

Various Approaches Of Text Summarization: A Literature Review

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Abstract

In the digital age, a vast reservoir of unstructured data has become readily accessible, offering opportunities for intelligent applications such as data analysis, Automatic Text Summarization (ATS), caption or headline generation, and rumor detection, among many others. There are different approaches in text mining; summarization is one of those approaches. Text summarization automatically creates a brief overview of a lengthy text document while retaining crucial details. Text summarization has many techniques or approaches according to need and expectation. In this review paper we describe the research scenario of text summarization from 1958 to 2024. The purpose of this paper is to understand the evolution between old techniques and new techniques. It presents a variety of datasets, assessment strategies, and automatic text summary approaches. Nowadays, deep learning provides significant results in text summarization. Selecting key phrases from the source text that accurately communicate the original meaning is crucial when summarizing text. These surveys do provide a comprehensive evaluation framework for assessing the approaches mentioned. Therefore, this survey provides three main contributions: 1) Explanation of techniques and classification of text summarization methods based on expected output and available data. 2) An exploration of datasets along with their evaluation techniques and results as discussed in some papers. 3) Identification of research gaps for further study. This paper provides an overview of text summarization and identifies opportunities for further research.

Keywords: Summarization, Automatic, Deep Learning, Evaluation, Extraction, Abstraction.

A. Introduction

The internet provides access to numerous articles and multimedia information daily. As of April 2024, there were 5.44 billion internet users worldwide; 5.07 billion, or 62.6 percent of the world's population, were social media users [1]. The digital age has produced a huge amount of unstructured data, creating opportunities like data analysis, data science, and full-stack development. Natural Language Processing (NLP) concentrates on the representation and analysis of human language. A broad range of technologies is available for the improved utilization of vast unstructured data, including text summarization, caption or headline generation, and rumor detection, among others. Summarization techniques are essential in text mining as they mitigate information overload, enhance information retrieval, and facilitate more effective decision-making across diverse domains [3]. Various methodologies exist for summarizing content, one of which is the fuzzy extractive approach. Fuzzy logic (FL) improves Automatic text Summarization (ATS) algorithms to manage significantly greater uncertainty or ambiguity, rendering it a useful asset in text mining. FL can facilitate decision-making regarding the relevance or significance of content in a summary by evaluating degrees of membership across many categories [4], [5].

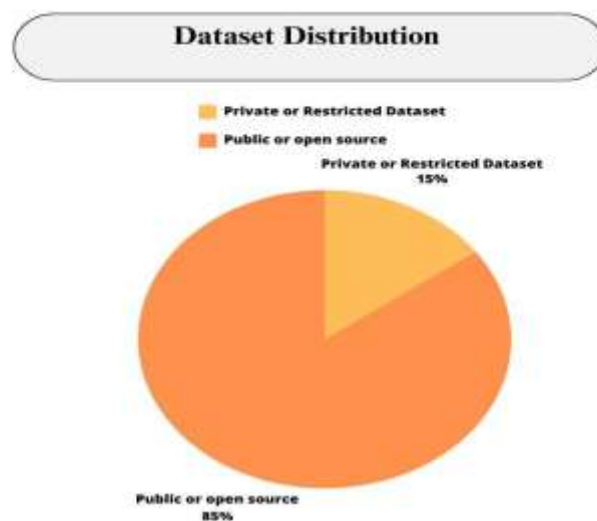
There are other difficulties, such as user-specific summaries, multi-document summaries, supported language issues, and evaluation techniques for the generated summaries. To address these issues, it is necessary to develop new procedures with enhanced precision. In addition, progress in natural language processing can enhance the precision and coherence of the produced summaries. This survey outlines text summarization techniques, explores datasets, and identifies research gaps, providing an overview of

expected output and available data, highlighting opportunities for further study. This study work aims to identify gaps and review prior techniques to advance further.

B. Dataset:

In ATS research, the selection of an appropriate dataset is essential for assessing the efficacy of suggested methodologies. Datasets may be classified as private or public. Public datasets are widely utilized, with approximately 85% of research depending on them, in contrast to 15% that utilizes private data. Document Understanding Conference (DUC) is a leading public dataset for text summarizing. It consists of news articles and abstracts, making it suitable for evaluating the performance of summarization algorithms on real-world data. Another popular public dataset is CNN/Daily Mail, which contains news articles paired with bullet point summaries. Researchers often use this dataset to compare the effectiveness of different summarization techniques. Private datasets, on the other hand, are typically more specialized and may require additional permissions for access.

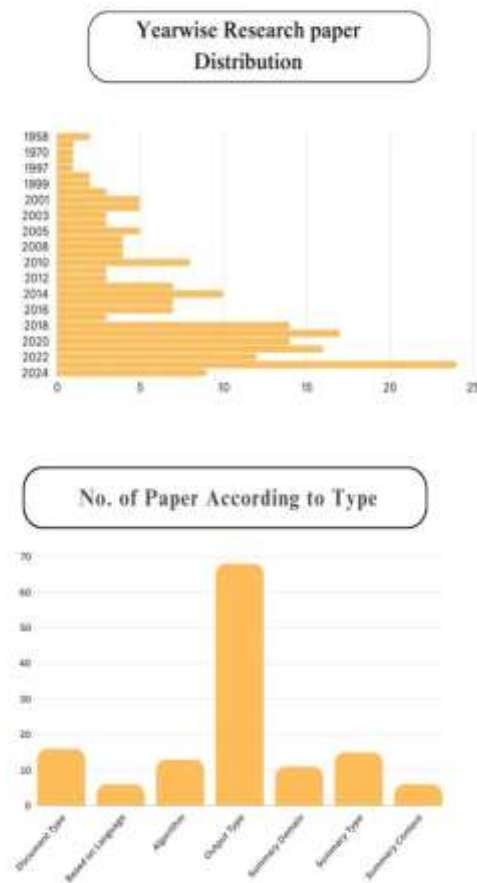
Dig. 1 Data Set Distribution



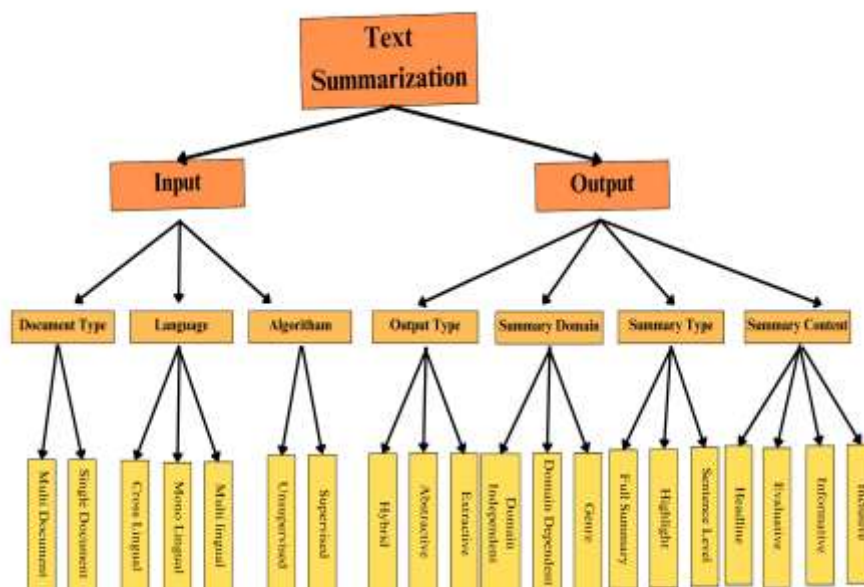
C. Distribution of Research:

Text mining research has been conducted for several decades. But since 2018, we've noticed a big shift in these sectors, with new topics of study appearing more frequently. This study examines literature from 1958 to 2024. Once more, we derive it from various types of input documents and output formats. We make an effort to wrap up research paper 201. This study aims to provide a comprehensive overview of the evolution of text mining research over the years (Dig. 2 (a)). By analyzing the distribution of research topics and methodologies, we can gain insights into the trends and advancements in this field ((Dig. 2 (b))). In the following diagram (Dig. 3) we illustrate the hierarchy of the ATS. Researchers can select the best technique from the following TS categories, depending on the type of text and the level of detail they want in the summary.

Dig. 2 (a) Yearwise Research (b) No. of papers studied according to type



Dig. 3 Classification of ATS



D. Review of Relevant Literature:

The review of relevant literature provides a comprehensive overview of the evolution of text mining research over the years, highlighting key advancements and trends. By analyzing the distribution of research topics and methodologies, researchers can gain valuable insights into the current state of the field and identify potential areas for future exploration. Initially, data is collected and examined to comprehend its substance. Ultimately, the vital information has been reduced and integrated into a brief overview.

1. Based on Document Type

A single-document summarization (SDS) algorithm identifies significant phrases from a singular source material [6]. Conversely, multi-document summarizing (MDS) entails utilizing several documents as input to produce a summary [7]. Mao et al. developed the Maximal Marginal Relevance (MMR) algorithm to help with issues that arise when there is only one document and not enough information is available to accurately judge the importance of each sentence [8]. Mandal et al. utilized the Cuckoo Search algorithm and sentiment analysis to evaluate phrases in a single-document extractive summarization approach [9].

Radev et al. proposed that relative utility (RU) serves as a robust metric for assessing the efficiency of extractive summarization methods for both individual and multiple documents [10]. Veningston et al. created Reinforcement Learning-MMR, a method that combines advanced neural single-document summarization algorithms with standard multi-document summarization metrics to handle the complexity of larger search spaces [11]. Zajic et al. conducted research on Contextual Multi-document Summarization (CMS) by employing multi-document summarization and Independent Multi-document Summarization (IMS), treating each email as a singular document summary task [12]. Wolhandler et al. used the Super-PAL model [13] to predict summary source alignment scores. This made it easier for summarization datasets and models to combine data from many sources [14]. Fabbri et al. presented Multi-News, the inaugural extensive MDS news dataset [15]. Ma et al. conducted a systematic examination of contemporary deep learning-based MDS algorithms [16]. Zhang et al. looked into how to adapt a state-of-the-art neural abstractive summarization model MDS. They found that it worked better with less tweaking on a small set of multi-document summaries [17]. Recent studies on encoder-decoder models for MDS and SDS provide multiple solutions. Challenges encompass the complicated process of generating summaries for lengthy meetings involving numerous participants and subjects, the constraints of conventional assessment metrics such as ROUGE, and the deficiency of parallel data for multi-document summaries.

Table no. 1 Representation of ATS methods considering Document Type

Source	Focus	Data / Methodology	Result
[6]	Non-negative Matrix Factorization (NMF)	DUC 2002 benchmark	Efficiently defining main topics, removing noise, and improving performance, using NMF.

[8]	Biased lexrank from neighborhood documents.	DUC 2001 and DUC 2002 datasets	Integrates prior scores from neighborhood documents.
[9]	Cuckoo Search algorithm	Opinosis dataset 1.0	Technique to assign scores to sentences, which helps in determining their importance and relevance.
[10]	RU method	DUC 2003 and 2004 multi-document	Demonstrate that RU is a valid and potentially superior metric for evaluation.
[11]	LSTM and RNN for Multi-document Extractive summarization Text	Daily Mail dataset, Multinews dataset	Personalized text summarization that adapts to user needs and specific tasks.
[12]	CMS and IMS	Half a million emails from the folders of 151 Enron employees.	CMS is generally more effective than IMS.
[14]	MDS models	DUC (2001 to 2007), TAC (2008, 2009, 2010, 2011), multinews	Fine-tuning on a single effective document, achieves better summary performance than fine-tuning on the full set of documents.
[15]	SDS system	DUC 2004 and Multi-News (First large-scale MDS news dataset)	PG-MMR gives highest Fluency, Non-Redundancy and Informative summary.
[16]	Survey on Deep-learning-based MDS models	Review	Comparison between dataset
[17]	RL-MMR for MDS)	DUC and TAC	Framework effectively bridges the gap between SDS and MDS

2. Based on Language

Effective summarizing models must account for the distinct features, syntax, vocabulary, and cultural specifics of each language to provide precise and coherent summaries. The Language Grid offers access to a variety of language datasets and tools, essential for training and enhancing language models for particular languages. The European Language Grid (ELG) [22] is one example of such a resource.

