# A comprehensive and systematic exposition on Automatic Text Summarization Technique: A deeper coverage on extractive, abstractive and hybrid methods

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**Abstract**

Artificial Intelligence's remarkable advancement and Natural Language Processing enabled innovations that fulfill various vertical requirements. News summarization has become a popular topic where systems extract valuable semantic content and generate shorter abstracts from the original content. News readers benefit from a quick understanding of essential details because an informative summary provides them with important points without forced reading of the whole article. This article covers essential NLP news summarization methods, including Abstractive summarization, Extractive summarization, and Hybrid summarization, together with recent datasets, evaluation metrics, applications and future challenges. The main benefit of this work serves both researchers by providing them with complete information about contemporary summarization developments to select suitable summarization models during application development.

**Keywords:** Extractive summarization; Abstractive summarization; Natural Language Processing; News Recommendations

## 1 Introduction

The system of news summarization creates multiple beneficial applications by helping information retrieval operations while supporting reading decisions, simplifying content management, and developing condensed news summaries suitable for brief reader attention. Modern summarization raises complexities because exact content decision-making, context protection, and subjectivity-free interpretation requirements must be met.[1] In an era dominated by information overload, effective summarization tools become increasingly critical in offering readers concise yet comprehensive overviews of large datasets of news articles. The sheer volume of daily news content generated across platforms further exacerbates the challenge, making it imperative to condense and filter key information. News summarization harnesses two primary methods: editors produce manual summaries, and automated systems employ NLP and ML techniques.While manual summarization offers precision and contextual depth, it is time-consuming and lacks scalability, which is where automated summarization algorithms provide a solution.Automated systems, particularly those driven by machine learning (ML) and natural language processing (NLP), can process vast quantities of data much faster and more efficiently than human editors, offering a scalable alternative for high-throughput environments.

The main goal of this article explore modern summarization algorithms operating within NL-based Newspaper summarization programs.to efficiently condense and present news articles without losing critical information.By examining these algorithms in detail, we aim to provide insights into their performance characteristics, strengths, and weaknesses, which will help in optimizing the selection of summarization methods for specific

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use cases. Summarization methods today span a wide range of techniques, from early rule-based approaches to the more recent deep learning models that leverage the power of large-scale pre-trained models such as BERT and GPT. These advancements are enabling more coherent, fluent, and context-aware summaries, which have improved the overall quality of news content delivered to readers.

The paper constructs an output summary using a specific feature in a non-QA-based general format to process news reports.The advantage of this method lies in its ability to produce summaries that maintain a broader context, preserving the original meaning and flow of information, which is particularly useful for news articles where understanding the narrative is key. The article examines summary methods alongside explanations of datasets, process descriptions, and news-oriented applications of the technique. These methods are further contextualized through practical examples, where various models are tested across different domains, such as political news, economic reporting, and technological developments, to evaluate their effectiveness in real-world scenarios. Additionally, we explore hybrid summarization approaches that combine the strengths of extractive and abstractive techniques to create more accurate and fluent summaries.

The article examines summary methods alongside explanations of datasets, process descriptions, and news-oriented applications of the technique. The article follows the PRISMA systematic review process, which led to article identification via figure 1 described in reference.[2] The diagram below illustrates the PRISMA framework, the collected articles, and details about how we pursued the literature research method.

As part of the analysis, the paper presents real-world applications of newsroom models using summary algorithms. Modern news organizations need real-time summary generation to keep up with the fast-paced evolution of breaking news. Real-time summarization systems present value for news organizations through enhanced journalist efficiency because the system frees them to analyze content and verify facts instead of writing summaries. News summarization systems powered by AI would provide remote readers from resource-poor areas access to breaking news content regardless of restricted internet capability and lengthy reading time.

The paper analyzes in detail the summary models' problems, including the biases that appear in training data and the need for fact-checking and ethical considerations. Automated summary solutions require extensive examinations of their fairness levels and accuracy to stop the spread of false information. This paper showcases current research into developing assessment standards that extend beyond text match algorithm measurements using human-enabled AI measurements to evaluate factual consistency in algorithm-generated content.

The paper propounds future study trajectories in summarization, which focus on processing combined documents and summarizing audio and video data types. Research continues to focus heavily on multi-document summarization because the advancement of single-document summarization techniques has not been sufficient. Future summarization tools need advanced models that extract coherent and relevant information from multiple sources to become the foundation of the next generation of summarization methods. The future of news consumption might be revolutionized by the ability to create multimedia summaries that would include podcasts alongside video news reports.

