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A Comparative Study and Analysis of Text Summarization Methods

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ABSTRACT

This Various text summarization methods, such as extractive, abstractive, and human abstraction concepts have been compared in terms of performance, each with its specialties and limitations. This research analyses comparisons among the methods and some of their techniques used in text summarization. Our initial contribution is to suggest a thorough overview of the methods. The research methodology aims to compare text summarization methods through a systematic literature review to understand the topic and select appropriate methods. The search method involves keyword-based and citation-based techniques using academic search engines. The comparison of methods will consider various evaluation criteria such as document structure, content importance, quantitative approach, qualitative approach, dependency on machine learning, sentence generation, central concept identification, human involvement, representation in mathematics, and historical approaches. The methods would be evaluated based on these criteria to provide an objective and comprehensive comparison. No method consistently produces accurate text summaries. The best course of action will depend on the particulars and constraints of the current work because each method has both positive and negative aspects. The two primary methods for text summarization were discovered to be extractive and abstractive. This comparison study analysed various text summary and revealing each method's positive attributes and drawbacks. By giving a comprehensive overview of the main two methods, this comparative analysis advances the subject of text summarizing.

1. INTRODUCTION

In today's era of information overload, an overwhelming amount of written content is generated daily, making the need for effective text summarization methods increasingly prominent. Text summarization plays a crucial role in extracting essential information from lengthy documents, enabling users to grasp the main ideas quickly without having to read the entire text. As the demand for automated summarization methods continues to rise, researchers have developed diverse approaches to tackle this challenge.

Despite over 50 years of research on text summarization, automated summaries still suffer from poor quality, and there are numerous fascinating topics recommended by end users for summarization in various scenarios [1]. The exponential growth of textual information across academia, research, and industry has led to advancements in technologies aimed at extracting valuable insights from diverse sources such as news, books, journals, scientific articles, databases, and medical records, among others, across different domains of application [1].

Automatic Text Summarization, which involves filtering a text to its key concepts, remains a complex task that faces multiple challenges for the research community [2]. It involves the process of extracting fundamental information from a source or set of sources to create an overview suitable for individuals and processes, commonly known as automatic summarization. The level of compression needed is critical to summarization, as people increasingly rely on the internet and the need to gather diverse information from it grows, making text summarization more crucial in today's world.

Text summarization serves to draw the reader's attention to the most essential information from a collection of scattered documents. By providing documents in an abridged form, text summary allows for a more user-friendly experience that aligns

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with their needs. Leveraging computational techniques, automatic text summarization breaks down lengthy texts into digestible pieces while preserving the core ideas and critical information. This process involves identifying key terms, gathering essential information, and presenting a clear overview using various algorithms and natural language processing techniques.

Summarization is often viewed as a two-step process. The first step involves extracting basic concepts from the source text and creating intermediate representations. The summary is then generated in the second stage [3]. Text summaries are widely used in news articles, textbooks, legal documents, and other content-heavy areas to save time and provide concise information, thus enhancing decision-making processes and information retrieval.

To achieve effective text summarization, two key questions need to be addressed:

1) How to identify a document's most vital information?
2) How to present the crucial information clearly and concisely in a condensed manner [2]?

The goal of text summarization is to preserve the overall character of a document while ensuring the extraction and presentation of critical information. To address the growing demand, researchers and experts are focused on developing various techniques for text summarization. This research aims to provide a comprehensive comparison to evaluate the strengths, limitations, and efficiency of different text summarization techniques in explaining various types of textual content. Through this analysis, a deeper understanding of the range of available techniques will be achieved, enabling the selection of the most suitable method for specific needs. The initial contribution of this study is to offer a thorough overview of the existing methods used for summary evaluation in form of a systematic literature review (such as [7] and [32]).

Table 1 contains research questions and their objectives, focusing on which this research motivation to be more consistent and focused.

Table 1. Research Questions and Objectives

Research Question	Objectives
What are the key text summarization methods employed in the field of natural language processing?	Identify the methods and techniques employed in the field of NLP
What are the major specialties and limitations associated with different text summarization methods?	Identify the pros and cons of the methods
What are similar and dissimilar among the methods?	Identify similarities and dissimilarities among the methods

2. LITERATURE REVIEW

Text summarizing techniques have been thoroughly examined and reviewed in the context of text summarization.

2.1 Lexrank (Graph-based lexical centrality as salience in text summarization)

Erkan and Radev presented an early study on extractive and abstractive summarization methods. They evaluated various statistical features such as word frequency and position, sentence length, and the presence of named entities. The authors compared these features with machine learning algorithms and found that the combination of features and support vector machines (SVM) yielded the best results for extractive summarization [4].

2.2 Automatic summarization

Nenkova and McKeown explored using linguistic and content-based features for automatic summarization. They introduced the Lexical Chains concept, which capture semantic relationships between words in a text. By incorporating these chains into a graph-based ranking model, they achieved improved extractive summarization performance [5].

2.3 A Neural Attention Model for Abstractive Sentence Summarization

In recent years, deep learning techniques have gained significant attention in many fields (such as [33], [34], and [35]) including text summarization research. Rush proposed an abstractive summarization method based on a sequence-to-sequence neural network architecture with attention mechanisms. Their model generated summaries by mapping input sequences to output sequences using an encoder-decoder framework [6].

2.4 The Automatic Creation of Literature Abstracts

One of the early studies in text summarization was conducted by Luhn, who proposed a keyword-based approach to extract key sentences from documents. This method relied on statistical analysis of word frequencies to identify important content, and while it provided a basic summary, it often failed to capture the semantic nuances of the original text [41].