Mihalcea et al. presented a language-agnostic extractive summarization technique, demonstrating its efficacy in English and Portuguese [23]. Li et al. created a way to get standard and up-to-date summaries by using topic modeling to figure out what's important and dynamic modeling to handle duplicate content [24]. By automatically extracting linguistic resources, Denkowski and Lavie made language-specific evaluation work for languages that hadn't been supported before. They found that Russian (WMT13) and Hindi had better performance than their baseline BLEU scores [25]. Widjanarko employed Latent Dirichlet Allocation (LDA) and significance sentence techniques [26]. Wang et al. tackled the challenging problem of processing texts exceeding BERT's window size with a cascade methodology [27]. Karmakar et al. used LSTM-based Sequence-to-Sequence (Seq2Seq) Neural Networks along with language-specific preprocessing techniques to make abstractive text summarization easier, which made it easier to understand texts in regional languages [28]. Aksenov et al. enhanced abstractive summarization by incorporating BERT information into a transformer-based model. BERT-windowing for extended texts employed two-dimensional convolutional self-attention within the encoder. This method outperformed both baseline and state-of-the-art models on English and German datasets [29]. ([18], [19], [20], [21]).

Table no. 2 Representation of ATS methods considering language

Source	Focus	Data / Methodology	Result
[22]	ELG address the European Language	Methodology	Development and deployment of European-built language.
[23]	Language-independent extractive summarization, using iterative graph-based ranking algorithms.	DUC 2002	The method performs equally well across both English and Portuguese languages.
[30]	Topic Modeling Approach for Salience Determination and Dynamic Modeling Approach for Redundancy Control	TAC 2008 and 2009	Dynamic modeling approach for potential to improve the quality and effectiveness of the summarization.
[25]	Meteor universal, statistical machine translation	Wmt13 Russian and wmt14 Hindi	Improve translation quality, particularly for languages such as Russian and Hindi.

[26]	Summarization for the Indonesian Language Based on LDA	5 news document from cnnindonesia.com	Significant sentences frequently found at the beginning of the documents, thus supporting the deductive structure commonly used in Indonesian online news articles.
[27]	Application of pretrained transformer encoders, particularly BERT	Chinese dataset (PKU Paraphrase Bank)	BERT encoders remain highly effective for specific IR tasks and offer a lower deployment cost.
[28]	Addressing the challenges in Indian regional languages	News-please library, Kaggle Hindi Text Summarization Corpus dataset and Github Marathi News Document dataset	Perform of existing methods, the challenges and potential future directions for improving abstractive summarization.
[29]	Conditioning the Encoder and Decoder on BERT	CNN/Daily Mail, swiss text dataset	Highlighting improvements in the coherence and relevance of the generated summaries.

3. Based on Algorithm

Deep learning models have shown impressive results in ATS, with most using an encoder-decoder framework. Radford et al. demonstrate that language models can acquire skills like question answering, machine translation, reading comprehension, and summarization without direct supervision when trained on WebText, a dataset comprising millions of webpages [31]. Supervised learning typically produces summaries that closely match human-generated ones, while unsupervised learning offers greater flexibility and adaptability to various text types but may result in less coherent or informative summaries [32], [33], [34], [35], [36].

Supervised learning algorithms were used to train summarizers to extract important segments [37], [38]. Srivastava et al. investigated an unsupervised approach to extractive summarization, combining clustering with topic modeling to reduce topic bias. They used Latent Dirichlet Allocation for topic modeling and K-Medoids clustering for generating summaries [39]. Amini and Gallinari looked into semi-supervised algorithms for text summarization so that they wouldn't need as much expensive labeled data. They tested

the new algorithms on the Reuters and TIPSTER SUMMAC datasets and compared them to systems that don't learn and systems that can be trained [40].

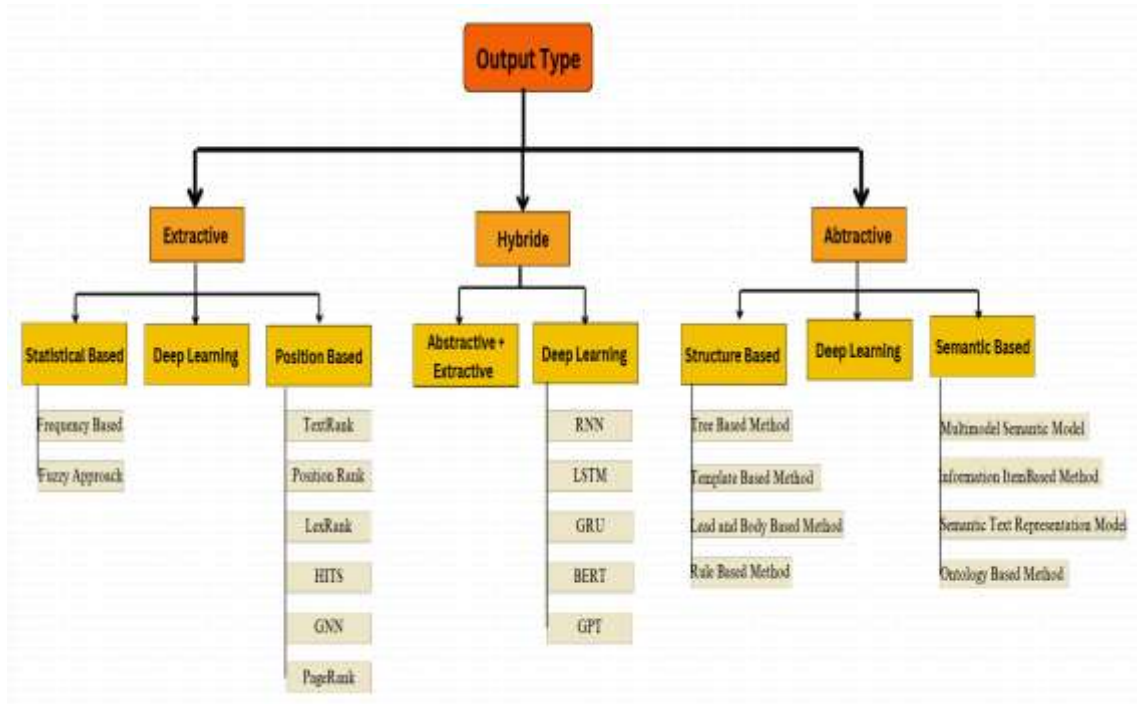
Nomoto et al. looked at supervised and unsupervised ways to ATS and found that an extended K-means clustering algorithm works just as well as or better than a decision tree-based method [41]. Fang et al. combined word-sentence relationships with a graph-based unsupervised ranking model [42]. Mao et al. proposed methods for single-document summarization, integrating both supervised and unsupervised learning techniques [43].

Table no. 3: Representation of ATS methods considering algorithm

Source	Focus	Data / Methodology	Result
[38]	Segmenting sentences and Feature representation	9 u.s. patent data	It performs favorably well compared to other methods.
[37]	Automatic Summarization using Reinforcement Learning (ASRL)	DUC 2004	Highlight the robustness and efficiency of the ASRL approach.
[39]	Unsupervised extractive summarization approach that combines clustering and topic modeling	Wikihow dataset, CNN / dailymail dataset and DUC 2002 corpus	Focus on subtopics offers significant improvements over generic topic modeling and deep learning.
[40]	Developing semi-supervised algorithms	The reuters newswire corpus and the computation and language (cmp_lg)	Effectively reduce the reliance on extensive labeled data.
[41]	Unsupervised text summarization approach to Information-Centric Evaluation	BMIR-J2 corpus	Concept diversity in unsupervised summarization and introduces a novel evaluation methodology.
[42]	Proposed word-sentence co-ranking model	600 documents	Comparison with other baseline models.

[43]	ATS using both supervised and unsupervised learning techniques	DUC 2001 and DUC 2002	Used unsupervised score as feature of supervised learning.
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Fig. 4 Classification of Output Type



4. Output Type

Output type has three techniques or approaches: extractive, hybrid, and abstractive summary. The Kasture proposed word-sentence co-ranking model was applied to 600 documents for comparison with other baseline models. The stated meaning of output type includes three techniques: extractive, hybrid, and abstractive summary. An extractive summary means extracting it as it is from the content; an abstractive summary rearranges highlighted content, and a hybrid is a combination of both abstractive and extractive [44].

4.1 Extractive Summarization

Extractive summarization involves selecting and presenting key sentences or phrases directly from the original content without any modification. This technique is commonly used in text summarization tasks to provide a concise overview of the main points in a document.

i. Statistical Based

Luhn proposed the first algorithm for automatic summarization ATS, high-frequency words are usually related sentences considered in summary. [45]. In that year, Baxendale used human scanning patterns in selecting topic sentences and phrases composed of nouns [46]. Edmundson and Wyllys utilized a relative frequency methodology to obtain an automatic extraction summary [47]. Knight and Daniel devised a statistical methodology for word selection using a decision tree and a noisy-channel model [48].

ii. Position-Based

Earlier studies concentrated on frequency words; however, Edmundson proposed methods to treat three additional components: pragmatic words (cue words), title and heading words and structural indicators (sentence location) [47]. Earl suggested two significant elements that provide structural information for each sentence. The requirement that Part of Speech (POS) supply the structure information for every sentence is one of the indicators used to determine a sentence's relevance [49]. Mihalcea and Tarau developed the TextRank algorithm, which was a rank- based approach for ATS [50].

Kupiec et al. presented novel methodologies in the domain of summarization and included machine-learning approaches, including Bayesian classification [51]. Radev introduced a stochastic rank-based method computing the relative importance of textual unit natural language processing. [52]. The noise in the data that could arise from a poor topical grouping of documents was not taken into account by the LexRank method. Suanmali et al. showed the drawback of traditional methods in terms of accuracy and fluency. [53]. According to the findings of Grover and Wason's, concluded in their comparative study, PageRank can be easily manipulated by creating links to pages with page rank, even if the pages are not relevant to each other. And it also stated that Hyperlink-Induced Topic Search (HITS) was not suitable for modern search engines because it was query-dependent and computationally expensive. [54].

It was shown by Pujari that the results from HITS were strongly related to the results of the Naïve Bayes classifier, which was used to give the document rank weight [55]. For the final score of each phrase [56], Goularte used the output membership function, which is divided into three separate membership functions: Output {Unimportant, Average, and Important}. This function took the fuzzy results from the inference engine and turned them into a precise output. FL may enhance the quality of summary results derived from general statistics.

A rank-based methodology has been extensively employed across numerous applications, including summarization, question answering, text categorization, sequence labeling, fact checking, and machine translation. In order to measure the weight assigned to a component that indicates how much the specific edge is related to the overall themes, Belwal suggested a new rank-based summarizing technique [57]. Additionally, Dehru et al. showed that TextRank was faster (by about 10%) and performed better than other extractive models because the sentences in the summaries made by other models were spread out. TextRank could show bias towards lengthy sentences or those with a greater number of keywords. This may result in summaries that fail to accurately reflect the key points of the text [58].

Cai observed that the words in different sentences do not have equal importance. They proposed a HITS-based attention-hierarchical encoder-decoder framework. However, in many domains and applications, representing data in traditional vectors or matrices is either inconvenient or not directly feasible. A prime example is the field of chemistry. [59].

iii. Deep Learning

Salchner and Jatowt demonstrated the evolution of graph neural networks (GNNs). Graph Neural Networks (GNNs) are a method for processing non-Euclidean data [60]. According to Yang, GNNs are an easy-to-use and powerful algorithm for text sentence rating. Its foundation was the notion that sentences that are similar to one another are more likely to be significant [61].

Dalal evaluated prior LexRank methodology like Pre-training with Extracted Gap-sentences for Abstractive Summarization (PEGASUS) for artificial summarization and

compared their results across six distinct documents. By achieving a superior ROUGE-F1 score, the LexRank model's generated summary outperforms the other examined models [62]. Gupta and Lehal noted that extractive summarizing possesses numerous errors, with one of the most significant being its potential to produce summaries that lack consistency and semantic integrity. This is due to the fact that extractive summarization disregards the interrelationships among phrases within a text corpus [63]. Cheng and Lapata used attention-based extractors to help in locating an important region. They basically used an RNN-based encoder-decoder for extractive summarization of documents [64].

4.2 Abstractive Summarization:

Abstractive summarization, on the other hand, aims to generate summaries that are more coherent and maintain the semantic integrity of the original text by paraphrasing and rephrasing information. This approach involves understanding the content of the text and generating a summary in a more human-like manner. Further, Saggion et al. expressed the need for a summarization technique based on syntactic and semantic analysis for abstractive information from multiple documents [65].

i. Structure-Based

Structure-based summarization focuses on organizing information in a logical manner to generate coherent summaries. This method involves analyzing the structure of the text to extract key information and present it in a concise format. Structure-based text summarization involves using the organization and relationships within a document's structure to generate summaries.

- **Tree-based method**

Barzilay and McKeown invented sentence fusion through the text-to-text generation methodology. It produces summary phrases that do not like the input materials [66]. Kikuchi determined that the sentence sub-tree technique markedly enhanced the ROUGE score [67].