## 2 Datasets – The most famous and available datasets

A comprehensive overview of the dataset accessibility appears in this section for both news summarization purposes and application creation and research applications. The figure below 2 lists the main datasets researchers use when working on news summarization applications.

### 2.1 Datasets availability for the News related text summarization applications.

This section shows a review of institutional datasets often employed for news summarizing. The datasets they use directly affect various aspects of NLP applications, including model performance, data quality and bias reduction, and generalization. Domain relevance is also decisively determined by datasets. The details about the datasets appear in Table 1.

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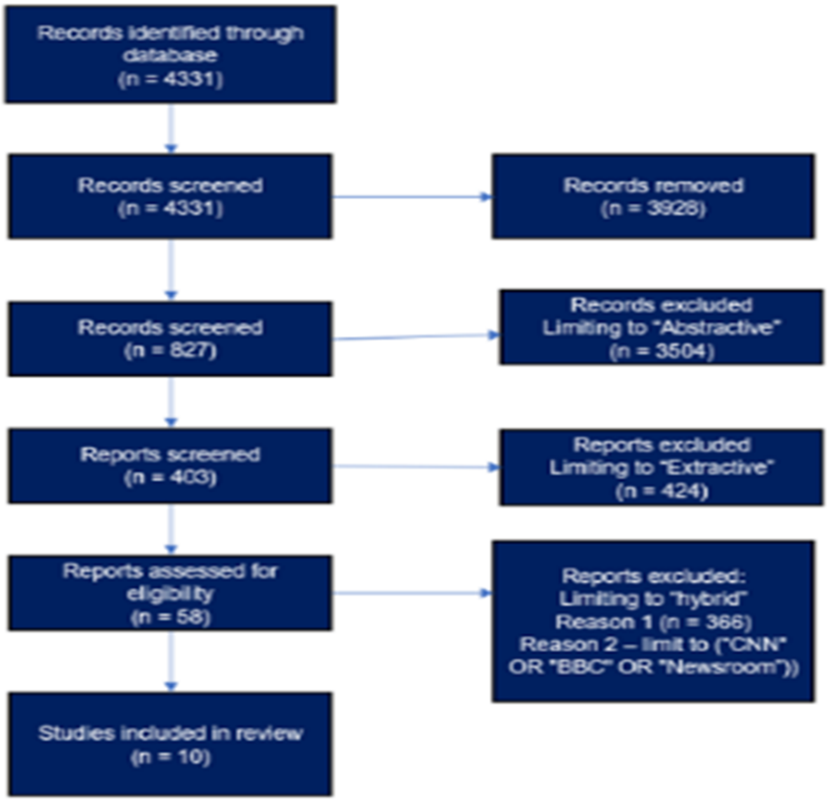


Figure 1: PRISMA Systematic Review.

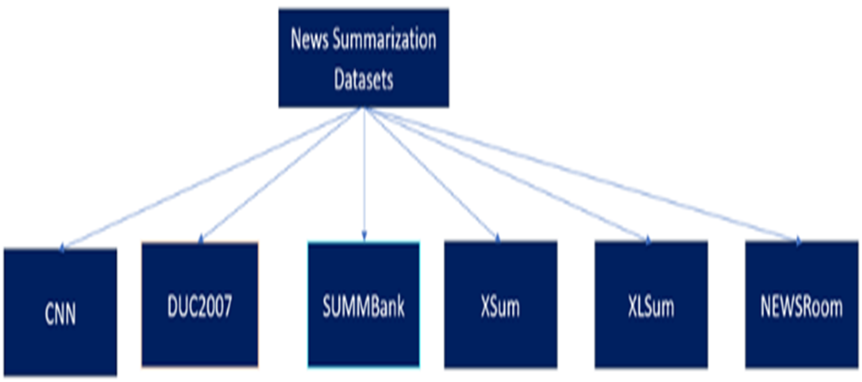


Figure 2: News summarization datasets.

