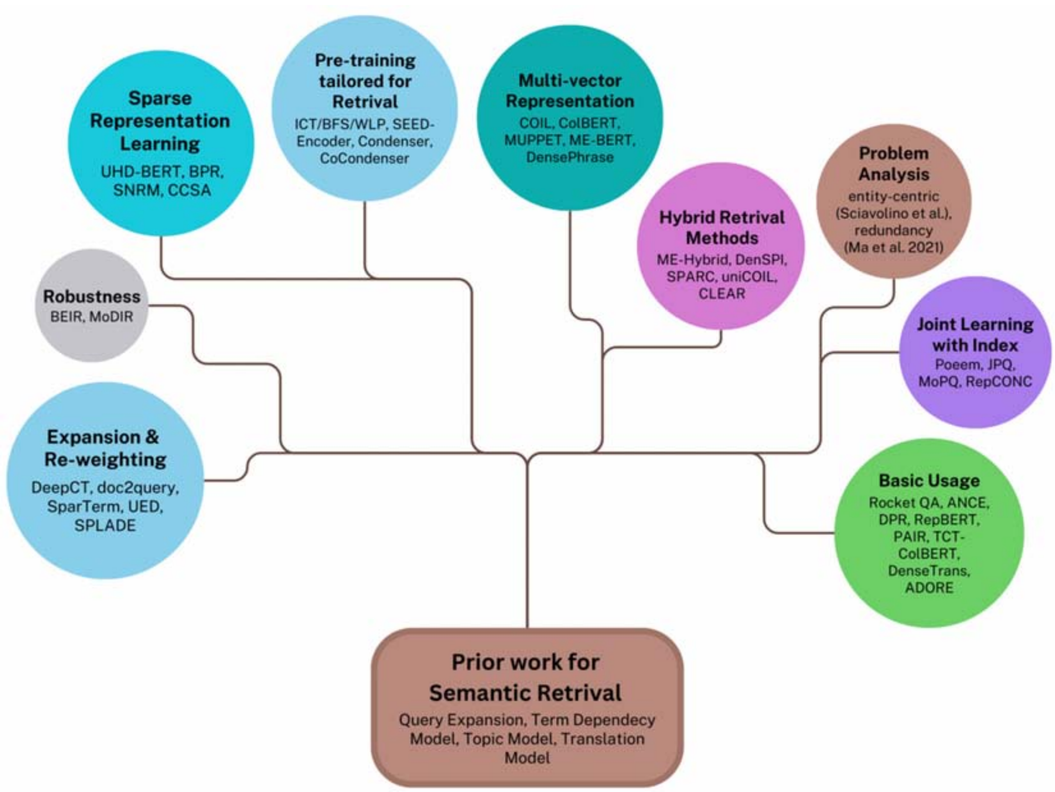

Fig. (1). Prior work for IR methods [18].

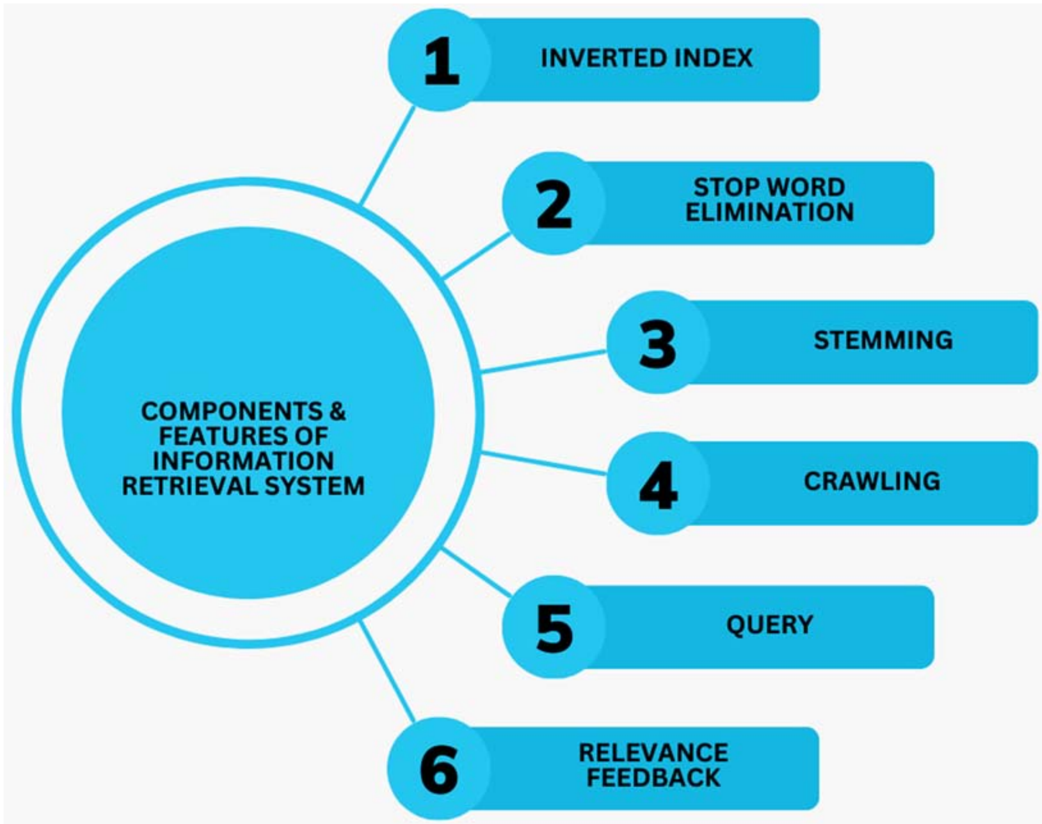

Fig. (2). Components of IR [19].

The paper is organized into a total of 5 sections. Section 1 is about the introduction of IR. The general prior steps, along with the components of IR, are explained. Section 2 discusses the literature review with the help of a literature summary table. Section 3 is about the proposed methodology, in which the proposed techniques are discussed in detail along with their merits and demerits. Section 4 presents the results and discussion, and graphs are used to explain in detail. Section 5 is the conclusion section, along with the future scope.

LITERATURE REVIEW

In paper [16], novel IR methods are used to employ generative models to link queries to related document identifiers. The work has been analyzed to enhance query generation excellence, examine learnable identifiers, and improve scalability, as well as integrate GR with multi-task learning frameworks. The author [17] proposed a model of integration of NLP and ML. It is based on a court case summary data. The proposed method automates citation retrieval by applying

CHAPTER 3

Comparative Analysis of Collaborative and Content Filtering Techniques on Web-Scraped Data for a Tourism Recommender System

Abstract: The significance of an improved user experience in recommender systems will continue to grow as tourism advances. Most such systems generally offer information to users that benefits third-party firms' commercial interests, often involving the implicit compromise of user privacy. In the proposed work, a tourism recommendation system is developed by the authors to deliver personal recommendations to users. For designing the proposed recommendation system, the authors have considered parameters such as ratings, user activity, time utilized by the user, certifications, and other relevant attributes. Four methods: Memory-based Collaborative Filtering (MCF), Matrix factorization Collaborative Filtering (MFCF), Cosine Similarity Content Filtering (CSCF), and Term Frequency-Inverse Document Frequency (TF-IDF) are used by the authors for designing a tourist recommendation system. For the assessment of the work, the authors have calculated Mean Average Error (MAE) and Root Mean Square Error (RMSE).

Keywords: Tourism recommended model, Content-based Filtering (CBF), Collaborative Filtering (CF), Web scraping, and cold-start problem.

INTRODUCTION

Due to advancements in technology, the tourism industry has also changed a lot. Technology has both positive and negative impacts on the tourism industry [34]. Personalized recommendation models have become a fundamental requirement for improving user experience in the tourism industry. There exist many different methods to create a recommendation system that can suggest destinations, experiences and activities as per users' preferences [35]. A recommendation system uses a huge amount of user data to recognize patterns and make predictions, thus enhancing customer satisfaction and engagement.