- **Template-based method**

Template-based methods involve using predefined templates to extract important information from the text and generate summaries. By filling in the template with relevant details, this method can create concise and informative summaries efficiently. Harabagiu and Finley developed the GISTEXTER system, which refers to information extraction. GISTEXTER uses information extraction (IE), lexical chaining, and discourse analysis to figure out how the text is structured so that a summary can be made [68]. Bilal determined that the template-based strategy summarizes content into three components: Main Story, Majority Opinion, and Minority Opinion, which facilitates improved information inclusion [69].

- **Lead and body phrase methods**

To enhance the informativeness of broadcast news lead sentences, one way is to incorporate more background information in the lead. According to Khan et al., the Lead and Body Phrase technique worked by replacing parts of the lead sentence with alternative phrases that maintained the same grammatical structures [70].

- **Rule-based Method**

The rule-based method involves using predefined rules to generate lead sentences that capture the main points of a news story efficiently. This method has been found to be

effective in improving the clarity and conciseness of broadcast news articles. To maintain satisfactory language quality and duplication standards. Le and Le suggested a method for abstractive text summarization using discourse rules, syntactic restrictions, and word ranks [71]. Vodolazova and Lloret proposed syntactic rules to convert text into its semantic representation utilizing the subject-verb-object framework [72].

ii. Semantic Model

Semantic-based text summarizing requires understanding the meaning and context of a document's content to produce more precise and relevant summaries. Semantic-based methodologies aim to clarify the fundamental semantics of the text. The following are essential elements of semantic-based text summarization [73]. To reduce the readability challenges encountered in extractive summarization, researchers proposed a semantic methodology. Khan et al. used the SENNA semantic role labeler to pull out predicate argument structures. They then found groups of predicate argument structures that were semantically similar across the text and used a genetic algorithm to rank them [70]. Mohamed and Oussalah advanced multi-document summarization by synthesizing knowledge derived from graphs and textual information [74].

• Semantic-Based Multimodel

To minimize the readability issues that occurred in extractive summarization, researchers introduced a semantic approach. Khan et al. used the SENNA semantic role labeler to extract predicate argument structure, then find clusters of semantically similar predicate argument structures across the text and make rank weighted by a genetic algorithm [70]. Mohamed and Oussalah contributed to MDS by integrating knowledge obtained from graphs and knowledge gained from text [74].

• Information-item-based methods

Information-item-based methods have also been explored, where the summary is generated by selecting important information items from the text and organizing them in a coherent manner. These approaches aim to improve the quality and coherence of the generated summaries by focusing on semantic relationships between information items. Genest and Lapalme gave the idea to collect the smallest element of meaningful information in a text for the summarization [75].

• Semantic Text Representation Model

By focusing on the underlying meaning of the text, this model can produce summaries that are not only accurate but also easily understandable for readers. Moawad presented the generation and deduction of semantically rich graphs. This model reduces around 50% of the data [76]. Khan et al. discovered a novel method for graphing nodes to illustrate predicate argument structures (PASs), with the similarity weight denoting the graph edges [77].

• Ontology-based

FL can be included with both extractive and abstractive summarizing methods. Lee et al. presented an ontology-driven methodology utilizing FL [78]. We learned about fuzzy ontology models of linguistic variables from Zhai et al. [79]. These models take into account the semantic relationships of fuzzy concepts, like set relations, order relations, equivalence relations, and semantic association relations. A FL based methodology includes the selection of fuzzy rules and membership functions, along with essential components such as a fuzzifier, inference engine, defuzzifier, and knowledge base. This strategy is utilized to determine the most significant sentence from a source document or

context, demanding duplication elimination for optimal outcomes. Suanmali et al. introduced a method for generating summaries by arranging ranking sentences from the original text [80]. Furthermore, many studies have investigated this methodology in their ATS research [81], [82], [83], [84], [85].

iii. Deep Learning

These models have also been incorporated into the methodology to enhance the accuracy and efficiency of ATS systems. These models utilize neural networks to learn patterns and relationships within text data, improving the overall performance of the summarization process. Nallapati et al. improved semantic representation of text with an attention-based encoder-decoder RNN [86]. Zhang et al. proposed a bi-GRU model that integrates a forward GRU network with a backward GRU network to extract semantic information from words [87].

4.3 Hybrid Summarization:

White et al. presented a summarizer that requires the retrieval of a collection of documents followed by the generation of an abstractive summary [88]. Hori and Furui showed a dynamic programming method in 2004 that used term co-occurrence, a tri-gram language model, and confidence score features to find a set of important phrases in a real document [89]. Barzilay and McKeown provided a summary that exclusively utilized words from the extractive summary and subsequently reassembled the sentences [66]. Yousfi-Monod proposed an alternative technique that eliminates nonessential components while maintaining grammatical accuracy [90].

Filippova applied term frequency for word graphs and subsequently integrated sentences based on POS tagging and term co-occurrence [91]. Gupta and Lehal suggested an integrated methodology utilizing probabilistic and generative algorithms [63]. Boudin et al. developed a technique for key-phrase extraction manipulation and presented N-shortest pathways for summarization [92]. Pontes and Montr evaluated the methods mentioned earlier and determined that Filippova's method yielded significantly more information than the alternatives [93].

The development of deep learning architectures has led to sustained and comparably high performance in numerous natural language processing applications [94]. Deep learning, namely deep neural networks, significantly enhances both abstractive and extractive summarization. Suleiman and Awajan mentioned that transformer models, which have attained state-of-the-art performance across numerous summary tasks, have served as a guide for text summarization. However, challenges in abstractive summarizing remain, including the dataset, evaluation metrics, and the quality of the produced summary [95].

1. Recurrent Neural Networks (RNN)

RNN have also been widely used in text summarization tasks due to their ability to capture sequential information. The traditional neural network involves the extraction of words from information to provide a summary. The deep learning component is considered within a hybrid methodology. Chopra et al. identified conditional RNN. They worked to construct concise sentences while maintaining their meaning [96]. According to Young et al. [97], recurrent neural networks (RNNs) have problems like the vanishing gradient, which is also known as the long-term dependency problem. This problem means that the network has trouble keeping information for long periods of time, which causes it to lose information quickly over time [97]. To address the vanishing gradient problem, two neural network methodologies have been proposed: the gated recurrent unit (GRU) and the long short-term memory (LSTM). RNNs are proficient in forecasting each succeeding character in a text and are capable of managing more complicated tasks. The OKAM-CGAN,

a knowledge-based ontology-aware multi-focus conditional generative adversarial network, was used to look at smaller semantic units and come up with new phrases [98]. OKAM-CGAN is evaluated against sophisticated techniques including RNN-W, CopyNet, GCU, Seq2Seq, and KESG with ROUGE scores.

2. Long Short-Term Memory (LSTM)

Gers and Schraudolph highlighted the advantages of LSTMs over traditional RNNs, using peepholes and forget gates to examine new techniques for LSTM in summarization [99]. The peephole enables all connection gates to examine the current cell state, even while the output gate is closed. Rahman and Siddiqui's proposed model has been improved using the Central Composite Design (CCD) combined with Response Surface Design (RSD). However, models indicate decreased efficiency when producing substantial quantities of content, such as summaries [100]. Aljumah and Berriche presented a bi-LSTM integrated with an attention model to generate a summary of comments. BiLSTM yields significantly superior outcomes compared to GRU [101]. LSTM networks have demonstrated superior efficacy compared to traditional RNNs [102]. Kaur and Sharma conducted precise sentiment analysis from the consumer review perspective with the LSTM summarization model for investors [103].

3. Gated Recurrent Unit (GRU)

It is an alternative form of recurrent neural network frequently used for tasks such as text summarization. GRU is more efficient and easy to use compared to LSTM. Chung et al. stated that GRU resemble RNNs, but with several significant differences. Gated Recurrent Units (GRUs) possess two gates: a reset gate and an update gate [104]. Rehman et al. implemented a GRU-based encoder-decoder combined with a Bahdanau attention mechanism to address the large amount of input content. This model was utilized for generating news headlines [105]. Alternative neural architectures that do not rely on CNNs and RNNs include GANs [106].

4. Bidirectional Encoder Representations from Transformers (BERT)

It is another example of a non-RNN architecture that has gained popularity for natural language processing tasks. BERT utilizes transformer models to achieve state-of-the-art results in various NLP applications. Devlin et al. were the first to introduce BERT. They developed the deep bidirectional architecture and a representation approach focused on fine-tuning. It consists of two phases: pre-training and fine-tuning. Interpretation of medical data might run into difficulties with BERT [107]. Turchin et al. conducted a comparison between complex medical concepts and standard BERT. Both BioBERT and ClinicalBERT outperformed standard BERT [108].

In 2019, Liu et al. advanced BERT by modifying its parameters and providing it with additional data [109]. He et al. enhanced prior methodologies by incorporating two further elements. The initial feature is calculating word weights by disentangled matrices according to their content and position, with the subsequent improvement being an optimized mask decoder [110].

5. Generative Pre-trained Transformers (GPT)

GPT is another example of transformer models that have been enhanced through modifications to their architecture and training data. These advancements have led to improved performance in natural language processing tasks, showcasing the potential for continued innovation in this field. Radford and Salimans enhanced understanding of languages using generative pre-training. GPT completed a two-phase training process that included unsupervised pre-training and supervised fine-tuning [111]. Brown et al.

suggested a trained model that can finish jobs fast even when the data is small in size. Nonetheless, there are certain disadvantages: few-shot learning algorithms can result in significant computing costs during training [112].

Table no. 4 Representation of ATS methods considering output type

Source	Focus	Data / Methodology	Result
[50]	Supervised techniques namely textrank for keyword extraction	Inspec , DUC 2002	Does not require deep linguistic knowledge, nor domain or language specific annotated corpora.
[51]	Focus more on the conceptual framework	30 reuters newswire documents(manually created abstract)	Trainable summarization model and discusses its methodology.
[10]	Unsupervised model , adaption of page rank	DUC 2003 and 2004	Rank-based centrality measures, adapted from the field of network analysis.
[53]	ATS based on General Statistic Method	125 documents from DUC 2002	Decision-support and expert systems with powerful reasoning capabilities.
[54]	Pagerank and HITS	Theoretically comparison	Comparison of the performance of pagerank and HITS in various scenarios.
[55]	Naive Bayes and HITS	90 News articles from Yahoo! Website	Focused on extracting opinionated sentences.
[56]	Handles Uncertainty, Reduced Rule Base	Brazilian Portuguese texts	Fuzzy rule-based method performed well than the other extractive summarization.
[57]	Rank-based used to find document similarity	DUC 2002	Considering document-to-sentence similarity , helps to join two sentences.

[58]	To handle long sentences, used the Bahdanau attention layer	1) News Summary Dataset from Kaggle 2) Food Reviews Amazon from Kaggle	Textrank slightly faster (about 10%).
[59]	Authority and hub scores from the HITS algorithm	CNN/daily mail dataset , New York times (NYT) annotated corpus	Relevance to the main topic and those cited by many other sentences receive more attention.
[60]	A comprehensive overview of models utilizing GNN	CNN/dailymail and DUC 2004	Capture long relationship between sentences and generate abstractive
[62]	Lexrank , PEGASUS, Transformer	Comparative study	Paraphrasing technique using the lexrank algorithm and PEGASUS transformer for abstractive summary.
[65]	Describe "sumum"	Journal Rapid Prototyping and journal Internet Research	Rich with indicative summary, in formativeness, and text acceptability.
[66]	Multigen system for multi document	DUC	Accurately identifies common information.
[67]	Based on RST use as extraction textual units	RST signaling corpus	Relations between sentences and relations between words
[68]	Techniques implemented in GISTEXTE	DUC 2002	Abstract and extract from single and multiple documents.
[69]	Opinion detection accuracy(specially opinions in micro blogs)	Tweeter (COVID-19 and UK Elections)	Addresses micro blogs like tweets It separates Main Story from Majority Opinion and Minority Opinion.
[113]	Improve news opening sentences	257 articles from news programs	Make the first sentence of news stories better.