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Table 1: Various Text Summarization Datasets

| Data Set | Year | URL to the Data set | Main Uses | Research Article |
|---|---|---|---|---|
| CNN/Daily Mail Dataset | 2017 | https://cs.nyu.edu/~kcho/DMQA/ | Abstractive and Extractive Text Summarization, Document Summarization, Sequence to Sequence Text Modelling, Question Answering, Text Generation | [3] |
| DUC2007 Dataset | 2018 | https://duc.nist.gov/duc2007.html | Text Summarization, Sentence Word Extraction, Semantic Word Ranking, single-Document and Multi-Document Summarization | [4] |
| SJMIMake Dataset | 2018 | https://www.aclweb.org/anthology/ | Text Summarization, Semantic word extraction, Sentence level document summarization | [5] |
| Xsum Dataset | 2018 | https://github.com/EdinburghNLP/XSum | Text Summarization, Text Generation, Abstractive and Extractive Summarization, Question Answering | [6] |
| XLSum Dataset | 2018 | https://github.com/google-research-datasets/xlsum | Text Summarization, Document Summarization, Abstractive Summarization | [7] |
| Newsroom Dataset | 2018 | https://www.github.com/harvardnlp/newsroom | Text Summarization, Document Summarization | [8] |

## 3 Summarization Process Overwiew

One should understand the steps involved in the summarization process. They are listed as follows:

### 3.1 UNDERSTANDING EXTRACTIVE SUMMARIZATION

Extractive summarization processes select significant text portions and make sentence or phrase deletions to create condensed versions of original content. Extracted lines and phrases from the original text get preserved in the summary while maintaining the source text's original wording and sequence. Extractive summarization serves several applications, including information retrieval, document summarization, and meeting minutes' summarization.[9] (Figure 3– extractive summarization models).

**Frequency Based Models**

Frequency-based models represent an NLP framework that relies on text corpus word frequency data to deliver predictions and perform multiple tasks. The following variations represent what frequency-based models typically take: The Bag of Words (BoW) strategy functions without considering either word order or grammatical structure to track word occurrences in databases. Text data appears as a "bag" containing words without a specific order. The fundamental nature of text classification applications, including spam detection and sentiment analysis, becomes achievable by implementing this approach.[10] Term Frequency Inverse Document Frequency (TF-IDF) analyzes term frequency (document-level term occurrence) and inverse document frequency (global frequency rarity) metrics.[3] This model type counts the number of times words appear in strings containing N successive words. Bigram (N=2) analysis matches two successive words, but trigram (N=3) analysis examines

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groups of three succeeding words. Frequency-based word embeddings employ word co-occurrence frequencies to train vector representations, which ultimately produce embeddings like Word2Vec and GloVe through standard training techniques on large text corpora.[4] The unsupervised learning algorithm GloVe provides popular word embedding generation services by producing dense vector representations for words through distributions in extensive text datasets. These vector representations reflect the semantic meaning aspects of words. The vector difference between the terms "king" and "queen" ought to align with the vector distinction between "man" and "woman." GloVe embeddings maintain a fixed positional value since they fail to incorporate contextual information during processing. Word2Vec is a commonly used algorithm that creates word embeddings from distributed text data by generating dense vectors that capture semantic meaning based on word occurrences. The algorithm presents itself in two primary forms, as Continuous Bag of Words (CBOW) alongside Skip-gram. Targeted predictions occur when the model uses surrounding contextual words to determine a word selection. In the Skip-gram modeling approach, developers use target words to instruct the model about context word prediction. Research has shown that the Skip-gram model achieves better results with infrequent words and sequential word understanding when compared to Continuous Bag of Words (CBOW).

**Heuristic Based Models** Natural language processing tasks employ heuristic models to solve multiple problems related to language understanding and generation according to.[5] Rule-based systems represent heuristic-based models in NLP through their predefined rules and patterns that enable applications such as part-of-speech tagging, named entity recognition, and syntactic parsing. NLP experts use linguistic knowledge, grammatical standards, and business-specific patterns to establish rules. Sentiment analysis lexicons contain sentiment scores, which help determine the polarities found within text sentiments. Feature engineering techniques within NLP employ specific domain-appropriate heuristics to both design and extract features from texts in training algorithms. Text data localization happens through pattern-based approaches, which let designers find linguistic structures by detecting established patterns and regular expressions within the text. Heuristic-based models suitable for particular domains are essential in most NLP applications.

**Linguistic Based Models** Language processing and understanding through linguistic models is a vital category of natural language processing (NLP) models based on linguistic theoretical foundations. Natural Language Processing utilizes syntactic parsers as linguistic models for analyzing sentence structures through tree or graph-based parsing. SRL models identify semantic roles of phrases and words through linguistic verb valency principles to establish proper subject, object and modifier functions in sentences. Text data analysis by NER models detects and classifies specific items such as personal entities, business organizations, and geographic terms within textual content. Morphological analysis models apply morphological rules alongside word formation linguistic theories to study word structure, including prefixes and suffixes, and inflections. These models serve applications across lemmatization and stemming, and word normalization processes. Sentiment analysis models that integrate linguistic models detect sentiment polarity in text data through linguistic features, including sentiment lexicons, syntactic patterns, and semantic representations. Text data analysis through discourse models examines language structures while investigating how texts interrelate based on discourse science frameworks that study organizational patterns in written materials.