2.5 Abstractive Text Summarization Using Sequence-to-Sequence RNNs and Beyond

Attention-based neural network models have emerged as a dominant approach in text summarization. Nallapati proposed the Abstractive Summarization with Attention-Generative Adversarial Network (AS-AGAN) model, that employed an attention mechanism to focus on important words and phrases during the summarization process. This model demonstrated improved performance in terms of summary coherence and informativeness compared to earlier methods [8].

3. METHODOLOGY

Text summarization is a key area of research in NLP, the field of natural language processing. This report describes how to reduce the amount of information in a text document and keep key points intact. The content must be condensed while retaining as much detail as feasible for the text summarizing technique. A comparison analysis of text summarizing approaches can be used to evaluate the benefits and drawbacks of various approaches as well as future research directions. A theory-based comparison analysis is used to analyse text summarization approaches in depth. This study employs a comprehensive and in-depth hybrid methodology that integrates concepts and contexts from systematic literature review techniques [9]. The primary objective is to thoroughly investigate and structure the existing body of literature

pertaining to the comparative analysis of various methods and techniques for text summarization. Additionally, the research seeks to identify potential pathways for future exploration within this domain [9]. The chosen approach adopts a methodical and reproducible process for conducting literature searches, assessing the quality of available sources, and synthesizing their findings [10]. This sets it apart from the typical narrative review, which often relies on biased sample selection and lacks systematic methodologies, consequently being labelled as 'unscientific' [11, 12]. Therefore, this research aims to provide a robust overview of the field of text summarization methods.

Furthermore, the study's hybrid methodology ensures that it transcends the constraints of traditional narrative reviews. The meticulous and transparent approach to gathering and evaluating literature enhances the credibility of the research findings. By adhering to systematic techniques [9], the study circumvents potential biases and inaccuracies that could arise from non-representative sample selections. One of the central strengths of the chosen approach lies in its structured process for synthesizing information [10]. By meticulously evaluating the quality of sources, the research aims to offer a balanced and comprehensive view of the comparative analysis landscape. This systematic methodology bolsters the study's contribution to the academic discourse and increases its relevance and applicability to both researchers and practitioners. The study aims to present an authoritative and objective assessment of the current state of comparative analysis techniques in text summarization. It bridges the gap between conventional narrative reviews and more rigorous, scientific methodologies, ultimately advancing the understanding and future directions of text summarization research within the academic community.

Furthermore, combining the concept and context in a hybrid review can yield more precise observations, delivering more elaborate, subtle, and distinct details regarding a specific concept (such as methods or techniques) within a given situation (like text summarization) [13].

Qualitative content analysis (e.g., [38], [39], and [40]) was utilized as the cornerstone of our investigative approach to scrutinizing the existing body of literature. This methodology empowers researchers to subjectively classify content into discernible themes, particularly applicable when grappling with a collection of articles that ranges from modest to moderate in size [13]. By embracing qualitative content analysis, researchers gain the capacity to draw broader conclusions. This is achieved by delving into the presence, interpretations, and interconnections of specific words, patterns, or themes embedded within qualitative materials [14]. This methodology offers a nuanced lens through which we can dissect the textual landscape. It allows us to not only discern prevalent themes but also unravel the intricate progression and interplay of ideas. Furthermore, it opens avenues to extrapolate overarching insights that extend beyond individual works.

In a landscape where the quantity of literature lies within the moderate spectrum, qualitative content analysis proves invaluable. It does not merely treat each article as an isolated entity but instead uncovers the threads that interweave them. This holistic approach illuminates the broader context in which these articles coexist, facilitating the identification of convergences, divergences, and evolving trends.

Through qualitative content analysis, the intricate tapestry of textual information, extracting meaningful clusters of concepts and their evolutionary trajectories have been navigated. This methodological choice isn't confined to the surface-level understanding offered by quantitative techniques. Instead, it offers a dynamic exploration of the qualitative dimensions of literature. It encourages us to explore the 'how' and 'why' behind the words, revealing the intricate dance of ideas that shapes the landscape of comparative text summarization methodologies. This research embarks on a journey guided by qualitative content analysis, an approach that unfurls the layers of textual content, exposes hidden connections, and empowers us to unearth the profound nuances in the study of text summarization methods.

This research adheres to the procedures outlined by Kumar et al [15] and Kushwaha et al [16] to organize the examination.

3.1 Planning the review

Systematic literature reviews employ a variant of inductive reasoning to distil and analyse information. This process necessitates the establishment and application of specific criteria, encompassing search databases, keywords, and subject domains. By adhering to these benchmarks, a curated collection of scholarly works is synthesized. This facilitates a meticulous, well-structured, lucid, and comprehensible evaluation of the existing body of literature [13]. In alignment with Kraus' assertions, their methodologies were adopted to procure data for our own research endeavours [17].

In the pursuit of pertinent publications for this study, Google Scholar and CORE were harnessed as academic search engines. Notably, Google Scholar was favoured due to its status as a preeminent global repository, encompassing published articles and citations, encompassing materials featured in high-impact journals. The broad spectrum of resources furnished by CORE rendered it a fitting choice.

Within the confines of our search parameters, exclusive focus was placed on English-language academic journal articles. While it is acknowledged that various literature streams broach the subject of text summarization techniques, our review exclusively centres on papers underpinned by a comparative analytical approach. This tailored approach was adopted to enhance the pertinence of the scrutinized journals.