[71]	Utilizes discourse rules, syntactic constraints, and word graphs	50 documents collected Vietnamese newspaper websites	Shorten sentences and also fix grammar issue.
[72]	Subject-verb-object concept	DUC 2002	Try to make theoretically correct sentences and identify important themes and ideas.
[78]	Ontology with crisp concepts	2002 , 2003 and 2004 typhoon news	Capturing and representing the uncertainty and imprecision.
[114]	Abstractive ATS	DUC 2002	Semantic similarity measures to make clusters.
[74]	Detailed SRL works	DUC 2002	Combination Semantic Role Labeling and Wikipedia-based explicit semantic analysis.
[76]	Rich semantic graph reduction	methodology	Reducing summary to fifty percent of original.
[77]	predicate argument structures, Semantic graph with nodes representation	DUC 2002	Predicate argument structures used to improve ranking algorithms.
[48]	Decision-based model using probability	Cmplg corpus	In evaluation they compare grammatical and important parts.
[88]	RapIdly Portable Translingual Information extraction and interactive multiDocumEnt Summarization. (RIPTIDES) system	TDT2	RIPTIDES presents a holistic system for user-directed MDS.
[89]	Extraction using Dynamic Programming	Newspaper text	This paper is based on audio summarization but can try to apply this in text too
[91]	Shortest paths in word graphs	Google news	Does not rely on syntactic information

[92]	Re-ranking step to the most relevant keyphrases	Google news	N-best reranking approach to improves the information and quality
[93]	Extraction used techniques Latent Semantic Indexing (LSI), LDA and textrank.	Boudin and Morin corpus	Give comparison with other model
[64]	Neural network-based hierarchical document reader and an attention-based hierarchical content extractor	DUC 2002 and dailymail news	Two model classes, focusing on sentence and word extraction
[86]	Capturing the hierarchy of sentence-to-word structure, Emitting words that are rare or unseen during training	Gigaword corpus	Consider hierarchy of sentence-to word structure
[99]	LSTM with Peephole Connections	Methodology	Peephole LSTM variant is emphasized as being capable of learning exact and extremely robust timing algorithms
[100]	Multi-layered Attentional Peephole Convolutional LSTM (MAPCOL)	CNN-Daily Mail	Use of CCD and RSM to get optimized parameters of model like batch size , epoch number
[101]	Source Code Summarization using Deep Learning	51 million Java methods from more than 5000 projects	Time Efficiency
[87]	Relation Extraction Based on Keywords Attention (REKA) using Bi- GRU	Semeval-2010 Task	Without the use of additional NLP reduce dependency on external tools.
[115]	Effective Use of GRU and Attention Mechanism	CNN/Daily Mail	GRU-based encoder and decoder, coupled with the Bahdanau attention mechanism, Single Sentence Summary for Headline Generation

[108]	Biobert and clinicalbert	MIMIC-III dataset	Biobert and clinicalbert gave better results than regular BERT.
[116]	Robustly optimized BERT approach	BOOKCORPUS) plus English WIKIPEDIA, CC-NEWS, OPENWEBTEXT	Critical Examination of Hyperparameters
[116]	DEBERT (Decoding-enhanced BERT with disentangled attention) that improves the BERT	Wiki+Book, openwebtext, Stories, CC-News	Word weights using disentangled matrices and enhancement mask decoder.
[117]	Greek abstractive text summarization models, based on umt5	Greeksum	Umt5, outperform greekbart
[118]	The purpose of this study is to leverage NLP for the knowledge summarization of High Entropy Alloys (HEAS).	HEAS available on the Google Scholar	Not implementation on algorithms like BERT, XL Net and GPT2

5. Based on the Summarization Domain:

ATS systems are classified into three groups based on their input and output domains:

- **Genre Specific:**

The distinctive characteristics and conventions of various text subject matter, such as news stories, scientific papers, novels, or legal documents, are taken into consideration while summarizing texts. Genre-specific text summarizing tailors the summary technique to various text genres. [119], [120], [121]. Seki proposed an artificial summarizing technique that combines document genre and text structure to enhance efficacy [122]. Goldstein et al. developed a methodology that commences with the identification of the document genre. The researchers evaluated 16 genres and compared various machine learning techniques, concluding that random forests had superior performance [123]. A unified framework for categorizing news genres that recognizes both the architecture of a news piece and the order of its components [124], [125]. Nenkova and McKeown emphasized the importance of language generation and an enhanced semantic comprehension of language for future progress in the discipline [126].

- **Domain Dependent:**

Additionally, the researchers highlighted the significance of domain-specific features in improving classification accuracy. They suggested that incorporating domain knowledge could further enhance the performance of machine learning models. Domain-dependent summarization is customized for a particular domain [127]. According to Sparck-Jones, their architecture requires background study to customize a template to an appropriate level of detail, providing it is domain dependent [128].

- **Domain Independent:**

The RAKE approach is effective for extracting keywords from individual documents regardless of the domain. It does not require specific domain knowledge to generate accurate results. Rose et al. came up with the Rapid Automatic Keyword Extraction (RAKE) method, which is unsupervised, doesn't depend on the domain, and works with any language to pull keywords from single documents [129]. A domain-independent summarization system isn't limited to any particular domain of the source materials. Borchers et al. highlighted domain independence simply, facilitating computers in understanding and aiding users effectively across diverse areas [130].

Table no. 5 Representation of ATS methods considering Summary Domain

Source	Focus	Data / Methodology	Result
[122]	Emphasizes the importance of document genre and text structure	Viewsumm30, newspaper editorials	Use document genre and text structure significantly
[123]	Addresses critical issues such as compression, speed, redundancy, and selection using domain-independent	Tipster	Handles the challenges of MDS by employing fast statistical processing
[125]	Focus on analyzing the task of automatic tweet generation from a text	10 different English and Spanish newspaper online	Better balance between indicativeness and interest
[124]	Comparison between printed text and text-to-speech (TTS) audio	Primary Data	SARA framework to analyze and systematically restore information content in headings during TTS presentation
[127]	Decision Express, an ATS system developed for legal document	Primary Data	Decision express is the first for legal documents
[129]	Comparison of textrank and RAKE	MPQA Corpus	RAKE effectively extracts keywords
[130]	Users pattern languages to gain knowledge	Methodology	

6. Based on Summary Type

- **Summary of the headline:**

Banko et al. examined headline generation with statistical translation algorithms [131]. Zhou et al. used a word selection-based clustering approach [120]. The process begins with the identification of significant sentences by document summarizing algorithms [66].

According to user studies, Tran et al. handled the challenges with automatic event selection by increasing relevance and understanding in comparison to current systems [132]. Sepúlveda-Torres et al.'s successful two-stage classifier Headline Stance Checker [133] addressed the problem of headline text irrelevance. Headings enhance the likelihood of topics being included in summaries [125], [134].

- **Sentence Level:**

Liu et al. presented a novel document-level encoding using BERT for semantic representation and sentence extraction [135]. Ferreira et al. evaluated 15 sentence scoring algorithms across several text forms, including news, blogs, and articles, and provided recommendations for improvement [136]. Al-Sabahi et al. modified the PageRank method to evaluate phrases utilizing both internal and external data [137]. Cao et al. chose sentences with good scores for summaries [17]. Han et al. evaluated diverse summarization techniques, including extractive methods (which choose high-ranking sentences) and abstractive methods (which rephrase the principal ideas) [138].

- **Highlight:**

Highlights are quick bullet points extracted from the source text. Nasar et al. created a supervised regression method for automatically pulling out the most important parts of scientific papers, which cuts down on the need for manual annotation [139]. Cagliero and Quatra introduced a new regression method for the automatic generation of highlights in scientific papers [121]. Liu et al. created the Highlight Transformer, enhancing abstract MDS by highlighting significant terms [140]. The CNN/DM dataset, frequently utilized for summarization, includes articles and their corresponding highlights.

Table no. 6 Representation of ATS methods considering summary type

Source	Focus	Data / Methodology	Result
[131]	Uses statistical models to jointly handle term selection and term ordering based on patterns learned	25,000 news articles	Generate coherent summaries that are shorter than a single sentence
[120]	To generate very short summaries, specifically headlines of 10 words or less	DUC 2003	Paper indicates that finer tuning of parameters related to the size limit
[66]	Evaluation of sentence fusion, a novel text-to-text generation method	100 themes	Ability to accurately identify and select common information

[132]	Novel framework for ATS for news stories	News articles	Users prefer the timeline summaries generated by the headline-based approach
[133]	Determine whether headlines accurately reflect the content of the articles or not	Fnc-1 and emergent dataset.	Highlights that the headlinestancechecker approach
[125]	Extractive summarization techniques for generating automatic tweets from news documents	News and tweets	Original tweets were not always considered the most interesting or indicative, despite being informative.
[134]	Neural sequence-to-sequence models for the task of headline generation	English Gigaword corpus	Performance improvements due to coarse-to-fine approach compared to baseline neural sentence summarization models
[140]	Highlighting mechanism within the encoder to enhance attention on key phrases	Multi-news dataset	Advantages of the highlight-transformer model and provide insights into its potential for improving summarization
[136]	Discusses RAKE (focusing on its performance and keyword extraction	MPQA Corpus	RAKE's efficiency in terms of computational resource usage and processing time
[137]	Combination of modified BM25 with word embeddings and a graph-based ranking method	DUC 2002 and DUC 2004	MBM25EMB, have enhanced the performance of textrank algorithm
[141]	Group-Based Extractive Text Summarization with Clustering Algorithms and Semantic Links	ACL-all dataset	Average length of source texts affects the performance and quality of group-based summaries compared to paragraph-based summaries.

[138]	Sentence-Level Semantic Graph Model (SLSGM) which exploits the semantic information	DUC 2004	Consider the sentence meaning and word ordering
[139]	Reduces input variable using FL	63 texts in Portuguese	Correlating feature gives better result than the data reduction techniques
[121]	Insights derived from the content of scientific articles. Done automatically, without doing manually	CSPubSumm	Regression models tailored to specific topics, potentially enhanced with fine-tuned embedding models

7. Based on Summary Content

There are different kinds of criteria can be developed, based on the user:

- **Inductive:**

This involves creating general conclusions from specific events or observations. An inductive summary provides a concise summary of a work, highlighting the essential facts and principal concepts without drawing new conclusions or making generalizations. When summarizing a research report, the focus should be on delineating the principal findings, methods, and key points [142], [143], [144].

- **Informative:**

This means providing fresh insight or information about a subject. Harabagiu and Lacatusu presented two new representations based on subject themes and discussed five previously recognized topic representations. An inductive summary of a research report involves constructing broad generalizations from the individual facts and observations expressed in the document [145]. Mishra et al. explored diverse methodologies for effective information extraction from text, including topic modeling (LSI, NMF), key phrase extraction Term Frequency-Inverse Document Frequency (TF-IDF), and text summarization (LSA, TextRank) [118]. Ježek et al. examined a range of summarization methods, from classical to modern approaches, addressing the ongoing challenge of information overload in the digital age [146].

Table no. 7 Representation of ATS methods considering summary content

Source	Focus	Data / Methodology	Result
[143]	Text summarization by employing FL to identify important and relevant sentences	News, Blogs and Article contexts	Enhances the quality of ATS conclusion drawn from specific details
[142]	Integrating latent semantic analysis into the FL system	Private Dataset	Hidden semantic relations between concepts in a text

[144]	Virtual graph concept , exhaustive shortest path algorithm	15 different Article	Builds from specific details to a general conclusion
[145]	Use of different topic representations for MDS (Presents main ideas and key points)	DUC	Improvement in summary quality using topic themes highlights the importance of choosing appropriate topic representations for MDS
[118]	Using advanced methods like LSI, NMF, weighted TF-IDF, LSA, and textrank, aims to improve the efficiency and effectiveness	Review	Demonstrates the potential of these techniques to significantly enhance the process of understanding and retrieving information
[146]	Comprehensive overview of the history and current state of automatic text	Methodology	Addressing the ongoing challenge of information overload in the digital age

E. Evaluation Metrics:

The quality of machine-generated text is crucial for assessing and improving models in natural language processing (NLP). There are some widely recognized metrics for this purpose are ROUGE (Recall-Oriented Understudy for Gisting Evaluation), BLEU (Bilingual Evaluation Understudy) and METEOR (Metric for Evaluation of Translation with Explicit Ordering)

ROUGE

ROUGE is an essential statistic for evaluating ATS systems. C. Lin and Rey introduced ROUGE, showing its efficacy in assessing both SDS and MDS tasks. They also mentioned ROUGE's stability and importance in automatic evaluation are highlighted. Despite challenges in achieving high correlation with human judgments, especially in MDS, ROUGE's stability and significance in automatic evaluation are emphasized. The study looks at 17 ROUGE score comparisons with human scores for summarizing tasks with multiple documents from DUC 2001, 2002, and 2003 [147]. ROUGE comprises multiple metrics:

- ROUGE-N with Multiple References: Calculates pairwise summary-level ROUGE-N scores between a candidate summary and each reference summary. ROUGE-N specifically measures the overlap of N-grams (sequences of N words) between the candidate summary and the reference summary.
- ROUGE-L: Utilizes the longest common subsequence (LCS) to assess summaries by examining the longest shared sequence of words between the candidate and reference summaries, emphasizing sentences over individual words.
- ROUGE-W (Weighted LCS): The weighted LCS (WLCS) technique enhances the fundamental LCS by prioritizing successive matches and distinguishing between sequential and non-sequential matches. This resolves limitations of the fundamental

LCS technique and offers a more precise assessment of the similarity between two sequences of words or phrases.