**Supervised Learning Methods** Through supervised learning, NLP performs numerous functions like text categorization, named entity identification, sentiment analysis, and machine translation, among other processing tasks. Naive Bayes serves NLP communities as an easy probabilistic classifier for text classification tasks. This statistical system follows Bayes' theorem. SVM represents one of the preferred methods for binary classification purposes, yet demonstrates effectiveness when applied to multi-class classification tasks in natural language processing. Logistic Regression represents the probability distributions for data class membership through a logistic function, while training calculates optimal feature weight values. Decision Trees operate through tree-based structure and serve natural language processing tasks for categorizing content and predicting outcomes. Random Forests enhance model accuracy and robustness through their framework that unites multiple decision trees. NLP practitioners can use Random Forests analysis to execute classification and regression models while performing feature selection. Neural Networks apply CNNs for text classification and sentiment analysis and named entity recognition, but RNNs, particularly Long Short-Term Memory (LSTM)[6] and Gated Recurrent Unit (GRU), perform sequence-to-sequence work in machine translation and text generation.

**Reinforcement learning (RL) methods** Reinforcement learning (RL) techniques help NLP systems perform sequential decision-making during environmental interactions for specific tasks.[7] Reinforcement Learning for Dialogue Systems demonstrates successful applications in developing conversational agents known as chatbots

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to understand user queries while generating appropriate responses. Machine Translation benefits from Reinforcement Learning when the system performs language translation between two linguistic domains. Billing Reinforcement Learning tools dedicated to Text Summarization create condensed logical summaries from extensive textual content sentiment Analysis using Reinforcement Learning measures written text's emotional nature and positive or negative attitude. The Reinforcement Learning technique enables the retrieval of important documents or information from big textual databases.

**Bidirectional Encoder Representations from Transformers** Researchers at Google created BERT (Bidirectional Encoder Representations from Transformers) as a well-known pre-trained deep learning model for natural language processing (NLP) tasks throughout 2018.[8] The research community at Stanford University and Carnegie Mellon University, and Google released XLNet in 2019 as a widely adopted pre-trained natural language processing (NLP) model.[11]

### 3.2 UNDERSTANDING ABSTRACTIVE SUMMARIZATION

Unlike extractive summarization that offers simple sentence or phrase selection and extraction from source material, abstractive summary generation transforms content through text normalization. Abstractive summarization aims to develop a brief, well-organized summary that properly represents essential points and important details from the source document through new, human-readable content. Abstractive summarization involves multiple techniques, including both rule-based heuristics manually established by humans as well as current machine learning procedures that employ methods such as neural networks and sequence-to-sequence models alongside transformer-based models, including the Transformer and BERT (Bidirectional Encoder Representations from Transformers). The abstractive summarization approach becomes clearer through Figure 4. Semantic based approach :The process of automatically creating a semantic graph representation from a given text or sentence is known as semantic graph generation in natural language processing (NLP). A text's semantic structure can be represented as a graph, allowing for a more thorough analysis and comprehension of the text's meaning.[12] There are several approaches and techniques used for semantic graph generation in NLP. Some of the commonly used methods include: Dependency Parsing: A method called dependency parsing examines the grammatical relationships between words in a sentence and represents them as a directed graph.Co-reference Resolution: Co-reference resolution is the process of finding references to the same person, place, thing, or idea throughout a text and connecting them to a single reference.Named Entity Recognition: The task of identifying and categorizing named entities, such as person names, organization names, and location names, in a text is known as named entity recognition (NER).

Word Sense Disambiguation: Finding the appropriate meaning of a word in a particular context is the task of word sense disambiguation (WSD).Ontology-based Graph Generation: Ontologies are organized representations of knowledge that capture the connections between concepts or entities in a particular domain. The process of creating a semantic graph representation from text using an existing ontology is known as ontology-based graph generation. Sequence to Sequence deep learning methods: BART: In 2019, researchers at Facebook AI Research (FAIR) proposed BART (Bidirectional and Auto-Regressive Transformers), a well-liked abstractive text summarization method in natural language processing (NLP).[13] bidirectional training method used by BART is one of its key characteristics. PEGASUS - In 2019, researchers at Google Research proposed PEGASUS (Pre-training with Extracted Gap-sentences for Abstractive Summarization), a cutting-edge method for abstractive text summarization in natural language processing (NLP).[14]GPT - GPT (Generative Pre-trained Transformer) is a popular and influential language model in the field of natural language processing (NLP) that has been used for abstractive text summarization.[15] T5 - The transformer architecture's T5 variant was created especially for text-to-text tasks where the input and output are both text sequences. Several NLP tasks, such as abstractive text summarization, have been accomplished using T5.[16]