Most recommendation systems are made using four filtering techniques- system demographic, content, hybrid, and collaborative [36]. This chapter focuses on the development and comparison of recommendation systems using four approaches

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namely MCF, MFCF, CSCF, and TF-IDF. The MFCF model is also known as the model-based content filtering. The techniques are studied and compared on data through web scraping from a tourism website. The dataset includes user activities, ratings, time taken to perform these activities, and other relevant attributes essential for building an effective model. The performance of the 4 approaches is evaluated and compared using MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error).

Fig. (**1**) signifies how the CBF method works in detail. The user submits a query in the form provided to them. From the queries, specific keywords are selected, and based on these keywords, features are identified in the images. After that, based on similarity in the retrieved documents, matching is done, and finally, the results are generated.

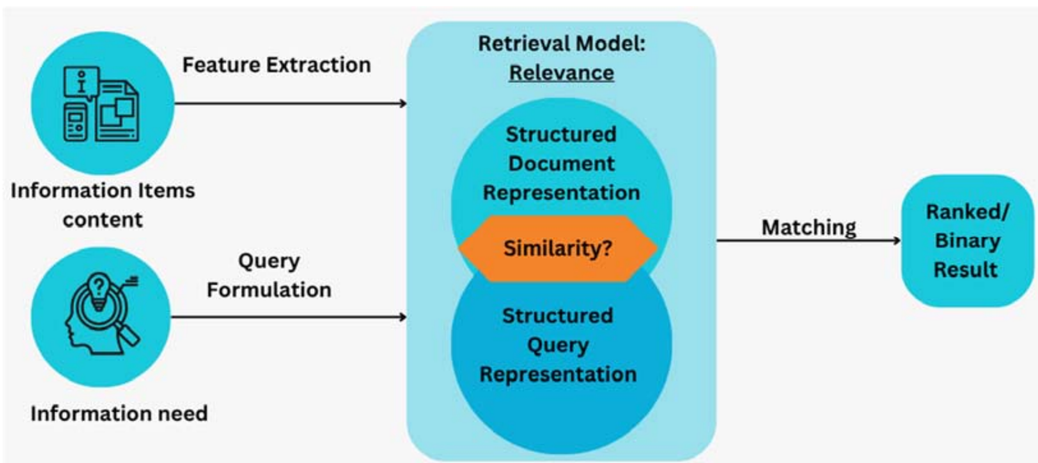

Fig. (1). Working of the CBF method.

Table **1** lists a detailed comparison of proposed recommendation techniques - a description, strengths, weaknesses, and best use cases. The chapter includes techniques, MCF, MFCF, CSCF, and TF-IDF.

LITERATURE SURVEY

This paper introduced a common evaluation framework for recommender systems with the new approach. They presented the new measure known as performance P to assess possibly different types of recommender systems. The framework describes how the end objective for recommendations is achieved by establishing a benchmark for further research [34]. Authors in 2012 focused more on aspects related to user experience than on accuracy in predictions. The authors claim algorithms need to be put into a user's context and introduce the idea that transparency, trust, and scrutability of recommendation systems are necessary. Authors perceive cold-start and scalability as significant challenges, pointing out the improvement of user interaction as an area of prime research interest [35].

Table 1. Proposed models detail [38].

Technique	Description	Strengths	Weaknesses	Best Use Cases
MCF	Utilises user-based CF by measuring likeness between users based on preferences. Uses correlational distance to find K-nearest neighbors (KNN), and averages ratings of KNN to predict unrated items for active users.	Easy to implement and interpret; good for users with sufficient history data; captures the tastes of similar users well.	Suffers from data sparsity and scalability issues; not ideal for cold-start problems; limited by the accuracy of user data.	Recommending items based on the preferences of similar users; effective for applications with large user activity datasets.
MFCF	Uses matrix factorization to discover hidden patterns among user-item interactions by factorizing the user-activity matrix. Optimizes with gradient descent and regularisation to reduce overfitting and enhance predictions.	Highly accurate; scalable, and effective for large, sparse datasets; resolves cold-start issues to an extent by predicting unrated items.	Requires significant computational power; difficult to interpret; needs extensive data to train the model accurately.	Suitable for applications with large, sparse data where predicting interactions with unrated items is crucial.
CSCF	Calculates similarity between TF-IDF vectors by assessing the cosine angle of different vectors. Creates user profiles from highly rated items and recommends items with high cosine similarity to user preferences.	Highly accurate for content-based recommendations; effective for cold-start issues; ranks items based on similarity scores, ensuring relevance.	Sensitive to feature vector quality; limited by the accuracy of TF-IDF representation; may result in repetitive recommendations.	Applications where personalized recommendations are key are especially useful for users with specific or niche preferences.

CHAPTER 4

An Information Retrieval-Based Framework for Analysing Viewer Sentiments in YouTube Comments

Abstract: The user engagement in YouTube comments could be utilized for sentiment analysis. The data is collected through web scraping from the YouTube comments. Natural Language Processing (NLP) and Bidirectional Encoder Representations from Transformers (BERT) are utilized by authors to analyze the sentiment of commenters. The current trends and user engagement in the market can be analyzed through YouTube comments. The thematic patterns are generated with the help of word clouds and sentiment distribution charts. Based on the outcome of the proposed work, it can be concluded that YouTube comments provide valuable feedback to researchers, which in turn can be used for sentiment analysis.

Keywords: Bidirectional Encoder Representations from Transformers (BERT), Natural language processing, User engagement, YouTube comments sentiment analysis.

INTRODUCTION

These days, everyone is using social media as a common platform to share their feelings, moods, habits, and opinions. This user-generated data is utilized by academics and researchers to identify trends and user engagement in the market [49]. The researchers are trying to find the current trends in the market, and YouTubers are utilizing this data to maximize the views on their content [50]. In the proposed work, the authors collected data through web scraping techniques, followed by pre-processing, and finally, analysis was done to determine the sentiments as represented in Fig. (**1**). The main aim of the chapter is to show how sentiment and theme analysis of YouTube comments can be used as an effective IR technique that provides insightful data on social media user behavior [51, 52].

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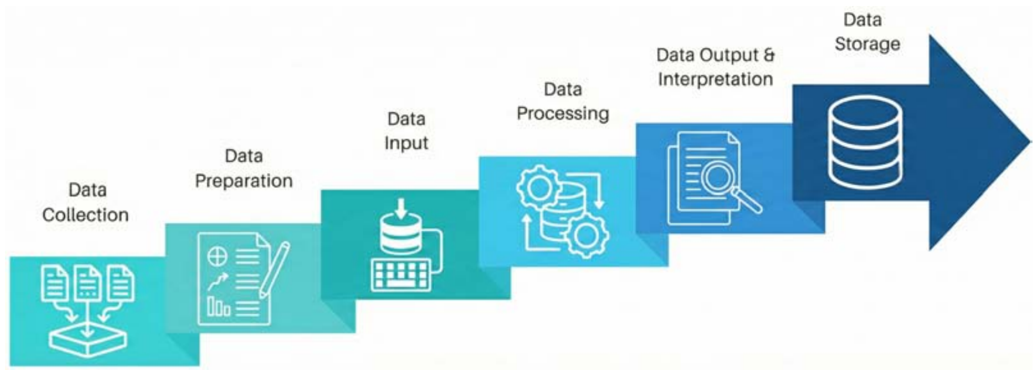

Fig. (1). Data pre-processing [54].

Authors add to the field of social media analysis in IR by visualizing thematic content and engagement patterns, demonstrating how automated methods can record and analyze sentiment from vast audiences [53]. The outcome of this chapter aims to provide a basis for further investigation of audience-driven insights in digital content ecosystems, informing research in areas such as sentiment analysis, user interaction modeling, and social media information retrieval.

Bias plays a significant role at various stages of the proposed framework, and if left unaddressed, it can adversely impact the overall results. This work encounters different forms of bias, including data bias, sampling bias, algorithmic bias, pre-processing bias, and model bias. For instance, if the collected comments are predominantly positive or negative, the sentiment analysis may become imbalanced. Sampling bias arises when only a subset of users—often those with extreme opinions—contribute comments. Algorithmic bias occurs when techniques disproportionately prioritize frequently occurring terms, potentially overlooking less common yet meaningful expressions. Pre-processing bias stems from the removal of stop words, non-English text, or emojis, which can carry important sentiment cues. Additionally, model bias may emerge if the sentiment classifier is trained on data that does not reflect the specific characteristics of YouTube comments.