- ROUGE-S (Skip-Bigram Co-Occurrence Statistics): These statistics quantify the number of similar word pairings, or skip-bigrams, that appear in both the candidate translation and a set of reference translations. It's a way to see how closely the candidate matches the references. It's a way to see how closely the candidate matches the references.
- ROUGE-C provides evaluation independent of human reference summaries and demonstrates strong correlation with approaches relying on reference summaries. Calculating the co-occurrence of successive n-grams (sequences of n words) between the candidate summary and the document, divided by the total number of n-grams in the candidate summary [148].

These metrics statistically evaluate the alignment of ATS with reference summaries, taking into account both included (accuracy) and omitted (recall) information. They offer a method to calculate precision, recall, and F1 score, essential to the effective evaluation of ATS systems.

$$Precision = \frac{\text{Total Number of Items in Candidate Summary}}{\text{Number of Correct Items in Candidate Summary}}$$

$$Recall = \frac{\text{Total Number of Items in Reference Summary}}{\text{Number of Correct Items in Candidate Summary}}$$

$$F1 \text{ Score} = \frac{(Precision + Recall)}{(2 \times Precision \times Recall)}$$

BLUE

Another commonly used method for evaluating summaries is BLEU, which also has its own set of limitations. BLEU primarily measures the n-gram overlap between the system-generated summary and reference summaries. However, it may not capture the overall coherence and fluency of the summary, leading to potential inaccuracies in assessment. However, BLEU scores alone may not provide a complete picture of a summary's quality, as they do not account for factors such as readability and relevance. Therefore, it is important to consider multiple evaluation metrics when assessing the effectiveness of a summary.

$$BLUE = BP * \exp \left(\sum_{n=1}^N w_n \log P_n \right)$$

where BP is the brevity penalty, w_n is the weight, and P_n is the precision of n-grams.

METEOR

METEOR is another commonly used metric for evaluating the quality of summaries. It takes into account not only n-gram precision but also word order and synonymy. According to research, using multiple evaluation metrics like BLEU and METEOR together can provide a more comprehensive assessment of summary quality. METEOR is an automatic metric for machine translation evaluation based on unigram matching between machine-produced translations and human-produced reference translations.

$METEOR = (1 - \text{Penalty}) \times F_{\text{mean}}$

$$METEOR = (1 - \text{Penalty}) * F_{\text{mean}}$$

Where:

F_{mean} is the harmonic mean of precision (P) and recall (R)

The penalty (Penalty) is a factor to penalize incorrect word ordering

$$Penalty = \gamma * \left(\frac{Chunk}{m}\right)^{\beta}$$

Where:

chunks is the number of contiguous matched word groups

γ and β are penalty parameters (default $\gamma=0.5, \beta=3$)

F. Drawbacks of Evaluation Method:

Firstly, it is challenging to establish a reliable standard for judging the quality of summaries produced by Automated Text Summarization (ATS) systems. An ideal summary is difficult to define because ATS systems might create effective summaries that differ from those generated by humans[150]. Human preferences vary, leading to different selections in both extractive and abstractive summaries [151]. This subjectivity makes manual evaluations less suitable for all types of summaries.

ROUGE, a common tool for evaluating summaries, has its drawbacks. It mainly focuses on counting matching word sequences between computer-generated and human-written summaries[152]. This approach has limitations because it does not recognize synonyms or different wordings that convey the same meaning. Additionally, ROUGE does not account for how well the summary reads or its natural flow. Therefore, while ROUGE is useful, it may not provide a complete picture of a summary's quality[153], [154], [155], [156], [157]

G. Application:

Text summarization applications offer a wide range of benefits, including time savings, improved productivity, better information retrieval, and enhanced decision-making[21], [158], [159], [160], [161]

- ***Microblog summarization:*** Microblogging is a form of online communication that allows users to publish short text updates, images, links, or other media content. Summaries can make information more accessible to a wider audience, including those with limited time [69], [161], [162], [163].
- ***Tweet summarization:*** Tweet summarization refers to the process of condensing the content of one or more tweets into a concise summary [164], [165], [166], [167].
- ***Social Media Monitoring:*** Text summarization applications can analyze social media posts, comments, and conversations to provide users with summaries of trending topics, sentiment analysis, or key insights [168], [169], [170], [171].
- ***Email thread summarization:*** Email chain or email conversation, refers to a series of related email messages exchanged between one or more individuals. These messages are typically grouped together in email clients, such as Gmail or Outlook. Email thread summarization involves condensing the content of a series of email exchanges into a concise summary [172], [173], [174], [175].
- ***Legal document summarization:*** Legal document summarization involves condensing the content of legal documents, such as contracts, court opinions, statutes, and legal briefs, into concise summaries while preserving the essential information and meaning [176], [177], [178], [179], [180].
- ***Meeting summarization:*** In meetings there are different types of people with different topics. So it becomes difficult to drop a summary. Meeting summarization involves condensing the key points, decisions, action items, and discussions from a meeting into a concise summary [181], [182], [183], [184].

H. Challenges:

These challenges can impact both manual and automated summarization processes. Some important problems when writing articles are:

- **Language-speech problems:**

Word comprehension is inconsistent (multiple meanings, syntactic ambiguity) [24], [185], [186], [187], [188]. In fact, there is much room for improvement and other issues such as morphology also need to be addressed [189].

- **Challenges in multiple document:**

Different data may present conflicting or opposing views on a topic. Summarization systems must be capable of handling the overload and extracting the most important information [145], [190], [191]. Comparative terms are often used for conflicting news, opinions, and product reviews. But note that there is currently a need for new techniques to handle this problem [192].

- **Challenges due to evaluation metrics**

The quality of the content may be as desired and may vary according to personal preferences. Many traditional metrics, such as ROUGE and BLEU, are based on n-gram overlap between the generated content and the reference content [27], [193], [194], [195], [196]. They may miss the opportunity to capture semantics, resulting in potentially damaging evaluations [197]

- **Challenges in Strategic Summaries:**

It's important to measure readability, ease, and overall quality, but these differences vary from person to person [171], [198]. Recently there is a need to focus on developing content collection systems according to specific goals and user needs [196].

- **Challenges due to dataset:**

Human dropped summaries are complete and detailed, covering all aspects of something; sometimes it becomes biased too. It is also expensive and time consuming, typically taking several months. Optimization of text content requires data that will show the structure of content-specific data [199], [200]. State-of-the-art summarization systems have been studied on large web-crawled datasets, but data quality issues are missing or unclear [135], [201]. Difficult to find information in languages other than English [202].

Conclusion:

In conclusion, the literature review on text summarization highlights the significant evolution of techniques and methodologies from 1958 to 2024, showcasing the transition from traditional methods to advanced deep learning approaches. The review emphasizes the importance of text summarization in managing the vast amounts of unstructured data generated in the digital age, addressing challenges such as information overload and the need for effective decision-making. Various summarization techniques, including extractive, abstractive, and hybrid methods, have been explored, with a focus on their applications across different domains, such as social media, legal documents, and email threads.

The paper identifies key datasets and evaluation metrics, such as ROUGE, while also acknowledging the limitations of these metrics in capturing the quality and semantics of generated summaries. Furthermore, it outlines the challenges faced in summarization tasks, including language ambiguities, conflicting information from multiple documents, and the need for user-specific summaries. In order to satisfy the changing demands of users in a world that is becoming more and more data-driven, the evaluation ends by highlighting research gaps and areas requiring additional research.

Bibliography:

- [1] A. Petrosyan, "Number of internet and social media users worldwide as of April

- 2023," Statista, vol. 2023, no. July, pp. 9–12, 2023, [Online]. Available: <https://www.statista.com/statistics/617136/digital-population-worldwide/>
- [2] D. Khurana, A. Koli, K. Khatter, and S. Singh, "Natural language processing: state of the art, current trends and challenges," *Multimed. Tools Appl.*, vol. 82, no. 3, pp. 3713–3744, 2023, doi: 10.1007/s11042-022-13428-4.
- [3] Z. Khan and T. Vorley, "Big data text analytics: an enabler of knowledge management," *J. Knowl. Manag.*, vol. 21, no. 1, pp. 18–34, 2017, doi: 10.1108/JKM-06-2015-0238.
- [4] S. Chakraborti and S. Dey, "Analysis of Competitor Intelligence in the Era of Big Data: An Integrated System Using Text Summarization Based on Global Optimization," *Bus. Inf. Syst. Eng.*, vol. 61, no. 3, pp. 345–355, 2019, doi: 10.1007/s12599-018-0562-0.
- [5] F. Kyoomarsi, H. Khosravi, E. Eslami, and M. Davoudi, "Extraction-based text summarization using fuzzy analysis," *Iran. J. Fuzzy Syst.*, vol. 7, no. 3, pp. 15–32, 2010.
- [6] D. Tsarev, M. Petrovskiy, and I. Mashechkin, "Supervised and Unsupervised Text Classification via Generic Summarization," *Int. J. Comput. Inf. Syst. Ind. Manag. Appl.*, vol. 5, pp. 509–515, 2013, [Online]. Available: www.mirlabs.net/ijcisim/index.html
- [7] W. E. I. E. Zhang, M. Guo, H. U. Wang, and Q. Z. Sheng, "Multi-document Summarization via Deep Learning arXiv : 2011 . 04843v3 [cs . CL] 9 Dec 2021," vol. 1, no. 1, pp. 1–35, 2021.
- [8] X. Mao, S. Huang, L. Shen, R. Li, and H. Yang, "Single document summarization using the information from documents with the same topic," *Knowledge-Based Syst.*, vol. 228, p. 107265, 2021, doi: 10.1016/j.knosys.2021.107265.
- [9] S. Mandal, G. K. Singh, and A. Pal, "Single document text summarization technique using optimal combination of cuckoo search algorithm, sentence scoring and sentiment score," *Int. J. Inf. Technol.*, vol. 13, no. 5, pp. 1805–1813, 2021, doi: 10.1007/s41870-021-00739-2.
- [10] D. R. Radev, D. Tam, and C. Science, "Single-document and multi-document summary evaluation using Relative Utility," pp. 1–28, 2007.
- [11] K. Venington, P. V. Venkateswara Rao, and M. Ronalda, "Personalized Multi-document Text Summarization using Deep Learning Techniques," *Procedia Comput. Sci.*, vol. 218, no. 2022, pp. 1220–1228, 2022, doi: 10.1016/j.procs.2023.01.100.
- [12] D. M. Zajic, B. J. Dorr, and J. Lin, "Single-Document and Multi-Document Summarization Techniques for Email Threads Using Sentence Compression *," vol. 44, no. March 2007, pp. 1600–1610, 2008, doi: 10.1016/j.ipm.2007.09.007.
- [13] O. Ernst et al., "Summary-Source Proposition-level Alignment : Task , Datasets and Supervised Baseline," pp. 310–322, 2021.
- [14] R. Wolhandler, A. Cattani, O. Ernst, and I. Dagan, "How 'Multi' is Multi-Document Summarization?," 2022.
- [15] A. R. Fabbri and D. R. Radev, "Multi-News : a Large-Scale Multi-Document Summarization Dataset and Abstractive Hierarchical Model," pp. 1074–1084, 2019.
- [16] C. Ma, W. E. I. E. Zhang, M. Guo, and H. U. Wang, "Multi-document Summarization via Deep Learning Techniques : A Survey Multi-document Summarization via Deep Learning Techniques : A Survey," no. January 2024, 2022, doi: 10.1145/3529754.
- [17] Y. Mao, Y. Qu, Y. Xie, X. Ren, and J. Han, "Multi-document Summarization with Maximal Marginal Relevance-guided Reinforcement Learning," vol. 2004, no. 2018, pp. 1737–1751, 2020.