In the systematic exploration of literature, an inductive mode of reasoning is adeptly wielded. Essential to this process is the establishment and application of specific criteria, spanning databases for exploration, identification of key terminology, and delineation of subject domains. This meticulous adherence to predetermined benchmarks culminates in the curation of a scholarly compendium. The resultant review manifests as a meticulous, logically organized, perspicuous, and intelligible dissection of the prevailing body of erudition [13]. Echoing the insights of Kraus, their prescribed protocols and techniques find application in the acquisition of data underpinning our own research endeavours [17].

The quest for pertinent literature mandates the engagement of academic search engines, in this instance, Google Scholar and CORE. Evidently, the reputation of Google Scholar as a venerated global repository, encompassing published articles and citations featured in high-impact periodicals, rendered it a judicious selection. The comprehensive nature of resources furnished by CORE complemented this choice.

Conforming to our predefined search criteria, exclusive emphasis was laid upon English-language scholarly journal articles. Although the discourse on text summarization techniques spans various literary conduits, our review distinctly focuses on papers that embrace a comparative analytical stance. This refined scope was opted for to amplify the applicability of the scrutinized journal content. In the systematic canvassing of literature, a brand of inductive reasoning assumes center stage. Pivotal to this methodology is the laying down and execution of specific criteria, spanning perusal databases, pinpointing pivotal phrases, and demarcating subject domains. Through unwavering adherence to these yardsticks, a curated assemblage of academic tomes is synthesized. The resulting review materializes as a methodical, impeccably organized, limpid, and coherent breakdown of the existent repository of erudition [13]. Reiterating Kraus' postulations, their prescribed guidelines and techniques are embraced to amass data buttressing our individual research initiatives [17]. In the expedition to unearth pertinent literature, the tools of Google Scholar and CORE were wielded as academic search engines. Notably, Google Scholar's stature as a preeminent global repository, enlisting published articles and citations from high-impact journals, rendered it a discerning choice. The panoply of resources extended by CORE harmonized seamlessly with this selection.

Aligned with our stipulated search parameters, exclusive primacy was accorded to English-language scholarly journal articles. While conceding the existence of discourse across diverse literary conduits concerning text summarization techniques, this review confines itself to papers that espouse a comparative analytical framework. This circumscribed focus was embraced to heighten the applicability of the surveyed journal compendium.

3.2 Conducting the review

The investigation encompassed the execution of searches using various keyword combinations (as mentioned in Table 2) like 'text summarization' and 'methods', 'comparative study' and 'text summarization methods', 'automatic' and 'text summarization', 'extractive' and 'summarization', as well as 'abstractive' and 'summarization'.

The followings are the list of keywords used for searching:

- Text summarization
- Text summarization methods
- Text summarization techniques
- Comparative study of text summarization methods
- Literature Review of Text Summarization Methods
- Automatic Text Summarization
- Latest text summarization approaches
- Comparison of text summarization methods
- Extractive summarization
- Abstractive summarization
- Text mining
- Text summarization in NLP

To refine search outcomes, these keywords were employed alongside advanced searching techniques (as mentioned in Table 2).

Table 2. Advanced Searching Techniques

Advanced Searching Techniques	
Phrase searching technique (quotation marks)	***Boolean searching technique***
"Text summarization methods"	Text summarization techniques or text summarization methods
"Comparative study of text summarization methods"	(Text summarization techniques or text summarization methods) or (literature review of text summarization methods)
"Literature review of text summarization methods"	(Text summarization or abstractive summarization or extractive summarization) and latest text summarization approaches
"Automatic text summarization"	Automatic text summarization and text summarization in NLP
"Latest text summarization approaches"	Comparison of text summarization methods or text summarization techniques
"Comparison of text summarization methods"	Extractive summarization and abstractive summarization and text mining

The procedure involved in this study encompassed a systematic approach to gather and assess articles pertinent to the realm of 'Comparative Analysis of Text Summarization Methods' as presented in Fig. 1.

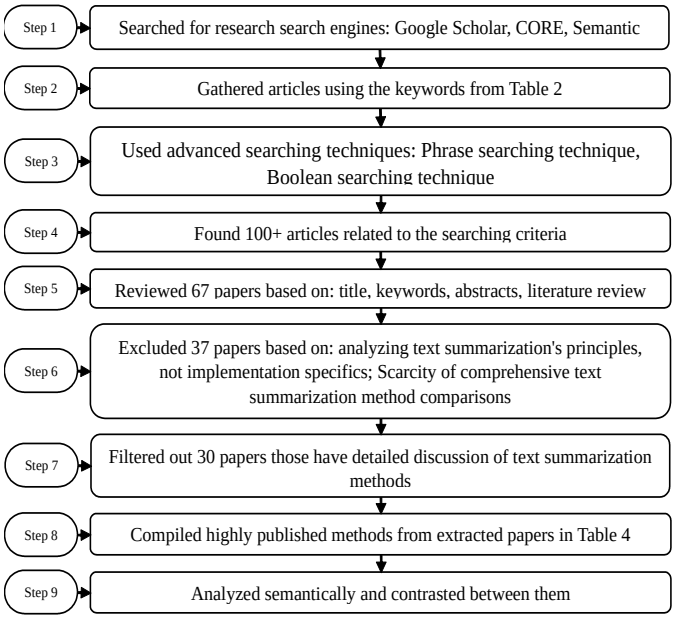

Fig. 1. Research Process

Initially, a set of search criteria was employed to sift through article titles, resulting in the initial identification of an extensive collection comprising over 100 articles. To refine the selection, the subsequent stage focused on narrowing down the pool exclusively to academic journal articles that substantially reduced the potential contributions to a count of 67.

Further honing the scope, the subsequent phase aimed at isolating articles that presented a comparative analysis of diverse text summarization methodologies. This meticulous

culling led to a further reduction, ultimately yielding a curated set of 50 articles that met this specific criterion. To ensure a more focused examination, articles featuring algorithmic implementations were systematically excluded in the fourth stage, resulting in a decrease from 50 to 46 articles.