The chapter carries five sections in total. Section 1 provides an introduction to the work. Section 2 provides the literature on the techniques related to the proposed work. After the literature review, the challenges have been listed, and based on those challenges, the problem statement has been created. In the next section, the proposed techniques are explained in detail. In Section 5, the results are discussed in terms of performance metrics. At the end, the chapter is concluded along with its future scope.

LITERATURE SURVEY

The basis for understanding and originating opinions from text, particularly utilizing lexicon-based and early Machine Learning (ML) techniques, was laid by Pang and Lee's work on sentiment analysis. They outlined techniques for sentiment-based text classification and highlighted some of the challenges in accurately interpreting complex language, particularly in informal online contexts such as social media. Their study opened the door for more advanced NLP methods that could better manage the complexity of user-generated content by highlighting the drawbacks of lexicon-based approaches, such as difficulties with context and sarcasm [49].

To identify trends, user interests, and content-related issues, Jaidka and colleagues performed a thematic analysis of social media posts. To classify and comprehend the primary themes in user comments—a useful tool for content analysis and user engagement research—their work employed refined NLP techniques. The work proved that thematic analysis might be utilized to analyse the theme structure of YouTube comments for the perseverance of creating targeted content because it is not only beneficial for retrieving subjects but also exposes latent interests within user discussions [53].

Latent Dirichlet Allocation (LDA) topic modelling and keyword extraction were used by Park *et al.* to find recurrent themes in YouTube comments. To help academics and content creators understand what appeals to audiences the most, their work proved that topic modelling might efficiently organize user comments into logical subjects. Through content alignment with these identified topics, brands can improve viewer engagement on YouTube channels. The proposed method worked well for analysing unstructured data and is very applicable to concluding the wide range of subjects covered in YouTube comment sections [54].

With a primary focus on Twitter data, Alam and colleagues created a computational framework that combines web scraping, NLP, and deep learning for extensive social media analysis. For handling massive amounts of unstructured text, their methodology demonstrated the efficacy and scalability of automated data gathering and analysis methods. This strategy is immediately applicable to the analysis of YouTube comments, where comparable methods may be used to gather and analyse enormous volumes of user feedback, allowing for the larger-scale extraction of useful insights [58].

CHAPTER 5

A Framework for Sentiment Mining in YouTube Comments Using Information Retrieval Methods

Abstract: With the continuous growth of user-generated data on social media platforms, its analysis requires a deep understanding of sentiment trends. Data from social sites is collected using web scraping techniques and then filtered for consistency through pre-processing methods. In this study, multiple techniques are applied to analyze YouTube comments. The BERT transformer model is used to classify comments into positive, negative, and neutral categories, enabling sentiment analysis and providing insights into user opinions and trends. Additionally, Latent Dirichlet Allocation (LDA) is employed for thematic analysis to identify key discussion topics within the comments. The performance of the proposed approach is evaluated using the F1-score metric. For future improvements, deep learning techniques could be explored to enhance the accuracy of sentiment analysis.

Keywords: BERT method, LDA method, Sentiment analysis, Thematic analysis, Web scraping.

INTRODUCTION

These days, everyone uses social media to share their thoughts, emotions, feedback, likes, and dislikes. YouTube is one of the common platforms for the exchange of views. The analysis of sentiments plays an important role in business, YouTube content creators, identification of frauds, and improved user engagement [66]. But it has been noticed that YouTube information is informal and unstructured. YouTube comments contain slang, different languages, emotions, abbreviations, memes, etc [67]. For addressing such types of issues, the authors proposed BERT and LDA methods. BERT performs sentiment analysis, and LDA performs thematic analysis. For the evaluation of the work, the F1-score is calculated.

Fig. (**1**) illustrates the features of an online IR system. This system offers centralized control and storage, enabling seamless access for multiple users. It operates significantly faster than manual methods, facilitating real-time communication without delays.

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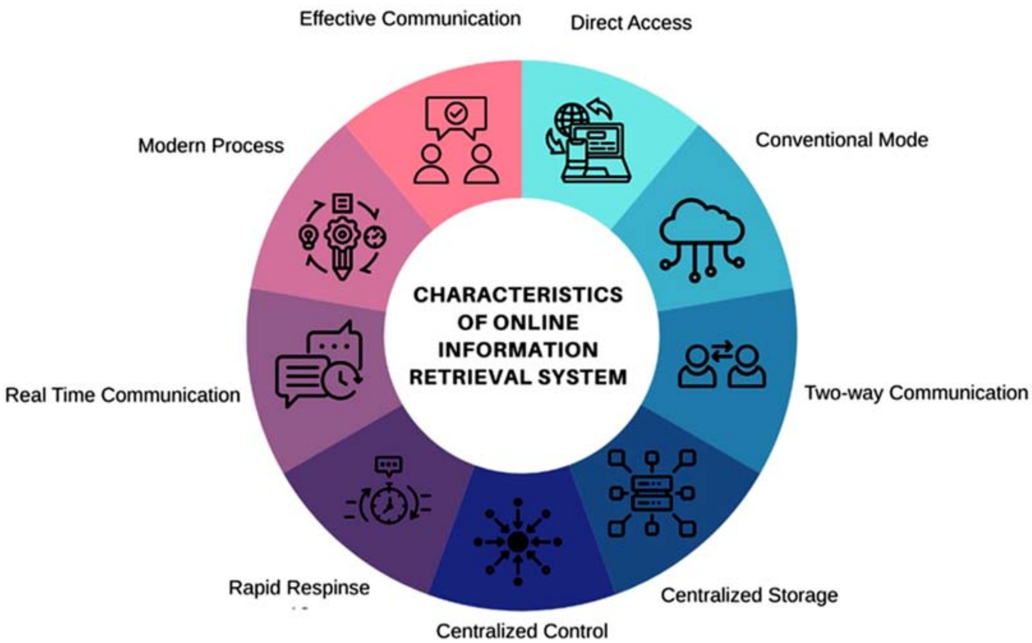

Fig. (1). Features of IR [69].

The online mode is considered the most convenient for information sharing, also enabling two-way communication between the sender and the recipient [68]. By leveraging modern processing techniques, it efficiently filters data. Since the data is stored online, users can access it promptly.

There are five sections in the paper. By outlining the background, driving forces, and goals of the research, Section 1 presents the introduction of the study. The literature survey is presented in Section 2, which reviews previous research and identifies knowledge gaps that this work fills. The methodical procedure used for data collection, pre-processing, analysis, and visualization is described in Section 3 name, Methodology. The main conclusions and a thorough examination of the results, together with their consequences, are presented in Section 4, which is devoted to results and discussion. The study's main contributions are summed up in Section 5, conclusion and future work, which also offers some possible directions for further research.

LITERATURE SURVEY

The basis for comprehending and deriving opinions from text, especially using lexicon-based and early machine-learning techniques, was laid by Pang and Lee's work on sentiment analysis [64]. They outlined techniques for sentiment-based text classification and highlighted some of the challenges in accurately interpreting complex language, particularly in informal online contexts such as social media. Their study opened the door for more advanced NLP techniques that could better manage the complexity of user-generated content by highlighting the drawbacks of lexicon-based approaches, such as difficulties with context and sarcasm. In [65], the NLP model was enhanced using an innovative design based on self-attention mechanisms. The proposed model effectively processes data within the context of user-provided information. Sentiment analysis was performed using the powerful transformer model, BERT, which efficiently handles cases where sentiments are often implicit and context-dependent.