- [18] L. F. Lebanoff Logan , Song Kaiqiang, "Adapting the Neural Encoder-Decoder Framework from Single to Multi-Document Summarization," 2018.
- [19] S. Sun, "The Feasibility of Embedding Based Automatic Evaluation for Single Document Summarization," no. iii, pp. 1216–1221, 2019.
- [20] J. Zhu, H. Li, T. Liu, Y. Zhou, J. Zhang, and C. Zong, "MSMO: Multimodal Summarization with Multimodal Output," vol. 2, pp. 4154–4164, 2018.
- [21] M. Zhong, D. Yin, T. Yu, and A. Zaidi, "QMSum : A New Benchmark for Query-based Multi-domain Meeting Summarization," pp. 5905–5921, 2021.
- [22] G. Rehm et al., "European Language Grid : An Overview," 2019.
- [23] R. Mihalcea and P. Tarau, "A Language Independent Algorithm for Single and Multiple Document Summarization Multi-Document Summarization," pp. 19–24, 1999.
- [24] L. Li, J. Li, H. Wang, and J. Nie, "Application of the transformer model algorithm in chinese word sense disambiguation: a case study in chinese language," *Sci. Rep.*, vol. 14, no. 1, pp. 1–15, 2024, doi: 10.1038/s41598-024-56976-5.
- [25] M. Denkowski and A. Lavie, "Meteor Universal : Language Specific Translation Evaluation for Any Target Language," pp. 376–380, 2014.
- [26] A. Widjanarko, R. Kusumaningrum, and B. Surarso, "Multi document summarization for the Indonesian language based on latent dirichlet allocation and significance sentence," 2018 *Int. Conf. Inf. Commun. Technol. ICOIACT 2018*, vol. 2018-Janua, pp. 520–523, 2018, doi: 10.1109/ICOIACT.2018.8350668.
- [27] H. Jin, Y. Zhang, D. Meng, J. Wang, and J. Tan, "A Comprehensive Survey on Process-Oriented Automatic Text Summarization with Exploration of LLM-Based Methods," pp. 1–20, 2024, [Online]. Available: <http://arxiv.org/abs/2403.02901>
- [28] R. Karmakar, K. Nirantar, P. Kurunkar, P. Hiremath, and D. Chaudhari, "Indian Regional Language Abstractive Text Summarization using Attention-based LSTM Neural Network," 2021 *Int. Conf. Intell. Technol. CONIT 2021*, no. June, 2021, doi: 10.1109/CONIT51480.2021.9498309.
- [29] D. Aksenov, P. Bourgonje, R. Schwarzenberg, L. Hennig, and G. Rehm, "Abstractive Text Summarization based on Language Model Conditioning and Locality Modeling," no. May, pp. 6680–6689, 2020.
- [30] H. Wang and G. Zhou, "Toward a Unified Framework for Standard and Update," vol. 11, no. 2, 2012, doi: 10.1145/2184436.2184438.
- [31] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever, "Language Models are Unsupervised Multitask Learners," 2018.
- [32] M. Patel, A. Chokshi, S. Vyas, and K. Maurya, "Machine Learning Approach for Automatic Text Summarization Using Neural Networks," pp. 194–202, 2018, doi: 10.17148/IJARCCCE.
- [33] M. Y. Saeed and M. Awais, "Unstructured Text Documents Summarization With Multi-Stage Clustering," vol. 8, 2020, doi: 10.1109/ACCESS.2020.3040506.
- [34] L. Alzubaidi et al., "A survey on deep learning tools dealing with data scarcity: definitions, challenges, solutions, tips, and applications," *J. Big Data*, vol. 10, no. 1, 2023, doi: 10.1186/s40537-023-00727-2.
- [35] J. L. Neto, A. A. Freitas, and C. A. A. Kaestner, "Automatic text summarization using a machine learning approach," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 2507, no. March 2014, pp. 205–215, 2002, doi: 10.1007/3-540-36127-8_20.
- [36] S. Adhikari, "NLP based Machine Learning Approaches for Text Summarization," *Proc. 4th Int. Conf. Comput. Methodol. Commun.*, pp. 535–538, 2020, doi: 10.1109/ICCMC48092.2020.ICCMC-00099.
- [37] S. Ryang, "Framework of Automatic Text Summarization Using Reinforcement

- Learning,” no. July, pp. 256–265, 2012.
- [38] L. Angeles, “Text Summarization by Sentence Segment Extraction Using Machine Learning Algorithms,” pp. 454–457, 2000.
- [39] R. Srivastava, P. Singh, K. P. S. Rana, and V. Kumar, “A topic modeled unsupervised approach to single document extractive text summarization,” *Knowledge-Based Syst.*, 2022.
- [40] M. Amini and P. Gallinari, “The Use of Unlabeled Data to Improve Supervised Learning for Text Summarization,” vol. 6, pp. 105–112, 2002.
- [41] T. Nomoto and Y. Matsumoto, “A new approach to unsupervised text summarization,” *SIGIR Forum (ACM Spec. Interes. Gr. Inf. Retrieval)*, no. September 2001, pp. 26–34, 2001, doi: 10.1145/383952.383956.
- [42] C. Fang, D. Mu, Z. Deng, and Z. Wu, “PT US CR,” *Expert Syst. Appl.*, 2016, doi: 10.1016/j.eswa.2016.12.021.
- [43] X. Mao, H. Yang, S. Huang, Y. Liu, and R. Li, “Extractive summarization using supervised and unsupervised learning,” *Expert Syst. Appl.*, 2019, doi: 10.1016/j.eswa.2019.05.011.
- [44] N. R. Kasture, N. Yargal, N. N. Singh, N. Kulkarni, and V. Mathur, “A Survey on Methods of Abstractive Text Summarization,” no. 6, 2014.
- [45] Luhn, “The Automatic Creation of Literature Abstracts *,” no. April, pp. 159–165, 1958.
- [46] Baxendale, “Machine-Made Index for Technical Literature - An Experiment,” pp. 354–361, 1958.
- [47] H. P. Edmundson, “New Methods in Automatic Extracting,” vol. 16, no. 2, pp. 264–285, 1969, doi: 10.1145/321510.321519.
- [48] K. Knight, D. Marcu, and M. Rey, “Statistics-Based Summarization — Step One : Sentence Compression,” 2000.
- [49] L. L. Earl, “EXPERIMENTS IN AUTOMATIC EXTRACTING A N D INDEXING *,” vol. 6, no. 00, pp. 313–334, 1970.
- [50] R. Mihalcea and P. Tarau, “132547658 \$ 9 @ 2BADCF8 " GHEPI RTSVU ` Q WFX ` Y acb e fhgpi d XqYsrth e 1u254 R 8 v v v v wyx 1u25476 8) 9 @ 2BA3CF8 " GHEPI Y r SV Q U ` WFX ` Y acb Q r a r © 3,” vol. 85, 1998.
- [51] J. Kupiec, J. Pedersen, and F. Chen, “Trainable document summarizer,” *SIGIR Forum (ACM Spec. Interes. Gr. Inf. Retrieval)*, pp. 68–73, 1995, doi: 10.1145/215206.215333.
- [52] D. R. Radev, “LexRank : Graph-based Lexical Centrality as Saliency in Text Summarization,” vol. 22, pp. 457–479, 2004.
- [53] L. Suanmali, N. Salim, and M. S. Binwahlan, “Fuzzy Logic Based Method for Improving Text Summarization,” vol. 2, no. 1, 2009.
- [54] N. Grover, “Comparative Analysis Of Pagerank And HITS Algorithms,” vol. 1, no. 8, pp. 1–15, 2012.
- [55] P. Rajkumar, S. Desai, N. Ganguly, and P. Goyal, “A Novel Two-stage Framework for Extracting Opinionated Sentences from News Articles,” pp. 25–33, 2014.
- [56] F. B. Goularte, S. M. Nassar, R. Fileto, and H. Saggion, “A text summarization method based on fuzzy rules and applicable to automated assessment,” 2018, doi: 10.1016/j.eswa.2018.07.047.
- [57] R. C. Belwal, S. Rai, and A. Gupta, “A new graph-based extractive text summarization using keywords or topic modeling,” *J. Ambient Intell. Humaniz. Comput.*, vol. 12, no. 10, pp. 8975–8990, 2021, doi: 10.1007/s12652-020-02591-x.
- [58] V. Dehru, P. K. Tiwari, G. Aggarwal, and B. Joshi, “Text Summarization Techniques and Applications,” 2021, doi: 10.1088/1757-899X/1099/1/012042.

- [59] X. Cai, K. Shi, Y. Jiang, L. Yang, and S. Liu, "Knowledge-Based Systems HITS-based attentional neural model for abstractive summarization," *Knowledge-Based Syst.*, vol. 222, p. 106996, 2021, doi: 10.1016/j.knosys.2021.106996.
- [60] M. F. Salchner and A. Jatowt, "A Survey of Automatic Text Summarization using Graph Neural Networks," 2021.
- [61] C. Yang, Y. Lin, Z. Liu, and M. Sun, *Graph Representation Learning*. 2023.
- [62] S. Dalal, A. Singhal, and B. Lall, "LexRank and PEGASUS Transformer for Summarization of Legal Documents," pp. 569–577, 2023.
- [63] V. Gupta, C. Science, and G. S. Lehal, "A Survey of Text Summarization Extractive Techniques," vol. 2, no. 3, pp. 258–268, 2010, doi: 10.4304/jetwi.2.3.258-268.
- [64] J. Cheng and M. Lapata, "Neural Summarization by Extracting Sentences and Words," pp. 484–494, 2016.
- [65] H. Saggion and G. Lapalme, "Generating Indicative-Informative Summaries with SumUM," 2002.
- [66] R. Barzilay and K. R. Mckeown, "Sentence Fusion for Multidocument News Summarization," no. March, 2005.
- [67] Y. Kikuchi, T. Hirao, H. Takamura, M. Okumura, and M. Nagata, "Single Document Summarization based on Nested Tree Structure EDU sentence subtree sentence selection selection," pp. 315–320, 2014.
- [68] S. Harabagiu and L. Finley, "Generating Single and Multi-Document Summaries with GIST EXTER," 2001.
- [69] I. M. Bilal, B. Wang, A. Tsakalidis, and D. Nguyen, "Template-based Abstractive Microblog Opinion Summarization," vol. 10, pp. 1229–1248, 2022.
- [70] A. Khan, N. Salim, and Y. Jaya, "A framework for multi-document abstractive summarization based on semantic role labeling A framework for multi-document abstractive summarization based on semantic role labelling," no. February 2015, 2020.
- [71] H. Le and T. Le, "An approach to Abstractive Text Summarization," pp. 372–377, 2013.
- [72] T. Vodolazova and E. Lloret, "The Impact of Rule-Based Text Generation on the Quality of Abstractive Summaries," pp. 1275–1284, 2019.
- [73] A. Jaiswal, A. R. Babu, M. Z. Zadeh, D. Banerjee, and F. Makedon, "A Survey on Contrastive Self-Supervised Learning," *Technologies*, vol. 9, no. 1, 2021, doi: 10.3390/technologies9010002.
- [74] M. Mohamed and M. Oussalah, "SRL-ESA-TextSum : A text summarization approach based on semantic role labeling and explicit semantic analysis ☆," *Inf. Process. Manag.*, vol. 56, no. 4, pp. 1356–1372, 2019, doi: 10.1016/j.ipm.2019.04.003.
- [75] P. Genest and G. Lapalme, "Framework for Abstractive Summarization using Text-to-Text Generation," no. June, pp. 64–73, 2011.
- [76] I. F. Moawad, "Semantic Graph Reduction Approach for Abstractive Text Summarization," no. November 2012, 2014, doi: 10.1109/ICCES.2012.6408498.
- [77] M. Khan, J. Bilal, I. Ahmed, and A. Paul, "Abstractive Text Summarization based on Improved Semantic Graph Approach Article," *Int. J. Parallel Program.*, 2018, doi: 10.1007/s10766-018-0560-3.
- [78] C. Lee, Z. Jian, and L. Huang, "A Fuzzy Ontology and Its Application to News Summarization," vol. 35, no. 5, pp. 859–880, 2005.
- [79] J. Zhai, M. Li, and Z. Kaitao, "Linguistic Variable Ontology and Its Application to Fuzzy Semantic Retrieval," *Inf. Comput. Appl.*, 2010.
- [80] L. Suanmali, N. Salim, and M. S. Binwahlan, "Fuzzy Logic Based Method for Improving Text Summarization," no. March, 2014.