A subsequent step aimed at rectifying potential duplication issues within the collected literature. By meticulously removing replicated articles, the overall count was streamlined to a total of 42 distinct articles. As the penultimate filtering step, a comprehensive review was conducted, scrutinizing titles, keywords, and abstracts to uphold stringent standards of relevance and academic excellence. This process of elimination resulted in a final selection of 37 articles.

With the selected corpus of literature in place, the subsequent course of action revolved around a meticulous reading and comprehensive evaluation of all 37 chosen articles. Upon the completion of this rigorous assessment, the focus shifted towards the organization of the selected articles into distinct categories based on the text summarization methods they explored. This categorization, performed by analysing the titles of the articles, revealed two primary and distinct categories: extractive summarization and abstractive summarization. The subsequent scrutiny cantered on articles that provided an in-depth and comprehensive exploration of these two methodologies. Finally, the following set of methods (as presented in Table 3) are figured out for comparison.

Table 3. Selected Methods and their Citation No.

Method No.	Method Name	Reference No.
1	Extractive Summarization	[2], [10]
1.1	Statistical Method	[11]
1.1.1	Title Method	[12]
1.1.2	Location Method	[13], [14]
1.1.3	Cue Word Method	[14]
1.1.4	TF-IDF Method	[15], [16]
1.2	Linguistic Approach	[17]
1.2.1	Lexical Chain Method	[11], [17], [18]
1.2.2	Clustering Method	[19]
2	Abstractive Summarization	[8], [20]
2.1	Structured Approach	[21]
2.1.1	Tree Based Method	[20], [23], [24]
2.1.2	Template Based Method	[8], [21], [22]
2.1.3	Lead And Body Phrase Structure	[21], [25]
2.2	Semantic-Based Approaches	[26]
2.2.1	Semantic Graph Based Method	[26]
2.2.2	Multimodal Semantic Model	[26], [27]
3	Human Abstraction Concept	[28], [29]

An illustration of a bar chart showing the distribution of articles is shown Fig. 2.

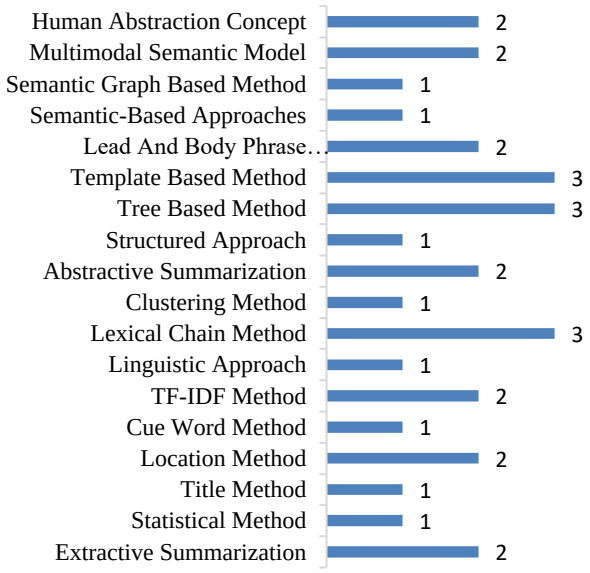

Fig. 2. Distribution of articles by summarization methods.

The bar chart provides a visual representation of the distribution of articles across the different summarization methods employed in this study. Each bar represents the number of articles that were processed and summarized using a specific technique.

Overall, this research methodology involves conducting a comparative analysis of the existing literature, searching for text summarization methods, identifying various techniques used in text summarization, and comparing the methods based on various criteria. This approach ensures a rigorous and objective analysis of the available text summarization methods. The outcome this study would help in quickly identifying about the text summarization methods, and selecting the suitable method based on the requirement of text mining application.

4. Comprehensive Overview of Text Summarization Systems and Methods

Only research into text summarization has often prioritized the result of the summary over delving into the cognitive mechanisms that underpin human summarization. Exploring these cognitive foundations is crucial for mitigating the limitations of current systems. However, in many cases, only a handful of phrases from source documents are utilized due to the ongoing research nature of encapsulating content from diverse open-domain papers. In many instances, only a handful of phrases are extracted from the pool of primary documents. This is due to the ongoing status of research surrounding the formalization of content within open-domain documents. The extraction of meaningful content from these documents remains an area of active exploration.

Text summarization systems can be categorized across multiple dimensions and tailored to different application scenarios. The suitability of diverse summarization forms varies according to the context. These systems can be stratified based on linguistic factors, input size, titles, thematic content, document contents, and summarization techniques.

Research on text summarizing has frequently focused more on the finished product of the summary than on the cognitive principles that underlie human summarization having a deeper understanding of the cognitive foundations of the task to address some of the shortcomings of present systems the majority of scenarios, however, only use a few phrases from the collection of original papers because formalizing the content of open domain documents is still a research subject [2].

Text summarizing systems can be divided into several categories according to various summaries that may be favourable in various applications. Various forms of summarization may be beneficial in various applications, and text summarizing systems can be divided into categories based on language, based on the size of inputs, based on title, based on the topic of the summary, based on contents, and based on summarization methods [3, 18].