### 3.3 UNDERSTANDING HYBRID SUMMARIZATION

Nature-based processing uses hybrid summarization to merge extractive and abstractive summarization methods for generating summary content that optimizes both techniques. According to the article,[17] the authors demonstrate a model which combines extractive and abstractive summarization through BERT integration

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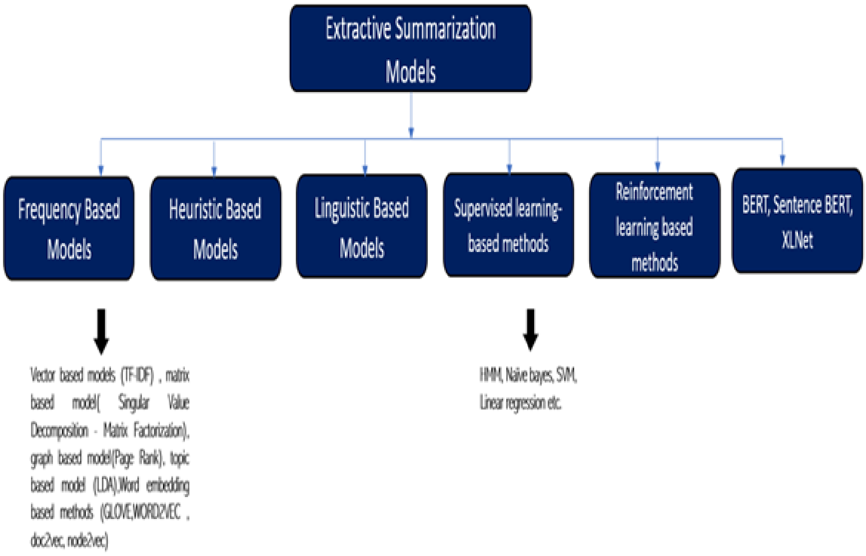


Figure 3: Extractive Summarization Models.

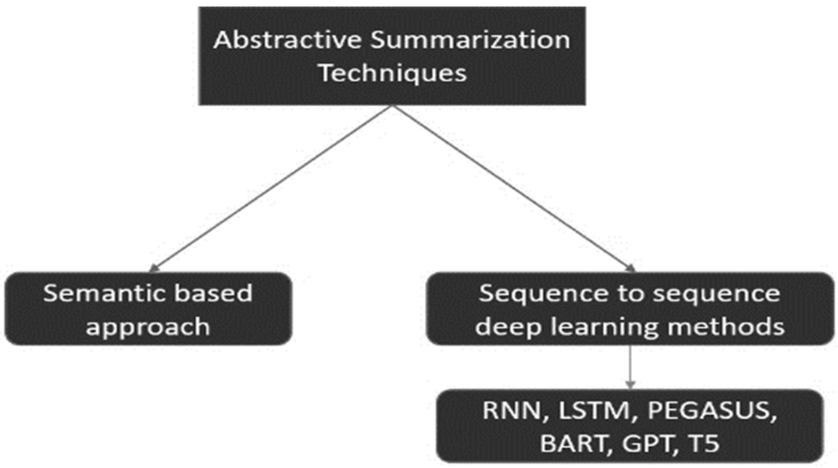


Figure 4: Abstractive Summarization Techniques.

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with reinforcement learning. Additionally,[18] documents SumItUp's hybrid method that implements extractive and abstractive summarization approaches. According to research in,[19] the latent structure detector performs hybrid summarization.