- [81] D. B. Patel, S. Shah, and H. R. Chhinkaniwala, "PT US CR," *Expert Syst. Appl.*, 2019, doi: 10.1016/j.eswa.2019.05.045.
- [82] F. Kiyomarsi, S. Branch, E. Eslami, P. K. Dehkordi, S. Branch, and A. Tajoddin, "Optimizing Text Summarization Based on Fuzzy Logic," no. March 2015, 2008, doi: 10.1109/ICIS.2008.46.
- [83] S. Dixit and S. Gwalior, "Improvement of Text Summarization using Fuzzy Logic Based Method Improvement of Text Summarization using Fuzzy Logic Based Method," no. January 2012, 2020, doi: 10.9790/0661-0560510.
- [84] J. Yadav, "Use of Fuzzy Logic and WordNet for Improving Performance of Extractive Automatic Text Summarization," pp. 2071–2077, 2016.
- [85] R. Abbasi-ghalehtaki, H. Khotanlou, and M. Esmailpour, "Fuzzy evolutionary cellular learning automata model for text summarization," *Swarm Evol. Comput.*, pp. 1–16, 2016, doi: 10.1016/j.swevo.2016.03.004.
- [86] R. Nallapati and B. Xiang, "Abstractive Text Summarization using Sequence-to-sequence RNNs and Beyond Cicero dos Santos," pp. 280–290, 2016.
- [87] Y. Zhang et al., "Bi-GRU Relation Extraction Model Based on Keywords Attention," pp. 0–2, 2022, doi: 10.1162/dint.
- [88] M. White, T. Korelsky, C. Cardie, V. Ng, D. Pierce, and K. Wagstaff, "Multidocument Summarization via Information Extraction," 2001.
- [89] C. Hori and S. Furui, "Speech Summarization: An Approach through Word Extraction and a Method for Evaluation *," no. 1, pp. 15–25, 2004.
- [90] M. Yousfi-monod and M. Yousfi-monod, "Compression automatique ou semi-automatique de textes par élagage des constituants effaçables: une approche interactive et indépendante des corpus To cite this version : HAL Id : tel-00185367 U niversité M ontpellier T hèse Compression automatique ou sem," 2008.
- [91] K. Filippova, "Multi-Sentence Compression: Finding Shortest Paths in Word Graphs," no. August, pp. 322–330, 2010.
- [92] F. Boudin, E. Morin, and L. U. M. R. Cnrs, "Keyphrase Extraction for N-best Reranking in Multi-Sentence Compression," no. June, pp. 298–305, 2013.
- [93] E. L. Pontes and E. P. De Montr, "Multi-Sentence Compression with Word Vertex-Labeled Graphs and Integer Linear Programming," pp. 18–27, 2018.
- [94] I. Goodfellow, D. Warde-farley, A. Courville, and Y. Bengio, "Generative Adversarial Networks," no. June, 2014, doi: 10.1145/3422622.
- [95] D. Suleiman and A. Awajan, "Deep Learning Based Abstractive Text Summarization : Approaches , Datasets , Evaluation Measures , and Challenges," vol. 2020, 2020.
- [96] S. Chopra, M. Auli, and A. Rush, "Abstractive Sentence Summarization with Attentive Recurrent Neural Networks," pp. 93–98, 2016.
- [97] T. Young, D. Hazarika, S. Poria, and E. Cambria, "Recent Trends in Deep Learning Based Natural Language Processing," pp. 1–32, 2018.
- [98] J. Martens, "Generating Text with Recurrent Neural Networks," 2011.
- [99] F. A. Gers and N. N. Schraudolph, "Learning Precise Timing with LSTM Recurrent Networks," vol. 3, pp. 115–143, 2002.
- [100] M. Rahman and F. Siddiqui, "An Optimized Abstractive Text Summarization Model Using Peephole Convolutional LSTM," 2019, doi: 10.3390/sym11101290.
- [101] S. Aljumah and L. Berriche, "applied sciences Bi-LSTM-Based Neural Source Code Summarization," 2022.
- [102] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," no. August, 2015, doi: 10.1038/nature14539.
- [103] G. Kaur and A. Sharma, "A deep learning - based model using hybrid feature extraction approach for consumer sentiment analysis," *J. Big Data*, 2023, doi:

- 10.1186/s40537-022-00680-6.
- [104] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Gated Recurrent Neural Networks on Sequence Modeling," pp. 1–9, 2014.
 - [105] T. Rehman, S. Das, D. K. Sanyal, and S. Chattopadhyay, "Abstractive Text Summarization using Attentive," pp. 1–9, 2023.
 - [106] R. Bhargava, G. Sharma, and Y. Sharma, "ScienceDirect Deep Deep Text Text Summarization Summarization using using Generative Generative Adversarial Adversarial Networks Networks in in Indian Languages Indian Languages," PROCS, vol. 167, no. 2019, pp. 147–153, 2020, doi: 10.1016/j.procs.2020.03.192.
 - [107] J. Devlin, K. Lee, M. Chang, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," pp. 4171–4186, 2019.
 - [108] A. Turchin, S. Masharsky, and M. Zitnik, "Informatics in Medicine Unlocked Comparison of BERT implementations for natural language processing of narrative medical documents," Informatics Med. Unlocked, vol. 36, no. August 2022, p. 101139, 2023, doi: 10.1016/j.imu.2022.101139.
 - [109] Y. Liu et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," no. 1, 2019.
 - [110] P. He, X. Liu, J. Gao, and W. Chen, "Deberta: Decoding-enhanced bert with disentangled attention," 2020.
 - [111] A. Radford and T. Salimans, "Improving Language Understanding by Generative Pre-Training," pp. 1–12, 2018.
 - [112] T. B. Brown et al., "Language Models are Few-Shot Learners," no. NeurIPS, 2020.
 - [113] H. Tanaka, A. Kinoshita, T. Kobayakawa, T. Kumano, and N. Kato, "Syntax-Driven Sentence Revision for Broadcast News Summarization," ACL-IJCNLP 2009 - UCNLG+Sum 2009 2009 Work. Lang. Gener. Summ. Proc. Work., no. January, pp. 39–47, 2009, doi: 10.3115/1708155.1708163.
 - [114] A. Khan, N. Salim, and Y. Jaya, "A Framework for Multi-document Abstractive Summarization based on SRL A framework for multi-document abstractive summarization based on semantic role labelling," no. October, 2015.
 - [115] T. Rehman, S. Das, D. K. Sanyal, and S. Chattopadhyay, "An Analysis of Abstractive Text Summarization Using Pre-trained Models," no. 1, pp. 253–264, 2022, doi: 10.1007/978-981-19-1657-1_21.
 - [116] Y. Liu and M. Lapata, "Text Summarization with Pretrained Encoders," pp. 3730–3740, 2019.
 - [117] N. Giarelis and N. Karacapilidis, "GreekT5 : A Series of Greek Sequence-to-Sequence Models for News Summarization," 2024.
 - [118] A. R. Mishra, "Extractive Text Summarization - An effective approach to extract information ([WUDFWLYH 7H [W 6XPPDUL] DWLRQ ± \$ Q HIIHFWLYH DSSURDFK WR H [WUDFW LQIRUPDWLRQ IURP 7H [W," no. March, 2023, doi: 10.1109/IC3I46837.2019.9055636.
 - [119] E. Hovy and C. Lin, "A U T O M A T E D T E X T S U M M A R I Z A T I O N AND THE SUMMARIST SYSTEM," pp. 197–214, 1998.
 - [120] L. Zhou and E. Hovy, "Headline summarization at ISI," Duc 2003, 2003, [Online]. Available: <http://www.isi.edu/natural-language/projects/webclopedia/pubs/03duc-headline.pdf>
 - [121] L. Cagliero and M. La Quatra, "Expert Systems with Applications Extracting highlights of scientific articles : A supervised summarization approach," Expert Syst. Appl., vol. 160, p. 113659, 2020, doi: 10.1016/j.eswa.2020.113659.
 - [122] Y. Seki, "Automatic Summarization Focusing on Document Genre and Text Structure," vol. 39, no. 1, pp. 65–67, 2005.
 - [123] J. G. Stewart and J. Callan, "Genre Oriented Summarization," no. December 2008,

- 2009.
- [124] R. F. Lorch, E. P. Lorch, K. Ritchey, L. Mcgovern, and D. Coleman, "Effects of Headings on Text Summarization," vol. 191, pp. 171–191, 2001, doi: 10.1006/ceps.1999.1037.
 - [125] E. Lloret and M. Palomar, "Expert Systems with Applications Towards automatic tweet generation : A comparative study from the text summarization perspective in the journalism genre," *Expert Syst. Appl.*, vol. 40, no. 16, pp. 6624–6630, 2013, doi: 10.1016/j.eswa.2013.06.021.
 - [126] A. Nenkova and K. McKeown, "Automatic summarization," *Found. Trends Inf. Retr.*, vol. 5, no. 2–3, pp. 103–233, 2011, doi: 10.1561/15000000015.
 - [127] E. Chieze, A. Farzindar, and G. Lapalme, "An automatic system for summarization and information extraction of legal information," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 6036 LNAI, pp. 216–234, 2010, doi: 10.1007/978-3-642-12837-0_12.
 - [128] K. S. Jones, "Automatic summarising : factors and directions," pp. 1–21, 1999.
 - [129] S. Rose, D. Engel, and N. Cramer, "Automatic Keyword Extraction from Individual Documents," no. October 2017, 2010, doi: 10.1002/9780470689646.ch1.
 - [130] J. O. Borchers, "Pattern approach to interaction design," *Proc. Conf. Des. Interact. Syst. Process. Pract. Methods, Tech. DIS*, pp. 369–378, 2000, doi: 10.1145/347642.347795.
 - [131] M. Banko and M. J. Witbrock, "Headline Generation Based on Statistical Translation," 1997.
 - [132] G. Tran, M. Alrifai, and E. Herder, "Timeline summarization from relevant headlines," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 9022, pp. 245–256, 2015, doi: 10.1007/978-3-319-16354-3_26.
 - [133] R. Sepúlveda-torres, M. Vicente, E. Saquete, E. Lloret, and M. Palomar, "Web Semantics : Science , Services and Agents on the World Wide Web
HeadlineStanceChecker : Exploiting summarization to detect headline disinformation," *Web Semant. Sci. Serv. Agents World Wide Web*, vol. 71, p. 100660, 2021, doi: 10.1016/j.websem.2021.100660.
 - [134] J. Tan, X. Wan, and J. Xiao, "From Neural Sentence Summarization to Headline Generation : A Coarse-to-Fine Approach," pp. 4109–4115, 2013.
 - [135] P. Tejaswin, D. Naik, and P. Liu, "How well do you know your summarization datasets?," *Find. Assoc. Comput. Linguist. ACL-IJCNLP 2021*, pp. 3436–3449, 2021, doi: 10.18653/v1/2021.findings-acl.303.
 - [136] R. Ferreira et al., "Expert Systems with Applications Assessing sentence scoring techniques for extractive text summarization," *Expert Syst. Appl.*, no. May, 2013, doi: 10.1016/j.eswa.2013.04.023.
 - [137] K. Al-sabahi and Z. Zuping, "Document Summarization Using Sentence-Level Semantic," vol. 29, no. 2, pp. 177–196, 2019, doi: 10.1142/S0218194019500086.
 - [138] X. Han, T. Lv, Q. Jiang, X. Wang, and C. Wang, "TEXT SUMMARIZATION USING SENTENCE-LEVEL SEMANTIC GRAPH MODEL," pp. 1–6, 2016.
 - [139] Z. Nasar, S. W. Jaffry, and M. K. Malik, "Textual keyword extraction and summarization : State-of-the-art," vol. 56, no. June, 2019, doi: 10.1016/j.ipm.2019.102088.
 - [140] S. Liu, J. Cao, R. Yang, and Z. Wen, "Highlight-Transformer : Leveraging Key Phrase Aware Attention to Improve Abstractive Multi-Documnet Summarization," pp. 5021–5027, 2021.
 - [141] M. Cao and H. Zhuge, "Grouping Sentences as a Better Language Unit for Extractive Text Summarization," 2020.