The following subsections, which go into further detail on every classification, are as follows:

4.1 Text Summarization Systems

- *Based on Language:* Text summarization systems can be divided into two categories based on language: monolingual, which focuses on summarizing materials published in a single language, and multilingual, which can summarize materials written in various languages [19].
- *Based on the Size of Inputs:* Text summarization systems can be classified into two main categories based on the number of documents they process: single-document summarization, where it focuses on summarizing the content of a single document, and multi-document summarization, where it involves summarizing information from multiple documents on a given topic [18]. The Columbia university-designed summons system serves as an illustration of a multi-document summary system. The earlier described single document summarizer, however, is the copy and paste system [18].
- *Based on the Topic of The Summary:* Based on the topic of the summary, text summarization systems can be divided into two categories:

  Generic summarization refers to the system of reducing a given text or document into a concise form that highlights the important points and primary concepts. It can be utilized by any sort of user, and the summary is independent of the document's subject. It is not user-specific [3].

  Query-based summarization involves generating a summary that directly answers a specific query or question. The original text's topic must be determined by the user in order for the system to extract that information [3]. Based on the frequency counts of words or phrases in query-based text summarization, each document's sentence scores are calculated. Sentences with query phrases score higher than those with only a single query term. For the output summary, the sentences with the highest scores and their structural context are taken out [20].

- *Based on Content:* Depending on the sort of detail, a summary can be either informative or instructive [18].

  An indicative summarization system condenses text by selecting vital information, allowing users to understand documents without reading everything. It could be viewed as an alternative to the main document [20]. Instructive summarization condenses text while keeping key information, offering guidance, and aiding understanding and application. Only a generalized concept of the original document is contained in it [20].
- *Based on Methods:* When it comes to summarizing text, there are two main methods: extractive summarization and abstractive summarization. Extractive summarization involves directly selecting sentences from the original document, while abstractive summarization includes information that may not be explicitly stated in the source text [3][18].

The two main methodologies for text summarization along with their respective sub-methods have been examined thoroughly. A comprehensive analysis and comparison were conducted to delve into the intricacies of these approaches.

4.2 Text Summarization Methods

4.2.1 *Extractive Summarization*

Extractive summarizing is a text summation approach that selects and extracts the most significant lines or phrases from a source document to produce a short summary. This method intends to give an overview of the selected key phrases from the initial text. Extractive summarization directly copies and rearranges sentences from the original text. The use of this approach is widespread in natural language processing, and much research has been carried out on its practical application.

Typically, extractive methods are carried out in two processes:

1) Pre-processing step.
2) Processing step [21].

Pre-processing involves transforming the original text into a structured form. This includes identifying sentence boundaries using periods in English, removing common words without meaning or relevant information, and reducing words to their root form to highlight their meaning [21].

The Processing step involves determining and calculating the features that impact the sentence's relevance. These features are assigned weights through a weight-learning method. The final score of each sentence is determined using a Feature-weight equation, and the top-ranked sentences are chosen for the summary [21].

Several sub-methods have been developed to improve the effectiveness of extractive summarization. These methods employ various techniques to identify important sentences, evaluate their relevance, and determine their order within the summary. The following are some prominent sub-methods in extractive summarization:

Two main sub-methods of extractive summarization are the Statistical Method and the Linguistic Approach.

4.2.1.1 *Statistical Method*

The statistical method relies on statistical techniques and algorithms to identify significant sentences or phrases based on

their statistical properties, such as word frequency, position, and relevance to the overall content. This approach considers phrase structure, word frequency, sentence length, keyword placement, use of capital letters, and placement throughout the text. In statistical methods that compare the statistical components of the phrase, such as location, term, frequency, and title to the keywords, the sentence with the most significant score is selected as the summary [18].

The key sub-methods under the statistical method include:

- *Title Method:* The Title Method is a statistical approach used in text summarization. It assigns scores to sentences based on their similarity to the document title and selects the highest-scoring sentences for the summary. This approach considers sentences in titles as more important, leading to their higher frequency in the summary. The score of a phrase is determined by the number of common words between a sentence and the title. If there is no title, the method is ineffective. This method was introduced by Barzilay and Elhadad in their paper "Using Lexical Chains for Text Summarization" [22].
- *Location-Based Method:* Location-based methods in statistical text summarization leverage the geographic information of textual data to generate concise summaries. These methods consider the geographical context of the text and use location-specific statistical approaches to extract key information [23]. Text is given importance based on its location in a paragraph or document, with the beginning, end, and central section being more significant for summarization. Hovy & Lin, and Edmundson adopted this approach. The placement technique is based on the intuition that headings, words at the start and end of the text, and text that are printed in bold all include crucial information for the summary [24].
- *Cue Word Method:* According to its importance, the text is given a weight, with positive weights like "confirmed," "significant," "best," and "this document" and negative weights like "hardly," "impossible," etc. Cue words typically vary by genre. Such cue phrases can be included in a summary statement. The cue phrase approach is predicated on the idea that these words offer a "rhetorical" background for recognizing crucial lines. In this instance, a group of cue phrases and the sentences that contain them serve as the source abstraction. Extractive text summarization uses statistical features in particular [24]. Text is given importance based on its location within a paragraph or document, with the introduction, conclusion, and key sentences being prioritized.
- TF-IDF Method (Term Frequency Inverse Document Frequency): TF-IDF is a statistical measure used to determine the importance of keywords in specific documents. It helps identify and categorize documents based on these keywords [25]. TF-IDF, short for Term Frequency-Inverse Document Frequency, is a technique that combines two factors to determine the importance of a term in a document. The first factor, Term Frequency (TF), measures the number of times a term appears in a document. It considers the length of the document, so even if a term appears frequently, its importance may be lower if the document is large. To calculate TF, the number of occurrences of a term is divided by the total number of terms in the document. The second factor, Inverse Document Frequency (IDF), addresses the issue of treating all keywords equally. IDF assigns lower weight to common words and higher weight to infrequent words. It calculates the logarithm of the ratio between the total number of documents and the number of documents that contain the term. By multiplying the TF and IDF values together, we obtain the TF-IDF score, which reflects the importance of a term in a particular document. A higher TF-IDF score indicates a higher occurrence of the term in the document and a lower occurrence in other documents [25] [26].