Authors [8] utilized NLP, web scraping, and deep learning on social media data like Twitter and Alam. For handling massive amounts of unstructured text, their methodology demonstrated the efficacy and scalability of automated data gathering and analysis methods. This strategy is immediately applicable to the analysis of YouTube comments, where comparable methods may be used to gather and analyse enormous volumes of user feedback, allowing for the larger-scale extraction of useful insights. Some of the research gaps are listed as follows [55 - 56 - 70]:

- The majority of sentiment analysis research ignores multimodal inputs, including audio, video thumbnails, and engagement metrics, in favour of concentrating solely on text data. There is still a dearth of research on multimodal data integration.
- Sarcasm, irony, and colloquial language on websites like YouTube are difficult for many traditional sentiment analysis techniques to manage, which creates a gap in their ability to capture contextual sentiment accurately.
- The majority of current research concentrates on English comments, ignoring the multilingual content seen on social media sites like YouTube.
- Existing frameworks frequently find it difficult to manage the enormous amount of real-time, dynamic social media data. Finding scalable and effective sentiment analysis techniques is still difficult.
- The relationship between particular sentiments (positive, negative, or neutral) and engagement metrics like likes, shares, and comments is not well understood.
- Understanding temporal patterns in social media sentiment is lacking since sentiment research seldom takes into account how sentiments evolve.
- The confusion matrix technique is frequently ignored in existing research when it comes to detecting particular misclassification patterns, like differentiating between neutral and positive/negative sentiments.

CHAPTER 6

Sentence Interpretation and Semantic Role Classification Using BERT

Abstract: In the digital era, sentence interpretation is crucial for understanding the meaning of sentences. As a key component of Natural Language Processing (NLP), it helps identify relationships between words and determine their roles within a sentence. Semantic Role Classification (SRC) assigns semantic roles to different actions in a sentence, enabling deeper language comprehension. This study analyses various SRC techniques, with a particular focus on transformer models. It provides a summary of existing SRC methods, highlighting their advantages and incorporating a Continuous Integration/Continuous Delivery (CI/CD) pipeline for seamless deployment. The effectiveness of the proposed approach is evaluated based on the accuracy achieved.

Keywords: Semantic Role Classification, Sentence Interpretation, Natural Language Processing, Transformer Models, Machine Learning, CICD Pipeline.

INTRODUCTION

Understanding natural language is a complex challenge for tasks such as machine translation, question answering, and text summarization [77]. Sentence interpretation involves analysing the relationships between subjects, objects, action verbs, and prepositions [78] and is considered a subfield of NLP. Traditional SRC approaches are often time-consuming and lack accuracy. Modern SRC techniques leverage transformer models, significantly improving role-labelling tasks [79].

This chapter provides an extensive literature review covering SRC techniques, transformer-based methods, and CICD models for continuous improvement. Advancements in machine learning and transformer techniques have significantly enhanced SRC by capturing complex linguistic patterns and contextual dependencies.

Transformer models like Bidirectional Encoder Representations from Transformers (BERT), T5, and GPT have improved sentence interpretation, enabling more accurate semantic representations and refining role classification.

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In this work, SRC techniques are integrated with transformer models and CICD to achieve enhanced results.

Fig. (**1**) represents how information is stored in a database and how it can be retrieved whenever required. The administrator has the right to add, update, delete, or modify the data. The entered data is indexed by the indexing subsystem. The next interface is the user at the end level. Theuser submits a query as a combination of text, special symbols, numerical values, and emotions. The query processing takes place, and the result will be displayed to the user based on his/her query.

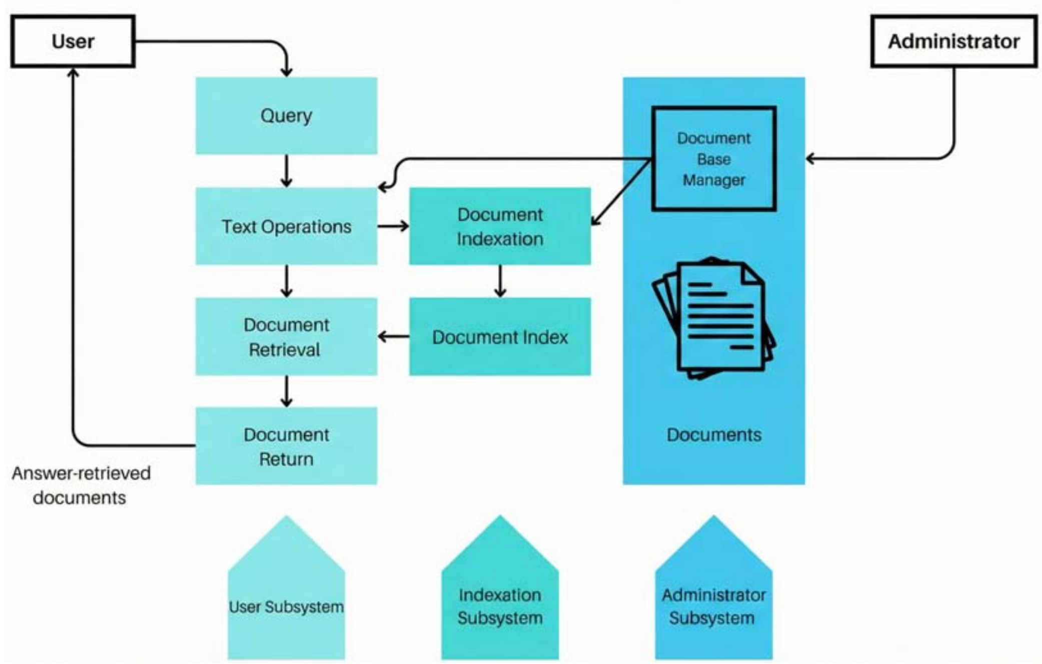

Fig. (1). Information retrieval system.

BERT is a deep learning model developed by Google in 2018 that has significantly advanced the field of Natural Language Processing (NLP). Built upon the Transformer architecture, BERT enables parallel processing of input text and supports bidirectional context learning — a key improvement over earlier models, which could only process text in a unidirectional manner. One of BERT's core innovations is the use of the Masked Language Model (MLM) during the pretraining phase, which allows the model to understand the context of a word based on both its left and right surroundings. Additionally, BERT incorporates Next Sentence Prediction (NSP) to help the model learn relationships between consecutive sentences, further enhancing its ability to capture deep semantic meaning in language.

The chapter is organized into five main sections. Section 1 is the introduction of sentence interpretation and semantic role classification techniques. In Section 2, a literature review is conducted based on related techniques. In Section 3, the BERT method is discussed in detail. In section 4, the results are discussed, and in section 5, the work is concluded along with future scope.

LITERATURE REVIEW

The SRC techniques have undergone significant improvements following the introduction of statistical models. In the paper [80-83], the authors have introduced PropBank, which is efficient in making annotations for sentences along with the semantic roles. Therefore, the classical models have been replacedby maximum entropy models due to these features.

In a study [84], Recurrent Neural Networks (RNNs) and Bi-LSTMs were utilized for sequential dependencies between words. In another study [85], the authors stated that the advanced models have removed the requirement of explicit syntactic parsing by using an attention mechanism. A study [86] introduced transformer-based models, which brought a significant leap forward in SRC.

Additionally, cross-linguistic SRC has emerged as a key area of research, where models were trained to perform SRC across multiple languages. The variation in the sentence structure and the role labeling between languages poses a significant challenge. Xia*et al*. (2020) explored the use of multilingual transformers like Mbert to handle SRC tasks across different languages, showing that a single pre-trained model could effectively generalize across diverse linguistic structures. A summary of the literature is given in Table **1** with author details, the dataset used for the implementation of the work, the outcome of the models, and the demerit of the work.

Table 1. Literature review.

Authors	Dataset	Method Output	Demerits
Palmer, Gildea, & Kingsbury (2005) [77]	PropBank	The feature-based method which is SVMs, was used. SVM attained a maximum entropy of 86.3%.	Limited ability to capture complex dependencies requires hand-crafted features.
Zhou & Xu (2015) [78]	PropBank	Bi-LSTM was applied with dependency parsing features, 89.1%.	Dependency parsing was computationally intensive and could introduce errors, impacting overall performance.

CHAPTER 7

Image-Audio Based Recommendations System for Information Retrieval

Abstract: This chapter presents the classification and analysis of fashion data, which consists of 90 images belonging to one class, using deep learning techniques. Data augmentation is done to pre-process the dataset. Features are retrieved using Convolutional Neural Networks (CNNs), VGG16, and ResNet50. These modes are trained on styles and patterns of images so that recognition can be done. For the styles and subtitles, another dataset of 144 audio files has been utilized. Voice is converted into text by using Machine Learning (ML) and Natural Language Processing (NLP) techniques. Pre-processing of audio files has been performed using Mel-Frequency Cepstral Coefficients (MFCC) along with normalization to reduce noise. The Recurrent Neural Networks (RNNs) technique converts the audio file into a text file. The proposed work is evaluated based on accuracy, reliability, and adaptability.