- [142] S. Babar and Patil, "Improving Performance of Text Summarization Improving Performance of Text Summarization," *Procedia - Procedia Comput. Sci.*, vol. 46, no. May, pp. 354–363, 2015, doi: 10.1016/j.procs.2015.02.031.
- [143] S. Babar and S. Thorat, "Improving Text Summarization Using Fuzzy Logic," 2014.
- [144] G. S. Budhi, R. Intan, R. Silvia, and R. R. Stevanus, "Indonesian Automated Text Summarization," 2007.
- [145] S. Harabagiu and F. Lacatusu, "Topic Themes for Multi-Document Summarization," pp. 202–209, 2005.
- [146] K. Ježek and J. Steinberger, "Automatic Text Summarization (The state of the art 2007 and new challenges) Automatic Text Summarization (The state of the art 2007 and new challenges)," pp. 1–12, 2007.
- [147] G. Wentzel, "Funkenlinien im Röntgenspektrum," *Ann. Phys.*, vol. 371, no. 23, pp. 437–461, 1922, doi: 10.1002/andp.19223712302.
- [148] Y. Graham, "Re-evaluating automatic summarization with BLEU and 192 shades of ROUGE," *Conf. Proc. - EMNLP 2015 Conf. Empir. Methods Nat. Lang. Process.*, no. September, pp. 128–137, 2015, doi: 10.18653/v1/d15-1013.
- [149] B. Hendrickx, "Meteor," *Sp. Explor. Humanit. a Hist. Encycl. Vol. 1-2*, vol. 1–2, no. June, pp. 344–346, 2010, doi: 10.1145/2567940.
- [150] N. Moratanch and C. Gopalan, "A Survey on Extractive Text Summarization," no. November, 2017, doi: 10.1109/ICCCSP.2017.7944061.
- [151] E. Lloret and L. Plaza, "The Challenging Task of Summary Evaluation : An overview," 2017, doi: 10.1007/s10579-017-9399-2.
- [152] B. J. Dorr, C. Monz, S. President, R. Schwartz, D. Zajic, and C. Park, "A Methodology for Extrinsic Evaluation of Text Summarization : Does ROUGE Correlate ? University of Maryland," no. June, pp. 1–8, 2005.
- [153] J. Steinberger and K. Ježek, "Evaluation measures for text summarization," *Comput. Informatics*, vol. 28, no. 2, pp. 251–275, 2009.
- [154] E. Clark, A. Celikyilmaz, and N. A. Smith, "Sentence Mover ' s Similarity : Automatic Evaluation for Multi-Sentence Texts," 2018.
- [155] A. Cohan and N. Goharian, "Revisiting Summarization Evaluation for Scientific Articles," pp. 806–813, 2015.
- [156] M. Peyrard, "Studying Summarization Evaluation Metrics in the Appropriate Scoring," no. 2014, pp. 5093–5100, 2019.
- [157] J. Sjobergh, "Older Versions of the ROUGEeval Summarization Evaluation System were Easier to Fool," 2007.
- [158] S. Zhang, A. Celikyilmaz, J. Gao, M. Bansal, and U. N. C. C. Hill, : "Abstractive Email Thread Summarization," 2020.
- [159] S. Ghosh, "Indian Legal Text Summarization : A Text Normalisation-based Approach," 2022.
- [160] A. Aliwy and A. Abbas, "NERWS : Towards Improving Information Retrieval of Digital Library Management System Using Named Entity Recognition and Word Sense," 2021.
- [161] Y. Wu, H. Zhang, B. Xu, H. Hao, and C. Liu, "Automatic Microblog Summarization Based on Unsupervised Key-Bigram Extraction," vol. 4, no. 5, pp. 363–370, 2015, doi: 10.17706/ijcce.2015.4.5.363-370.
- [162] B. Sharifi, M. A. Hutton, and J. K. Kalita, "Experiments in microblog summarization," *Proc. - Soc. 2010 2nd IEEE Int. Conf. Soc. Comput. PASSAT 2010 2nd IEEE Int. Conf. Privacy, Secur. Risk Trust*, pp. 49–56, 2010, doi: 10.1109/SocialCom.2010.17.
- [163] N. Saini, S. Saha, S. Bhattacharyya, Pushpak Mrinal, and S. K. Mishra, "On multimodal microblog summarization.," *IEEE Trans. Comput. Soc. Syst.* 9, pp. 1317–1329, 2021.

- [164] A. Dusart, K. Pinel-Sauvagnat, and G. Hubert, "TSSuBERT: Tweet Stream Summarization Using BERT," no. ii, 2021, [Online]. Available: <http://arxiv.org/abs/2106.08770>
- [165] S. Naik, S. Lade, S. Mamidipelli, and A. Save, "Tweet Summarization: A New Approach," Proc. Int. Conf. Inven. Commun. Comput. Technol. ICICCT 2018, no. Iccct, pp. 1022–1025, 2018, doi: 10.1109/ICICCT.2018.8473327.
- [166] M. A. H. Khan, D. Bollegala, G. Liu, and K. Sezaki, "Multi-tweet summarization of real-time events," Proc. - Soc. 2013, pp. 128–133, 2013, doi: 10.1109/SocialCom.2013.26.
- [167] D. Rudrapal, A. Das, and B. Bhattacharya, "A survey on automatic Twitter event summarization," J. Inf. Process. Syst., vol. 14, no. 1, pp. 79–100, 2018, doi: 10.3745/JIPS.02.0079.
- [168] X. Qian, M. Li, Y. Ren, and S. Jiang, "Social media based event summarization by user-text-image co-clustering," Knowledge-Based Syst., vol. 164, pp. 107–121, 2019, doi: 10.1016/j.knosys.2018.10.028.
- [169] K. Fu, C. T. Lu, R. Nune, and J. X. Tao, "Steds: Social Media Based Transportation Event Detection with Text Summarization," IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC, vol. 2015-Octob, pp. 1952–1957, 2015, doi: 10.1109/ITSC.2015.316.
- [170] M. E. Moussa, E. H. Mohamed, and M. H. Haggag, "A survey on opinion summarization techniques for social media," Futur. Comput. Informatics J., vol. 3, no. 1, pp. 82–109, 2018, doi: 10.1016/j.fcij.2017.12.002.
- [171] F. A. Ghanem, M. C. Padma, and R. Alkhatib, "Automatic Short Text Summarization Techniques in Social Media Platforms," Futur. Internet, vol. 15, no. 9, 2023, doi: 10.3390/fi15090311.
- [172] T. Oya and G. Carenini, "Extractive summarization and dialogue act modeling on email threads: An integrated probabilistic approach," SIGDIAL 2014 - 15th Annu. Meet. Spec. Interes. Gr. Discourse Dialogue, Proc. Conf., no. June, pp. 133–140, 2014, doi: 10.3115/v1/w14-4318.
- [173] D. M. Shockley, "Email Thread Summarization With Conditional Random Fields," Analysis, 2010.
- [174] J. Ulrich, "Supervised Machine Learning for Email Thread Summarization," Computer (Long. Beach. Calif), no. September, 2008.
- [175] O. Rambow and J. Chen, "Summarizing Email Threads," 2004.
- [176] N. Van De Luijngaarden and M. Thesis, "Automatic Summarization of Legal Text," 2019.
- [177] M. Koniaris, D. Galanis, E. Giannini, and P. Tsanakas, "Evaluation of Automatic Legal Text Summarization Techniques for Greek Case Law," Inf., vol. 14, no. 4, pp. 1–32, 2023, doi: 10.3390/info14040250.
- [178] R. Kumar and K. Raghuveer, "Legal document summarization using latent dirichlet allocation," Int. J. Comput. Sci. Telecommun., vol. 3, no. 7, pp. 114–117, 2012.
- [179] D. Jain, M. D. Borah, and A. Biswas, "Summarization of legal documents: Where are we now and the way forward," Comput. Sci. Rev., vol. 40, p. 100388, 2021, doi: 10.1016/j.cosrev.2021.100388.
- [180] S. Sharma, S. Srivastava, P. Verma, A. Verma, and S. N. Chaurasia, "A Comprehensive Analysis of Indian Legal Documents Summarization Techniques," SN Comput. Sci., vol. 4, no. 5, 2023, doi: 10.1007/s42979-023-01983-y.
- [181] L. P. Kumar and A. Kabiri, "Meeting Summarization: A Survey of the State of the Art," 2022, [Online]. Available: <http://arxiv.org/abs/2212.08206>
- [182] T. Yu, Z. Ji, and P. Fung, "Improving Query-Focused Meeting Summarization with Query-Relevant Knowledge," IJCNLP-AACL 2023 - 13th Int. Jt. Conf. Nat. Lang.

- Process. 3rd Conf. Asia-Pacific Chapter Assoc. Comput. Linguist. Find. Assoc. Comput. Linguist. IJCNLP-AA, no. 1, pp. 48–54, 2023, doi: 10.18653/v1/2023.findings-ijcnlp.5.
- [183] V. Rennard, G. Shang, J. Hunter, and M. Vazirgiannis, “Abstractive meeting summarization: A survey,” *Trans. Assoc. Comput. Linguist.*, vol. 11, pp. 861–884, 2023, doi: 10.1162/tacl_a_00578.
- [184] Y. Hu, T. Ganter, H. Deilamsalehy, F. Dernoncourt, H. Foroosh, and F. Liu, “MeetingBank: A Benchmark Dataset for Meeting Summarization,” *Proc. Annu. Meet. Assoc. Comput. Linguist.*, vol. 1, pp. 16409–16423, 2023, doi: 10.18653/v1/2023.acl-long.906.
- [185] A. Laukaitis, “Reversal of the Word-Sense Disambiguation Task Using Deep Learning Model Reversal of the Word-Sense Disambiguation Task Using Deep Learning Model,” 2024, doi: 10.20944/preprints202405.1045.v1.
- [186] Rupesh Mahajan, “Effect of Supervised Sense Disambiguation Model Using Machine Learning Technique and Word Embedding in Word Sense Disambiguation,” *J. Electr. Syst.*, vol. 20, no. 1s, pp. 436–443, 2024, doi: 10.52783/jes.783.
- [187] C. Karnik, M., Mishra, V., Gaikwad, V., Wankhede, D., Chougale, P., Pophale, V., Zope, A. and Maski, “State of the Art Analysis of Word Sense Disambiguation,” *Int. Conf. Intell. Comput. Sustain. Dev.*, pp. 55–70, 2023.
- [188] Adedoyin Tolulope Oyewole, Omotayo Bukola Adeoye, Wilhelmina Afua Addy, Chinwe Chinazo Okoye, Onyeka Chrisanctus Ofodile, and Chinonye Esther Ugochukwu, “Automating financial reporting with natural language processing: A review and case analysis,” *World J. Adv. Res. Rev.*, vol. 21, no. 3, pp. 575–589, 2024, doi: 10.30574/wjarr.2024.21.3.0688.
- [189] V. Gujjar, N. Mago, R. Kumari, S. Patel, N. Chintalapudi, and G. Battineni, “A Literature Survey on Word Sense Disambiguation for the Hindi Language,” *Inf.*, vol. 14, no. 9, 2023, doi: 10.3390/info14090495.
- [190] S. Kandasamy, Y. Asawa, V. Balaji, and I. Dey, “Modern Multi-Document Text Summarization Techniques,” *Int. J. Recent Technol. Eng.*, vol. 9, no. 1, pp. 654–670, 2020, doi: 10.35940/ijrte.a1945.059120.
- [191] M. Arnold, M. Goldschmitt, and T. Rigotti, “Dealing with information overload: a comprehensive review,” *Front. Psychol.*, vol. 14, no. June, 2023, doi: 10.3389/fpsyg.2023.1122200.
- [192] T. Ströhle, R. Campos, and A. Jatowt, “Contrastive text summarization: a survey,” *Int. J. Data Sci. Anal.*, 2023, doi: 10.1007/s41060-023-00434-4.
- [193] D. Van Veen et al., “Clinical Text Summarization: Adapting Large Language Models Can Outperform Human Experts,” *arXiv*, 2023, [Online]. Available: <http://arxiv.org/abs/2309.07430>
- [194] P. Babakhani, A. Lommatzsch, T. Brodt, D. Sacker, F. Sivrikaya, and S. Albayrak, “Opinerium: Subjective Question Generation using Large Language Models,” *IEEE Access*, vol. 12, no. May, pp. 66085–66099, 2024, doi: 10.1109/ACCESS.2024.3398553.
- [195] A. de S. Inácio and H. S. Lopes, “Evaluation metrics for video captioning: A survey,” *Mach. Learn. with Appl.*, vol. 13, no. June, p. 100488, 2023, doi: 10.1016/j.mlwa.2023.100488.
- [196] Supriyono, A. P. Wibawa, Suyono, and F. Kurniawan, “A survey of text summarization: Techniques, evaluation and challenges,” *Nat. Lang. Process. J.*, vol. 7, no. October 2023, p. 100070, 2024, doi: 10.1016/j.nlp.2024.100070.
- [197] A. Al Foysal and R. Böck, “Who Needs External References?—Text Summarization Evaluation Using Original Documents,” *AI*, vol. 4, no. 4, pp. 970–995, 2023, doi:

- 10.3390/ai4040049.
- [198] K. Gligoric, A. Anderson, and R. West, "Causal effects of brevity on style and success in social media," *Proc. ACM Human-Computer Interact.*, vol. 3, no. CSCW, 2019, doi: 10.1145/3359147.
 - [199] T. Goyal, J. Xu, J. J. Li, and G. Durrett, "Training Dynamics for Text Summarization Models," *Proc. Annu. Meet. Assoc. Comput. Linguist.*, pp. 2061–2073, 2022, doi: 10.18653/v1/2022.findings-acl.163.
 - [200] K. Papineni, S. Roukos, T. Ward, and W. J. Zhu, "BLEU: A method for automatic evaluation of machine translation," *Proc. Annu. Meet. Assoc. Comput. Linguist.*, vol. 2002-July, no. July, pp. 311–318, 2002.
 - [201] C. Raffel et al., "Exploring the limits of transfer learning with a unified text-to-text transformer," *J. Mach. Learn. Res.*, vol. 21, pp. 1–67, 2020.
 - [202] A. A. AL-Banna and A. K. AL-Mashhadany, "Natural Language Processing For Automatic text summarization [Datasets] - Survey," *Wasit J. Comput. Math. Sci.*, vol. 1, no. 4, pp. 102–110, 2022, doi: 10.31185/wjcm.72.