4.2.1.2 *Linguistic Approach*

The linguistic approach of extractive summarization involves analyzing the linguistic and structural aspects of a given text to identify important information and generate a summary. It focuses on understanding the content and meaning of the text through language patterns, and relationships between words and sentences. Consideration of word relationships and an attempt to identify the underlying idea through word analysis are the basis of linguistic approaches [27]. The techniques employed in this approach are discussed further here:

- *Lexical Chain Method:* A continuous arrangement of text structures is achieved through the utilization of lexical chains. Essentially, these chains make use of the interconnectedness among various terms to ensure coherence. By linking together sets of words that share semantic connections, lexical chains can be generated within a given document. Words can be associated in multiple ways, such as having the same meaning, being synonyms, or falling under a broader category, resulting in their classification within the same lexical chain [27]. Information retrieval and grammatical error correction are done using lexical chains. Using a model of the subject progression in the text built from lexical chains, the authors of [28] have presented a novel method for producing a summary of an original text without requiring its entire semantic interpretation [18].
- Clustering Method: A technique for extracting text summarization called lexical chain focuses on finding and connecting words or phrases that are semantically related across a document. It involves the use of clustering algorithms to cluster sentences based on their semantic similarity or other features. A frequently employed technique for extractive summarization is the K-means clustering algorithm. Its objective is to divide a given dataset into K clusters, with K being a predetermined number specified by the user. The algorithm follows an iterative process: it assigns each sentence to the cluster centroid closest to it and subsequently updates the centroid based on the newly assigned sentences. This iteration continues until convergence is achieved. Clustering assists in identifying significant sentences within each cluster that encapsulate the primary themes or topics found in

the document. These noteworthy sentences are subsequently employed as summary sentences, effectively preserving the essential information from the original document [29].

4.2.2 *Abstractive Summarization*

Abstractive summarization is a natural language processing (NLP) technique that involves generating a concise summary of a given document or text while retaining its key information and meaning. Unlike extractive summarization, which selects and combines existing sentences or phrases from the original text, abstractive summarization generates new sentences that may not be present in the source material. Abstractive text summarizers produce a summary by first utilizing NLP techniques to understand the key concepts in the input document, then paraphrasing the text to represent those concepts in fewer words and with more clarity [20].

Structured approach and Semantic-based approach are the two primary categories under which abstractive text summarization falls [30].

4.2.2.1 Structured Approach

One approach to abstractive summarization is the structured approach, which involves breaking down the summarization process into several sub-methods. These sub-methods focus on different aspects of the summarization task, such as sentence compression, paraphrasing, and language generation.

The focus of the structured approach is to capture crucial information from documents using cognitive patterns such as templates, extraction rules, and various structures like trees, ontologies, lead and body structures, rule-based systems, and graph-based structures [31]. The different methods employed in this approach can be summarized as follows.

- *Template Based Method:* In certain fields, human summaries exhibit common sentence structures that can be categorized as templates. According to the text genre provided, the abstractive summary can be generated by utilizing the information within the text and inserting it into appropriate pre-established templates [18]. This method utilizes a template to convey the entirety of a document. By comparing linguistic patterns or extraction rules, specific sections of the text are identified and linked to corresponding template placeholders. These identified sections serve as indicators of the summarized content [31].
- *Tree Based Method:* This method uses a dependency tree to represent a document's text and contents. This method uses a shallow parser to pre-process sentences [42]. The predicate-argument structure is then mapped to those phrases. The common phrases from the sentences can be chosen to use a variety of algorithms, including the theme algorithm [30]. Tree-based methods for text summarization utilize the hierarchical structure of parse trees to capture semantic relationships, improving the accuracy and informativeness of summaries. The Tree LSTM model recursively updates hidden states in a bottom-up manner, considering nodes and their children to capture compositionality. The Tree Transformer model employs hierarchical attention mechanisms to attend to different levels of the parse tree, extracting fine-grained information. These methods require high-quality parsers and can be computationally intensive but have shown promise in generating abstractive summaries [43].
- *Lead And Body Phrase Structure:* This strategy depends on the insertion and substitution of phrases that have the same syntactic head chunk in the lead and body sentences to rewrite the lead sentence [31]. This method identifies crucial elements, including significant entities, events, and relations, by examining the syntactic and semantic relationships between sentences. The first phrase briefly states a summary's core idea or central subject. It gives the summary a brief introduction and directs the reader's attention. The process of creating the lead phrase often involves taking the key information from the source text and organizing it into a clear, concise sentence. The structure-based approach's body phrase structure entails developing new phrases to support the lead phrase's key point. The relationships and dependencies between the sentences in the source text are considered when creating these sentences. The goal is to produce sentences that represent the key details from the source in a persuasive and contextually appropriate manner [44].

4.2.2.2 *Semantic-Based Approach*

The semantic-based approach is a prominent method for abstractive text summarization that aims to generate concise summaries that capture the meaning and essence of the source text. This approach focuses on understanding the semantic structure and relationships within the text to produce a coherent and informative summary. The Semantic-Based Approach involves providing a semantic representation of the document to a natural language generation system. This approach primarily concentrates on recognizing noun and verb phrases through the analysis of linguistic information. The following techniques are employed within the Semantic-Based Approach [36].