Keywords: Convolutional neural network, Image recommendation system, Subtitles recommendation system, VGG16, ResNet50, Mel-Frequency Cepstral Coefficients (MFCC), Recurrent neural networks.

INTRODUCTION

In the digital era, information plays an important role in the lives of users in various domains like media streaming, social media platforms, and e-commerce. Similarly, information retrieval techniques play an important role in identifying user preferences concerning the content they require [91]. These days, due to advancements in technology, information is available in various formats like text, images, audio, and video. The traditional techniques are not so efficient in analyzing this data [92]. So to resolve these issues, modern image and audio-based techniques are required [93]. Modern techniques revolutionized the fashion sector into a more intelligent recommendation system.

These techniques analyse the data and find patterns, trends, and latest designs. The proposed models were found to be the most suitable and complex relationships between the data [94]. For pre-processing, normalization, and augmentation methods are applied to the given dataset. Transfer learning is

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utilized to pre-train the dataset so that computational cost and time can be reduced [95]. The results are validated based on values of performance metrics.

NLP aims to bridge the gaps that still exist between human and machine learning [96]. NLP has a feature known as Automatic Speech Recognition (ASR), which transforms audio into text files [97]. To improve the accuracy of the converted text files, pre-processing is necessary to remove unwanted extra information. It also retrieves the required features, such as frequency, amplitude, and duration. These features are then mapped to phonemes, the fundamental units of sound, enabling the accurate interpretation of spoken words [98].

Fig. (**1**) illustrates various parameters that can be used to evaluate machine learning or information retrieval techniques. Precision, recall, F-measure, and ranking algorithms serve as quantitative metrics for evaluation. In contrast, the remaining parameters are qualitative and are used to assess techniques based on non-numeric criteria.

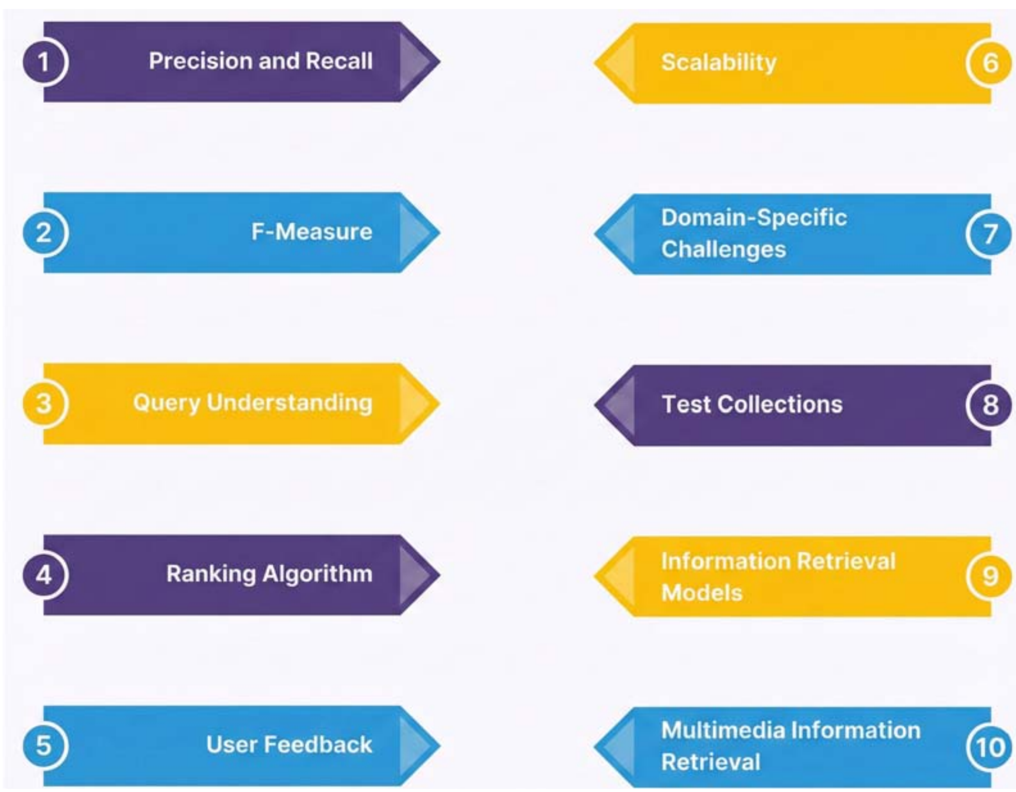

Fig. (1). Parameters for evaluation of IR methods.

LITERATURE REVIEW

Video content that is generated from social sites like YouTube and Netflix faces the cold-start problem. To address this, profound learning models can extract visual elements straightforwardly from the substance, like scene organization and variety ranges, bypassing the requirement for manual comments. This methodology [91], approved through disconnected and online tests, outflanked customary metadata-based strategies and further developed client fulfilment by settling the coldstart issue. Moreover, captions can be broken down utilizing NLP to remove topical data, upgrading proposal quality. Datasets like DeepCineProp13K and CineSub3K provide a foundation for future upgrades in recommendation frameworks.

The objective of this work [92] was to characterize and formalize a Multimedia Proposal Framework (MMRS), with an emphasis on Content-Based MMRS (CB-MMRS). MMRS utilizes mixed media content, including sound, video, and images, to provide personalized suggestions. This study features that MMRS is not restricted to explicit media types like music or video, yet can be applied extensively by examining visual, sound, and text-based information to develop proposals further. Unlike frameworks that depend on client appraisals or cooperative sifting, CB-MMRS extricates natural media highlights, for example, a variety of examples or sound attributes, empowering altered ideas even with restricted client information and resolving issues like the cold-start problem.

The study [93] not only presents another structure for assessing philosophies in this space but also proposes a customized suggestion model custom-made for image-based style ideas. This model aims to upgrade the exactness of proposals by coordinating high-level image handling with client-specific information, offering significant knowledge for design retailers trying to embrace simulated intelligence-driven answers for work on their tasks. By and large, this study presents the preparation for future exploration in artificial intelligence-controlled style innovation.

This study investigates the upgrading of recommender frameworks by coordinating textual and visual data, addressing the limitations of conventional TF-IDF-based approaches. While numerous frameworks center on restricted spaces like news, this work [94] influences semantic vocabularies, ontologies, and PC vision to remove further bits of knowledge from multimodal content, like films. By combining visual-semantic data from pictures with text data, the proposed cross-breed strategy more accurately captures client preferences. Utilizing cosine closeness and angle learning models, the Movie Lens dataset probes show that the methodology outperforms conventional techniques in

CHAPTER 8

Hybrid Book Recommendation System Integrating Collaborative and Content-Based Filtering Techniques

Abstract: Due to the digital era, there is a flood of information available online . Recommendation systems can be utilized to improve user experience. Authors in this chapter proposed to develop a hybrid book recommendation system using Collaborative Filtering (CF) and Content-based Filtering (CBF) techniques. The content filtering method identifies the features of the object, and then, based on those features, a decision can be made. Collaborative filtering works based on user interaction patterns. The proposed method overcomes the drawbacks of data sparsity in collaborative filtering and the cold-start problem in content-based systems. To overcome these issues, the dataset is pre-processed to find the popular books, ratings, and a list of active users. Authors have applied k-Nearest Neighbors (k-NN) for feature and metric selection so that the recommendation engine can work properly. The performance of the proposed model is measured in terms of performance metrics, and the outcome has proved that it is a precise and accurate recommendations model with high recall, precision, F1-Score, and accuracy metrics.

Keywords: Book recommendation systems, Collaborative filtering, Content-based filtering, K-nearest neighbours.