## 4 Major Evaluation Methods For Summarization

Various evaluation approaches support summarization assessment in a broad scope. Several of the top evaluation methods appear in this section. Rogue: The automated system output receives evaluation through the ROUGE assessment, which measures comparison between candidate summaries or translations and human reference documents.[20] The summarization system performs well when measured through elevated ROUGE scoring systems. BERTScore operates by utilizing BERT embeddings, which generate semantic similarity information, contextual appropriateness evaluations, and word order alignment between reference and candidate texts. It calculates context-based word embeddings by feeding both reference and candidate texts into BERT. The finished BERTScore results from calculating the harmonic mean between precision alongside recall.[21] Relevance: When assessing information retrieval systems or text generation systems through natural language processing techniques, relevance represents a subjective assessment of how well one text or information matches another. Consistency: Text-generation tasks such as dialogue systems, story-generation, and sequence-to-sequence generation require the evaluation metric "consistency" for measuring text coherence and stability. We measure story coherence, logical structure, and style stability by consistently evaluating the generated text according to.[22] The evaluation process of consistency uses both quantitative and qualitative methods. Fluency: The evaluation metric "Fluency" evaluates the naturalness and linguistic quality of generated text. Text fluency gauges the target language alignment of generated text, combining structural adherence, grammatical correctness, and flowing narrative without grammatical mistakes.[23] In text generation tasks like document summarization, story generation, and other sequence-to-sequence generation tasks, "coherence" is an evaluation metric that gauges the text's logical flow and connectivity. Human evaluation: Ana's evaluation metric, named "coherence," assesses text logical flow and connectivity during sequence-to-sequence generation, document summarization, and story generation tasks.[24] Evaluation of people requires various assessment approaches, including rating scales, rankings, preference judgments, and qualitative assessments. The following typical NLP human evaluation techniques are presented in:[25] Rating scales: The process involves annotators using numerical scoring systems with metric ranges from 1 to 5 or 1 to 10 to assess different text generation or system output product qualities. Understanding the generated text requires annotators to evaluate its fluency, relevance, coherence, or comprehensive quality assessment ratings. Annotators rank multiple generated texts or system outputs according to various criteria, including quality. Preference judgments: A panel of annotators uses a predefined set of criteria to rank multiple generated text outputs and system outputs. Annotators respond to unstructured texts, passage annotations, or detailed defensives of their conclusions.

## 5 Application of Summarization Models in News Paper Summarization in a Research Perspective

Natural language processing (NLP) applications utilize short news updates to give users brief overviews of news content or occurrences. These applications use NLP techniques for automatically processing news information before summarizing and presenting it in condensed formats that are easy to understand. The NewsBlog summarizer application is a text summarization tool explicitly made to process news articles and blogs within natural language processing (NLP). By applying natural language processing (NLP), research article summarization automatically produces clear and condensed summaries to help researchers conserve effort and better understand multiple research articles simultaneously. Natural language processing detection of fake news represents an essential application that seeks to recognize and categorize news content fabricated as deception tools for readers on social media platforms. Graph-based methods for categorizing news articles based on topics show value in multiple applications such as news recommendation systems and news clustering, summarization, trend analysis, and content filtering systems.[26] A general Automated Text Summarization process functions according to Figure 5.

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## 6 INTEL oneAPI AND NLP

This section briefly overviews the Intel packages and tools that enhance NLP summarization performance. These Intel tools include Intel distribution for Python, Intel oneAPI Data Analytics Library, Intel oneAPI Deep learning Neural Network Library, and Machine Learning with oneAPI to handle this matter.[27] Intel® Distribution for Python is a high-performance Python that provides access to the latest CPU instructions to improve performance, being available for CPU cores on laptops, desktops, and powerful servers, increases productivity by optimizing instructions, and helps an easy integration with Intel native tools with the developed Python Project. Intel oneAPI Data Analytics Library includes high-speed algorithms required for analysis functions, libraries used for training, and library prediction functions that could be used for NLP-based applications. Through Intel oneAPI Deep learning Neural Network Library, developers obtain optimized deep learning building blocks appropriate for NLP applications. It also provides access to OpenVINO™ toolkit, Intel® AI Analytics Toolkit, Intel® Distribution for PyTorch*, and Intel® Distribution for TensorFlow*, which is vital for developers to develop faster deep learning applications and frameworks for application-specific code.[28] Intel Machine Learning Using oneAPI provides data scientists, developers, and researchers to build end-to-end application pipelines using Intel Architecture. All these toolkits will aid in importing data, preprocessing, building linguistic models, evaluating them, to deploying them in the workspace. Researchers deploy various NLP applications using Intel architecture according to reference.[29]

## 7 Results and Implications

This text substantially evaluates NLP's news summarization methods, including Abstractive summarization, Extractive summarization, and Hybrid summarization alongside their datasets, evaluation measures, practical applications, and anticipated developments. In the chart below, multiple news datasets, such as Newsroom and Sum, and Dataset appear alongside the XL Sum Dataset, SummBank, DUC 2007, and CNN/Daily Mail. Figure 6 demonstrates the development of dataset use throughout time. We will investigate how different algorithms affect dataset performance while examining rogue value results. Various Rogue measures, including Rogue-1, Rogue-2, and Rogue-L, are calculated in Table 2. The study presented in Figure 7 provides clear insight into each method's obtained Rogue 1,2, L values while demonstrating understanding of various state-of-the-art approaches. The number of citations for most literature survey works needs to be understood in addition to