- *Semantic Graph Based Method:* The semantic graph approach involves representing the input document using a semantic graph. Nouns and verbs from the sentences are depicted as nodes in the graph, while the relationships between them are indicated by edges. This method generates sentences that are concise, coherent, and grammatically accurate, minimizing redundancy [36].
- *Multimodal Semantic Model:* A multimodal semantic model captures concepts and establishes relationships between them. The Multimodal approach involves building a semantic model that captures connections between different concepts. It assigns scores to important concepts using a specific measure, and the selected concept is then presented as a summary. The focus of this approach lies in ensuring the inclusion of a wide range of information content [36].

4.2.3 *Human Abstraction Concept*

Text summarization is a prominent area of research in natural language processing (NLP) that focuses on condensing

large volumes of text into concise summaries while preserving the key information and meaning. The concept of text summarization is grounded in the human abstraction process, which involves extracting essential details and discarding redundant or less relevant information. This process enables individuals to grasp the main ideas of a text efficiently, aiding comprehension and information retrieval.

Several approaches have been developed in the field of text summarization, including extractive and abstractive methods. Extractive summarization involves selecting and combining important sentences or phrases from the source text, while abstractive summarization goes a step further by generating new sentences that capture the essence of the original content. These techniques mimic the cognitive process of human abstraction by identifying the salient concepts and constructing coherent summaries.

Research conducted by [45] Nenkova and McKeown demonstrates the effectiveness of human abstract summarization in comparison to other methods. They conducted a study where human summaries were compared to various automatic summarization techniques. The results indicated that human summaries consistently outperformed the automated approaches in terms of content coverage, coherence, and overall quality. This highlights the superiority of human abstraction in capturing the essence of a text and producing coherent summaries. Furthermore, the concept of text summarization aligns with the principles of cognitive psychology and information processing. Cognitive psychologists argue that humans have limited cognitive resources and rely on selective attention to filter and process information efficiently. Text summarization serves as a cognitive aid by condensing information into manageable units, allowing individuals to allocate their attention more effectively and comprehend the main ideas without being overwhelmed by the entire text.

Text summarization techniques also draw inspiration from linguistic and semantic theories. By employing linguistic and semantic cues, these techniques emulate the human abstraction process, where individuals identify important terms, phrases, and relationships to create meaningful summaries.

5. RESULTS AND FINDINGS

Through the systematic review following key points have been derived using content analysis:

1) Provide an accurate assessment of the insights gained from the study.
2) The author needs to compare results with other studies.
3) Effectively contextualize the results within the existing body of knowledge.
4) Acknowledge any limitations or constraints encountered during the research (limitations of study or threats to validity).
5) Offer specific and well-justified recommendations for fellow researchers.

There are many distinct approaches to text summarizing, including extractive and abstractive summarization, and numerous techniques have been proposed to perform this task. Furthermore, different text summarizing methods and techniques can be compared. By doing an analytical comparative study of a text presenting methods and procedures, it is possible to better comprehend the positive and negative traits of different methods. Here we have found some specialties and limitations of the methods as presented in Table 4 and Table 5 respectively.

Table 4. Method's Specialties

Methods	*Specialties*
Extractive Summarization	results in a higher accuracy; retains original context; works well for short texts
Statistical Method	relies on statistical analysis; scalable for large volumes of text; provides a quantitative approach
Title Method	focuses on identifying the key elements of a document; relatively simple and efficient approach; provides a quick overview of the content
Location-based method	utilizes geographical information; efficient filtering of irrelevant
Cue Word Method	effective keyword identification; contextual understanding of text
TF-IDF Method (Term Frequency Inverse Document Frequency)	weights important words based on their frequency and rarity; efficient in handling large document collections; identify the most significant words in a document; calculates the relevance of a term in a document
Linguistic Approach	linguistic analysis; utilizes syntactic and semantic analysis; considers grammatical relationships between sentences
Lexical chain method	captures important keywords and their relationships; emphasizes the significance of key terms in the text
Clustering method	grouping similar sentences together; identifying key topics and themes; handling diverse types of documents
Abstractive Summarization	generates concise summaries by understanding the context; paraphrase and rephrase information creatively; uses natural language processing techniques to generate human-like summaries
Structured Approach	able to generate concise summaries; enhanced semantic understanding
Template Based Method	can handle specific domains or topics effectively; enables the inclusion of specific details or keywords in the summary
Tree Based Method	efficient hierarchical organization of information; able to capture the structural relationships between sentences; ability handling of long documents by breaking them into manageable segments
Lead and body phrase structure	provides a high-level overview; concise and informative introduction
Semantic-based Approach	captures contextual meaning; underlies relationships between words and phrases
Semantic Graph Based Method	captures semantic relationships between words and concepts; supports multi-document summarization

Multimodal Semantic Model	able to incorporate diverse modalities; semantic representation of text; enhanced summarization through multimodal context
Human Abstraction Concept	flexible to adapt summarization style based on the target audience or purpose; recognizes key topics of an article