INTRODUCTION

Currently, in the digital world, recommendation systems are playing a crucial role. Recommendation systems are very helpful for making decisions. Some of the major application areas of the recommendation system are digital libraries, streaming platforms, and e-commerce. In the proposed recommendation system, the authors have selected two methods, which are CF and CBF. The working of CF depends on user actions, and CBF works based on the properties of the objects. Both approaches, however, have intrinsic drawbacks: CF is impacted by dataset sparsity and scalability constraints, while CBF frequently faces cold-start problems for new items or users [111, 112].

Hybrid recommendation methods, which combine the advantages of several approaches to provide more varied and accurate recommendations, have become a

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strong remedy for these drawbacks. The goal of the work is to create a hybrid book recommendation method that uses a k-NN algorithm to combine CF and CBF. The proposed work overcomes the limitations of the solo techniques utilized for the book recommendation. Authors have utilized publicly available datasets having details like book titles, ratings, and ISBNs. The proposed work is invaluable for use in a variety of ways.

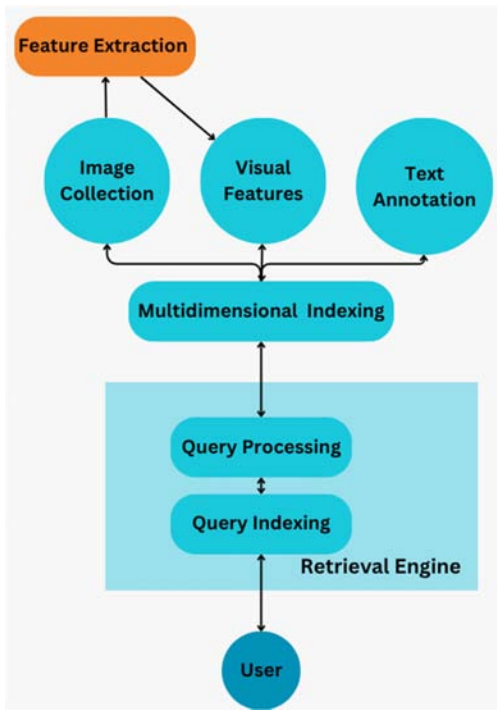

Fig. (1). Working of CBF.

Fig. (**1**) illustrates a working content-based filtering method for retrieving the required information. Initially, data is collected from different sources like forms, surveys, social media sites, interviews, questionnaires, literature, web scraping, commercial datasets, and many more. The information may be collected in text form or in the form of images. Then, the features are selected from the input, which is used to retrieve the required results.

While the hybrid technique enhances recommendation accuracy, it does not entirely eliminate underlying biases. Literature suggests that CF tends to be more biased than CBF. CF often favors highly rated or popular books, thereby marginalizing lesser-known titles. On the other hand, CBF recommends books that are similar to those previously read by the user, which can restrict diversity and limit the discovery of new genres or authors. Additionally, the proposed system is susceptible to the cold-start problem, where books with insufficient historical data—particularly newer or less-reviewed titles—are recommended less frequently than well-established ones. Furthermore, if user profiles lack comprehensive information such as name, age, interests, region, or preferred language, the system may exhibit cultural and demographic biases, affecting the fairness and inclusiveness of recommendations.

LITERATURE SURVEY

In Table **1**, a literature survey from the existing work in the field is conducted depending on various features available in the work. The techniques utilized by the authors are listed along with the merits of the work.

Table 1. Literature Survey

Authors	Objectives	Algorithms Used	Results
Rajalakshmi, S., *et al*. [111]	To create a personalized online book recommendation method utilizing hybrid machine learning approaches.	Hybrid Machine Learning	Improved recommendation precision and user satisfaction in online systems.
Paudel, Anil & Kandel, Deepak [112]	To develop a book recommendation system using hybrid methods of matrix filtering.	Matrix Filtering, CF	Enhanced accuracy and diversity of book recommendations.
S, Rashika [113]	To build a personalized book recommendation system leveraging TF-IDF and k-NN hybrid techniques.	TF-IDF, k-NN	Achieved high precision in book recommendations with effective text-based filtering.
Devika, P. & Milton, A [114].	To improve book recommendations using sentiment analysis and ensemble hybrid deep learning models.	Hybrid Deep Learning Models, Sentiment Analysis	Demonstrated higher accuracy and diversity in recommendations through sentiment integration.
Jiali Liao and Tianxiang Li [115]	To combine capsule networks and attention mechanisms for personalized book recommendations.	Capsule Networks, Attention Mechanisms	Achieved improved accuracy and relevance in recommendations for large datasets.
Chongwarin, J., *et al*. [116]	To enhance recommendation accuracy using user rating analysis and CF techniques.	CF	Delivered better user engagement and higher recommendation accuracy.
Pijitra Jomsriz, *et al*. [117]	To propose a hybrid recommender system model for digital libraries from multiple online publishers.	Hybrid Recommender System	Enhanced coverage and diversity in recommendations across multiple sources.
Paudel, Anil & Kandel, Deepak [118]	To implement a hybrid book recommender system.	Hybrid CF	Improved scalability and cold-start problem resolution

CHAPTER 9

Medicine Recommendation System using TF-IDF and Machine Learning

Abstract: Due to advancements in computer vision techniques, medical healthcare data is available to users in a very large amount. With the use of this data, an intelligent medicine recommendation system can be prepared. Authors in this chapter utilized Term Frequency-Inverse Document Frequency (TF-IDF) and Machine Learning (ML) for the development of an intelligent medicine recommendation system. The recommendation system recommends proper medicines by exploring the symptoms of patients and their medical history. The TF-IDF technique retrieves suitable features from the dataset and then applies machine learning for the classification of diseases and the recommendation of medicine to patients. The proposed recommendation system provides valuable and accurate suggestions to users, adding flexibility to the healthcare system.

Keywords: Medicine recommendation, Disease symptoms, Term Frequency-Inverse Document Frequency (TF-IDF), Machine Learning (ML).

INTRODUCTION

As computer vision techniques continue to develop, we now have sufficient data to analyze and develop a medicine recommendation system. The raw data presents several challenges. For designing a strong medicine recommendation system, the authors selected many parameters such as patient symptoms, complexity of data, diagnoses taken by patients, drug descriptions, and interactions with medical professionals. LR and SVM algorithms train the model based on the significant features retrieved through TF-IDF.

TF-IDF is a statistical approach that performs text analysis and finds the importance of words in the document. It identifies the words that are meaningful and efficiently differentiates one document from others.

Equation 1 is used to find how many times the word appears in the document [125]. IDF measures how rarely a word is present across all documents in the corpus, as signified by Equation 2 [126]. TF-IDF integrates two measures to calculate the significance of a term in a document, as shown in Equation 3 [127].

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$$TF(t,d) = \frac{Number\ of\ times\ term\ t\ appears\ in\ document\ d}{Total\ number\ of\ terms\ in\ document\ d} \tag{1}$$

$$IDF(t,D) = \log(\frac{Number\ of\ documents\ in\ corpus\ |D|}{Total\ number\ of\ documents\ containing\ t}) \tag{2}$$

$$TF - IDF(t,d,D) = TF(t,d) \times IDF(t,D) \tag{3}$$

Common words such as "the," "on," "our", or "and" are encountered in almost all documents, resulting in a low IDF value, making these techniques less important. Domain-specific words receive a higher score because they are less frequent in the complete corpus and are more commonly used in specific documents. Search engines are utilized for ranking documents depending on query significance. Features are retrieved for training ML algorithms, which are logistic regression and SVM. The recommendation system identifies key terms to propose relevant content. TF-IDF is a fundamental technique for jobs including text processing and remains the most popular technique despite the growth of deep learning-based techniques such as Word2Vec or BERT.

Logistic regression is the classification method used to classify as true or false. It finds the connection between input features and the probability of an outcome by using the sigmoid function. Equation 4 [128] signifies a sigmoid function for mapping detected values to probability in the range of [0, 1]. In Equation 5 [129], w stands for the weight vector, x stands for the input feature vector, and b stands for bias. The outcome of the sigmoid function signifies the probability of a positive class. If the probability exceeds the threshold, the occurrence is identified as a positive class; otherwise, it is classified as a negative class. In it, a linear boundary is used to separate two classes. The threshold is a numerical value used to find the cut-off point for making decisions.