Table 2: Results of Abstractive summarization for various datasets and the Rogue measures.

| Dataset Considered | Technique Used | ROUGE-1 | ROUGE-2 | ROUGE-L |
|---|---|---|---|---|
| **Xsum** | PEGASUSLARGE | 47.21 | 24.56 | - |
| | BART | 45.14 | 22.27 | 37.25 |
| | BERTSumExtAbstr | 38.91 | 16.65 | 31.27 |
| | PEGASUS | 44.17 | 21.47 | 40.11 |
| | BART | 44.16 | 21.28 | 40.59 |
| **CNN/Daily Mail** | BERTSumExtAbstr | 42.13 | 19.6 | 39.18 |

quantitative analysis.[30] As displayed in Figure 8, you will find the information here. Users can easily view a comprehensive linked network of derived works through this interface in Figure 9.

## 8 Conclusion and Future Work

Several criteria determine how summarization occurs, while the selected approach depends on the intended application. Researchers should choose datasets specifically for ablation research that demonstrate the unique features of their proposed algorithm. Text quality within input documents and training materials influences the

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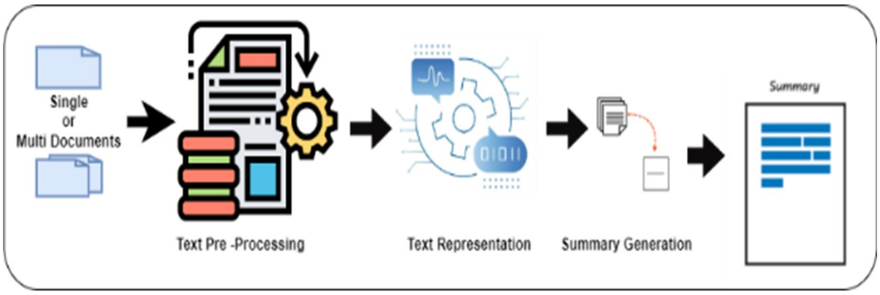


Figure 5: ATS process.

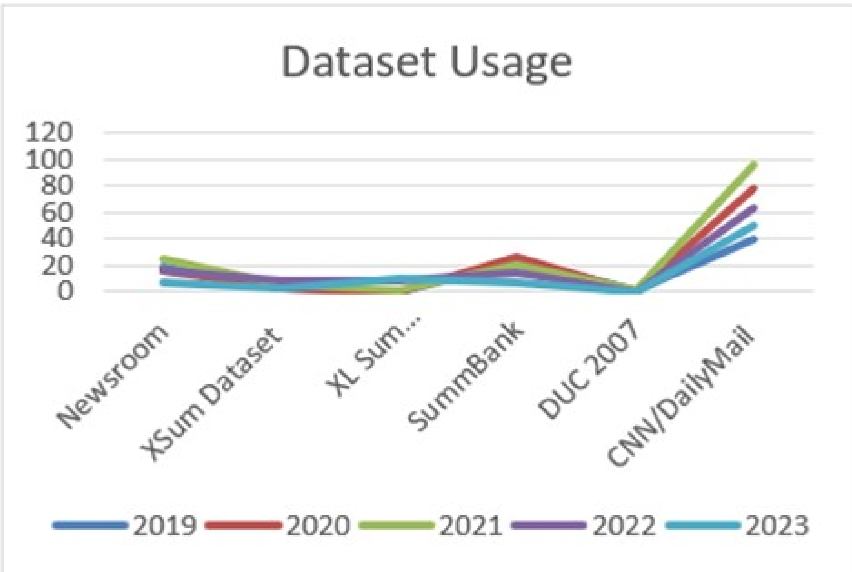


Figure 6: Dataset Usage.