Table 5. Method's Limitations

Methods	*Limitations*
Extractive Summarization	unable to generate new information; loss of Contextual Understanding; difficulty in summarizing long or complex texts; dependency on sentence relevance
Statistical Method	limited contextual understanding; lack of ability to identify important information outside of statistical patterns
Title Method	does not consider the overall context or structure of the document; ineffective when document titles are ambiguous; not suitable for documents with lengthy or complex titles
Location-based method	lack of diversity in sources; requires extensive location tagging of textual content
Cue Word Method	relies heavily on cue word; difficulty handling complex sentence structures; struggles with understanding ambiguous language
TF-IDF Method (Term Frequency Inverse Document Frequency)	ignores the semantic meaning of words; does not consider the order or context of words; fails to capture the relationships between words and their co-occurrence
Linguistic Approach	lack of domain-specific knowledge; sensitivity to sentence structure and grammar
Lexical chain method	relies heavily on the availability of explicit lexical links; requires extensive preprocessing and linguistic resources
Clustering method	sensitivity to the choice of clustering algorithm; limited ability to generate new insights
Abstractive Summarization	difficulty in maintaining factual accuracy; prone to generating inaccurate or misleading summaries; may overlook important details or omit crucial information
Structured Approach	relies on predefined structures; difficult to capture contextual information
Template Based Method	limited flexibility due to the reliance on fixed templates; less effective for summarizing complex or abstract concepts
Tree Based Method	computationally expensive; requires manual annotation or labeling of tree structures
Lead and body phrase structure	dependency on the quality of the input text; lack of originality
Semantic-based Approach	relies heavily on the availability of high-quality semantic resources; requires extensive computational resources for processing and analysis
Semantic Graph Based Method	requires accurate semantic parsing and entity recognition; relies heavily on the accuracy of the underlying semantic graph
Multimodal Semantic Model	requires labeled multimodal training data; limited generalization to unseen modalities; longer processing times due to the incorporation of multiple modalities
Human Abstraction Concept	limited ability to summarize non-textual content; may not capture the author's tone or style accurately

6. DISCUSSIONS

This study has presented the findings of comparative analysis of various text summarization methods. It aimed to evaluate and compare the performance of different techniques for generating summaries of textual content. To achieve this, a diverse of articles and applied a range of summarization approaches are selected, focusing on both extractive and abstractive methods. The analysis results are presented in the form of a table of similarities and dissimilarities (see table 6), along with two more tables of methods specialties and methods limitations (see tables 4 and 5).

The given table 6 utilizes symbols to indicate the presence or absence of certain characteristics of the summarization methods. A checkmark (✅) signifies that a method possesses the mentioned criteria, while a cross (❌) indicates its absence.

Table. 6. Table of Similarities and Dissimilarities.

Methods / Criteria	Extractive Summarization	Statistical Method	Linguistic Approach	Abstractive Summarization	Structured Approach	Semantic-based Approaches	Human Abstraction Concept
Relies on document structure	✅	✅	✅	❌	❌	❌	❌
Considers content importance	✅	✅	✅	✅	✅	✅	✅
Quantitative approach	✅	✅	❌	❌	❌	❌	❌
Qualitative approach	❌	❌	✅	✅	✅	✅	✅
Machine learning based	❌	❌	❌	✅	✅	✅	❌
Identifies main concepts	✅	✅	❌	❌	❌	❌	❌
Requires human involvement	❌	❌	✅	✅	✅	✅	✅
Mathematical representation	❌	❌	❌	❌	❌	❌	❌
Based on historical approaches	✅	✅	✅	❌	❌	❌	✅

The figure provides insights into both the similarities and differences among the summarization methods. Extractive Summarization, Statistical Method, and Linguistic Approach rely on the structure of the document, consider the importance of content, and identify main concepts. However, Extractive Summarization and Statistical Method employ quantitative

approaches, whereas the Linguistic Approach adopts a qualitative approach.

Abstractive Summarization, Structured Approach, and Semantic-based Approaches all employ qualitative approaches, consider the significance of content, and involve human participation. They also utilize machine learning techniques. However, these methods do not depend on the document structure or offer a mathematical representation.

The Human Abstraction Concept is the only method that relies solely on a qualitative approach and necessitates human involvement. It does not rely on the document structure or provide a mathematical representation. This method is rooted in historical practices that involve human summarization techniques.

In a nutshell, the figure gives a thorough overview of the many traits and strategies used by various summarizing methods. Overall, the figure of similarities and dissimilarities provides a comprehensive overview of the strengths and weaknesses of different text summarization methods. These findings offer valuable insights for researchers and practitioners seeking to leverage summarization techniques in various applications.

7. CONCLUSION

A comparative analysis of various text summarization methods has been discussed in this study. The study aimed to provide an overview of different approaches and techniques used in text summarization, focusing on their strengths and limitations. Through the analysis, it was evident that extractive and abstractive summarization techniques have their own advantages and disadvantages, similarities and dissimilarities between them and the choice of method depends on the specific requirements and constraints of the task at hand.

However, it is important to acknowledge the limitations of this study. Firstly, the analysis was conducted solely based on existing research papers and publications, which might not capture the most recent advancements in text summarization. Moreover, the absence of algorithmic implementation restricted the evaluation of the methods' performance on real-world datasets. Future studies should focus on implementing and benchmarking these methods on diverse datasets to obtain more comprehensive and reliable results.

Looking ahead, future research in text summarization should address several areas of interest. Firstly, there is a need to explore hybrid approaches that combine extractive and abstractive methods to leverage their respective strengths and overcome their limitations. Additionally, developing techniques that can handle multi-modal and multi-document summarization will be crucial to cater to the increasing complexity and diversity of textual data. Furthermore, investigating the use of advanced deep learning architectures, such as transformer-based models, and incorporating external knowledge sources like pre-trained language models can enhance the quality and coherence of generated summaries. Lastly, focusing on domain-specific summarization, where the summarization model is trained on specialized datasets, can lead to more accurate and domain-tailored summaries. In conclusion, this comparative analysis provides valuable insights into text summarization methods without algorithmic implementation. Despite the limitations of the study, such as the reliance on existing research and lack of implementation, it lays the foundation for future research in this field. By addressing the limitations and focusing on areas of future work, we can continue to advance the field of text summarization and make significant contributions to applications like information retrieval, document summarization, and natural language understanding.

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