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{4}$$

$$z = w^t x + b \tag{5}$$

SVM has its applications in classification as well as regression tasks. The SVM objective is to calculate the ideal hyperplane that splits data points of diverse classes in the feature space. Support vectors are the points near the hyperplane, and these points play a significant role in defining the location and orientation of the hyperplane. Margin is the distance between the hyperplane and the neighbouring data point of each class. The SVM algorithm attempts to maximize the gap between points to achieve generalized results.

The chapter overcomes the gaps between unstructured medical data and modern techniques. It offers an efficient, reliable, and scalable solution for a personalized medicine recommendation system.

These days, due to advancements in technology, lots of advanced information retrieval techniques have been developed. These techniques offer numerous benefits, as illustrated in Fig. (**1**). These techniques are scalable, which means their performance is not affected by the platform. Personalized recommendation systems are developed to get the latest trending medicines. These interfaces are user-friendly, and that is the feeling of the individual users. User queries are processed efficiently to provide accurate results. These advanced techniques provide high accuracy for the recommendation of medicines.

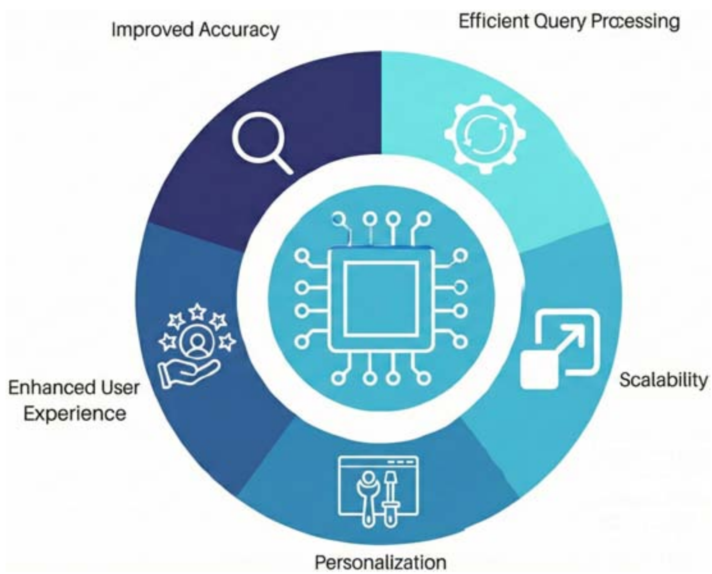

Fig. (1). Advanced information retrieval system.

LITERATURE REVIEW

The generation of radiology reports is a critical task for professionals. Accurate and reliable radiology report generation requires an experienced professional. The traditional method of generating radiology reports is very time-consuming and less accurate. To resolve these challenges, authors proposed an automatic deep learning technique that uses chest X-ray images to generate diagnostic radiology reports. The authors utilized novel text modeling and visual feature extraction strategies in the proposed work. The authors also designed a web portal that takes chest X-rays as input, and as output, a radiology report is generated. The work was evaluated on multiple parameters and compared with the existing work. The proposed work was found to be satisfactory [125].

CHAPTER 10

Image-Based Recommendation System for Various Fashion Styles

Abstract: The fashion industry has undergone a transformation thanks to the rapid development of computer vision, which has enabled the automatic classification and analysis of clothing products. In this work, Convolutional Neural Networks (CNNs) are used to categorize a varied fashion dataset with more than 15,000 images from Kaggle. The dataset's diversity of clothes and accessory categories reflects the intricacy of real-world fashion datasets. The authors focused on data preprocessing, augmentation, and fine-tuning to enhance the model's classification accuracy using a CNN. The aim of this work is to demonstrate how well CNNs handle visual diversity and identify patterns in the dataset while addressing issues such as dataset imbalance and inter-class similarity.

For validation of the proposed work, the authors have calculated accuracy, precision, recall, and F1-score. The outcome of the CNN model demonstrates that Artificial Intelligence (AI) has its application in the fashion industry, and performance metrics justified the work. The confusion metric highlights the merits and demerits of the CNN model. In the future, a bigger dataset could be utilized for the incorporation of transfer learning, resulting in enhanced accuracy.

Keywords: Artificial Intelligence, Convolutional neural networks, Fashion industry, Detection, Classification, Image-based recommendation systems.

INTRODUCTION

Due to the advancements in computer vision, applications of AI can be seen in various fields, including fashion, trend prediction, healthcare, education, and military, among others [157].

In this work, a CNN model has been utilized for the recommendation of fashion styles. The CNN could efficiently retrieve the features from input images from the complicated dataset. The dataset utilized by the authors is publicly available on Kaggle, and it has 15000 plus images of different apparel. The objective of this work is to handle the difficulties of fashion datasets having high inter-class similarity and varied visual representations [158].

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The dataset utilized in this work encapsulates the diversity of modern fashion, featuring items with varying styles, textures, and colors. Such variability often leads to overlapping features between categories, making classification a non-trivial task [159]. Fig. (**1**) represents how data can be collected from different means. Data collection is divided into primary and secondary sources. The primary way of data collection includes surveys, questionnaires, interviews, observations, experiments, *etc*. Secondary sources of data collection are literature reviews, government databases, web scraping, commercial databases, *etc* [160].

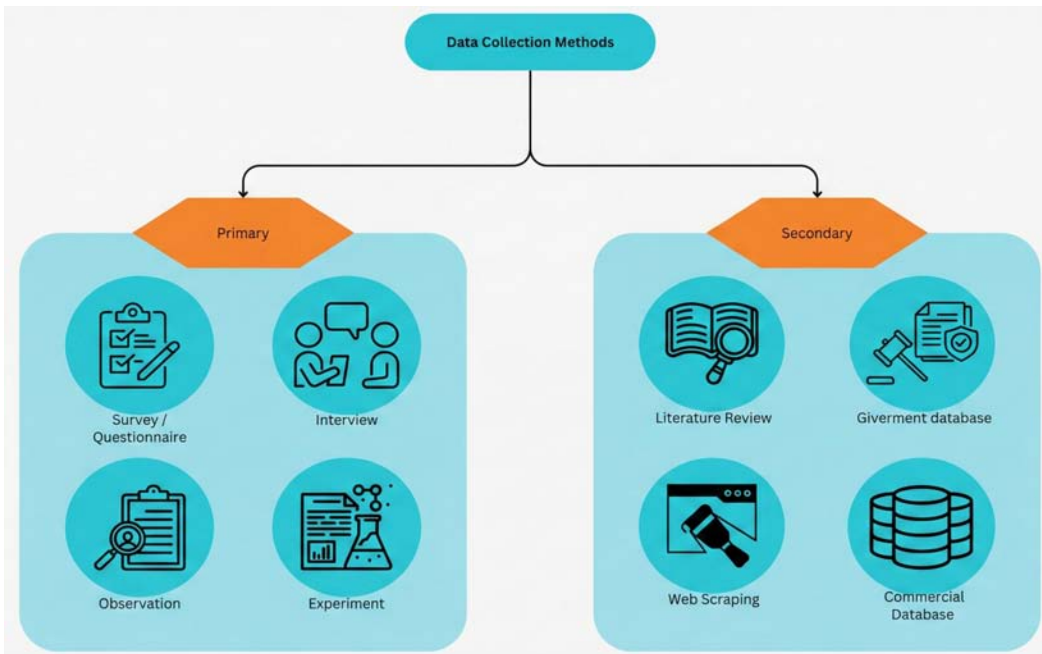

Fig. (1). Different ways of information collection [161].

The CNN model utilizes a deep learning approach for processing the input images. CNN has applications in object detection, classification, and segmentation. CNN has a number of layers, and each layer has its specific applications. Under preprocessing, the noise is removed from the input images. The important features are selected for the prediction of results.

LITERATURE SURVEY

To solve the vanishing gradient issue in deep networks, ResNet included skipping connections as proposed by He *et al*. (2016) [158]. ResNet is prepared to train incredibly deep models; this architecture has usually been utilized for fashion datasets. This enables superior feature extraction for intricate clothing textures and patterns. ResNet is a well-liked option for transfer learning in fashion applications due to its resilience.

As network depth increased, VGGNet highlighted the need to employ smaller convolutional filters as proposed by Simonyan and Zisserman (2015) [159]. Because VGG architectures are easy to use and effective at capturing complex patterns, such as textures and fabric details, in garment photos, many academics in the fashion industry use them. Zalando (2017) [160] proposed an alternative to the conventional MNIST dataset, the Fashion-MNIST dataset, which comprises 28x28 greyscale photos of apparel products. This dataset influenced several follow-up studies by serving as a standard for assessing classification models for fashion products and testing lightweight CNN architectures.

Liu *et al*. (2016) [161] proposed a deep fashion dataset, which unveiled a sizable dataset with a variety of fashion categories, characteristics, and landmarks. The proposed work emphasized the value of landmark detection in fashion photos, which enhances localization and feature extraction for uses such as outfit identification and supports CNN-based categorization.

The study focused on how pre-trained models achieve state-of-the-art accuracy in fashion-specific tasks while lowering training time and computing expenses. After the literature review, some of the challenges are listed as follows [162 - 165]:

- The inherent complexity of classifying fashion images was the main cause of the project's numerous difficulties.
- Fashion goods with similar textures, colors, or patterns were frequently misclassified due to inter-class similarity between categories, which was one of the main challenges.
- Another major problem was the dataset imbalance, where certain categories were under-represented, which resulted in worse performance for certain classes.
- The model found it challenging to consistently extract relevant information due to the variety of visual representations of fashion products, including different lighting, backdrops, and perspectives.
- The requirement for substantial computer resources to properly train the deep neural networks exacerbated these problems. Notwithstanding these difficulties, the experiment offered insightful information on CNN's potential for fashion classification and model optimization.

PROBLEM STATEMENT

Several challenges exist in the fashion industry such as the unavailability of a balanced dataset, overlapping attributes in the dataset, and inter-class similarities.

CHAPTER 11

Personalized Web Crawler for Retrieving Patent and Research Paper Information from Google Patents and IEEE Xplore

Abstract: The rapid expansion of scientific literature has made it challenging for researchers to find relevant studies on specific topics efficiently. The traditional search methods require extensive time and manual effort to identify, filter, and extract essential information from numerous sources. This paper proposes an automated keyword-based web crawling system aimed at streamlining the retrieval of research papers and patents from sources, IEEE and Google patents, respectively. In the proposed work, the authors type the keyword of the research paper or patent, and then the system provides the results accordingly. The details of a patent or research paper may include details like the name of the author, the DOI, the publisher, the title of the article, publication date, and many more. The proposed technique decreases manual work and enhances the accuracy of collecting the required data.

Keywords: Personalized web crawler, Patent scraping, Patent data mining, Selenium automation.

INTRODUCTION

In today's digital era, effective data organization is crucial. With vast amounts of information generated daily by internet users, proper data management and the security of personal information have become essential. Traditional information management techniques are often time-consuming and lack accuracy. To overcome these challenges, automated machine learning techniques can be employed to structure data efficiently and accurately. Structured data is not only easier to access but also enhances readability [171]. In this work, the authors utilize Python and Selenium for data collection, compilation, and presentation. Two primary sources—IEEE and Google Patents—were selected for data extraction.

The web scraping method enables the system to navigate complex web structures, efficiently handle pagination issues, and systematically retrieve web pages in a structured manner. The proposed method facilitates automated data handling and efficient large-scale information retrieval. It extracts key details about research

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papers or patents, such as titles, publication dates, author details, and DOIs. This helps readers avoid redundant data filtering [83]. Automating information retrieval saves users' time and efforts while providing a reliable, independent, and customizable approach to capturing data from various sources.

Furthermore, the system can analyze a large number of web pages to meet user requirements. User-provided quotes assist in organizing the information, and in complex data environments, semantic and focused crawling techniques help filter relevant data effectively [172].

Fig. (**1**) illustrates how various strategies can be employed to enhance search results. All the steps in the diagram represent the truncation process. It permits search engines to utilize the multiple versions of a single word. It adds special characters, such as double quotes, single quotes, commas, and question marks, for sentence shortening. It matches singular as well as plural forms of the words and searches results accordingly. It allows for spelling variations. It also avoids typing words manually, resulting in saving time for users.

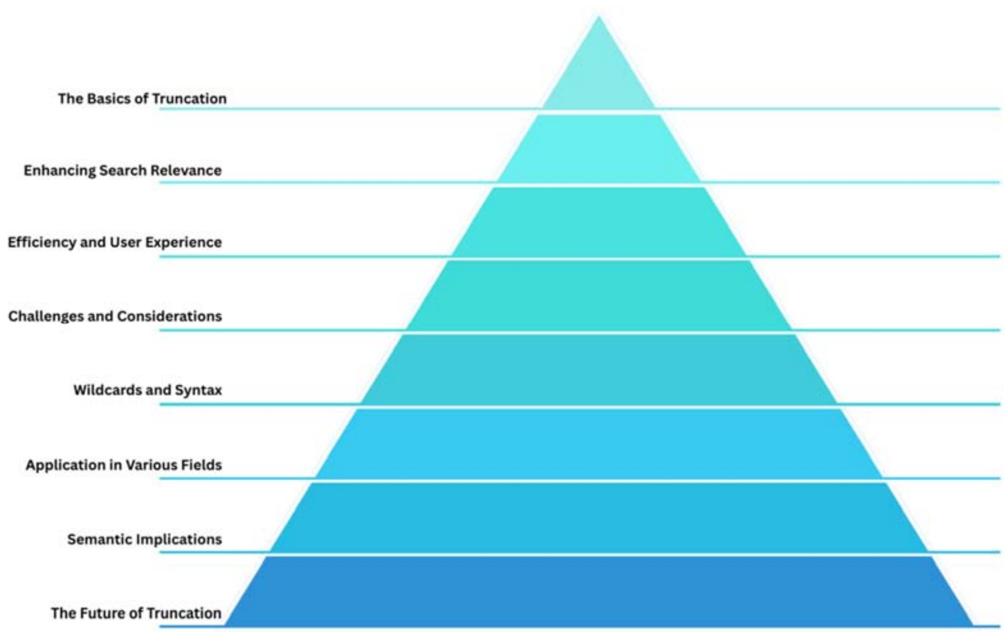

Fig. (1). Information retrieval strategies [173].

Data security has become increasingly critical in today's digital era, where individuals extensively use online platforms and maintain digital accounts. To protect sensitive digital information, various security techniques and protocols are employed; however, cyber threats continue to evolve with increasingly sophisticated attacks. This chapter focuses on information retrieval from platforms like Google Patents and IEEE Xplore. In the context of personalization, certain user-specific inputs such as search history, interests, and profile details are often necessary. Therefore, the web crawler developed in this work is carefully designed to collect only the essential information required for personalized retrieval, while deliberately avoiding the extraction or storage of sensitive personal data. This approach ensures a balance between functionality and user privacy, aligning with responsible data handling practices.

LITERATURE REVIEW

Table **1** summarizes the literature review based on author names, techniques used, performance metrics achieved, and demerits of the work. In the reviewed papers, the methodology of techniques used is studied in detail along with the merits and demerits of the methods.

Table 1. Literature summary.

Authors	Methodology	Result	Demerits
Hernandez *et al*. (2020) [171]	This paper proposed a novel semantic-focused web crawler that uses a knowledge representation schema instead of a traditional ontology to define the crawler's domain. A similarity measure combining IDF with other statistical metrics was developed to filter web page content based on the defined domain.	The crawler was validated through experiments in several domains (computer science, politics, and healthcare), showing high precision in retrieving domain-relevant pages. The combination of similarity metrics improved the harvest ratio and overall relevance of crawled content.	Limited scalability when the knowledge schema is not comprehensive.
Palmer *et al*. (2005) [83]	This paper introduced a corpus annotated with semantic roles, providing a more in-depth understanding beyond syntactic parsing. It labels semantic roles for verbs and their arguments in sentences to improve the accuracy of natural language processing tasks.	The semantic role labeling significantly improved performance in tasks that required understanding sentence structure, such as question answering and information retrieval. The corpus became a widely used resource for language understanding systems.	Complex to implement due to the need for distributed nodes.

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