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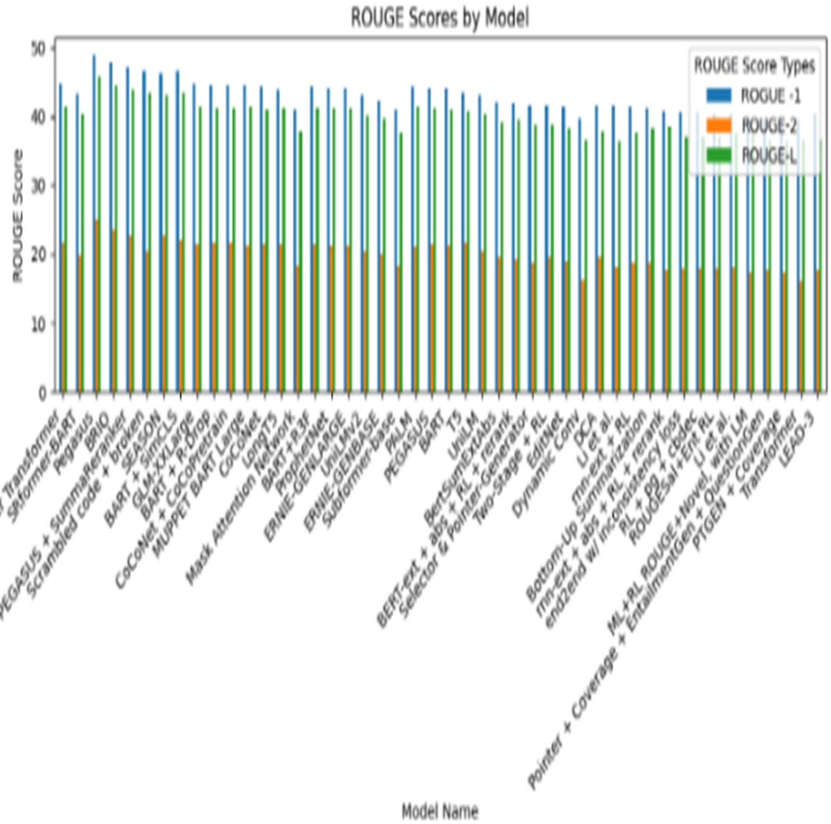


Figure 7: Model details based on the latest publication on text summarization topics (ref: State of the art methods.

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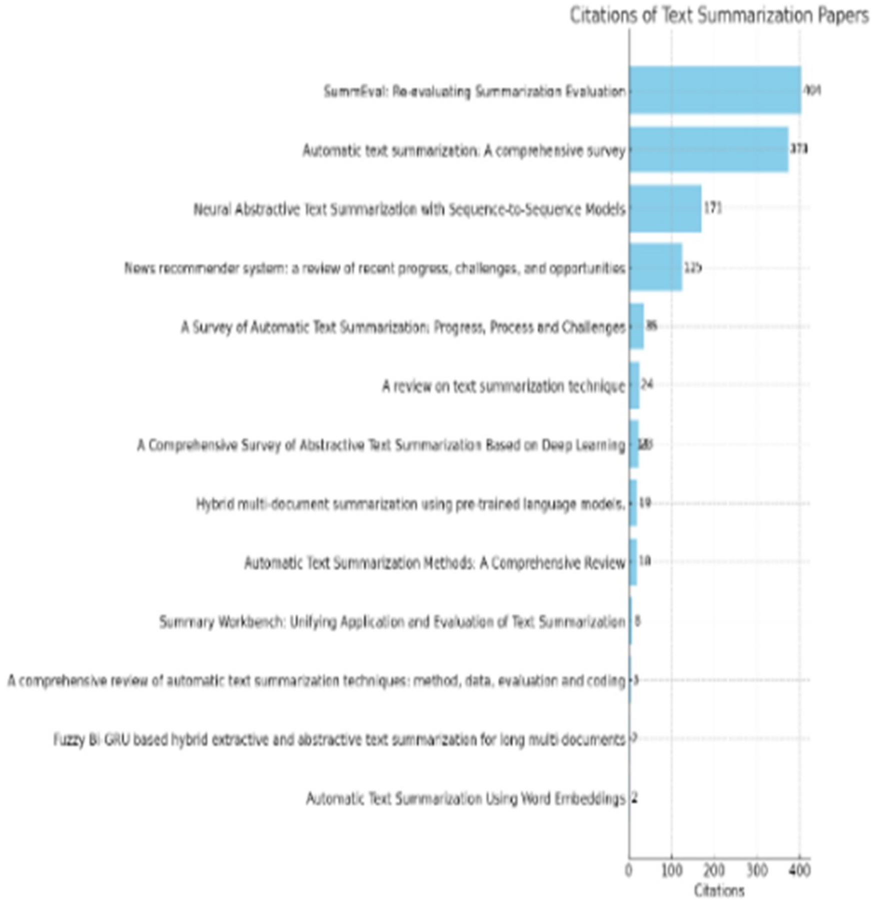


Figure 8: Citation and references.

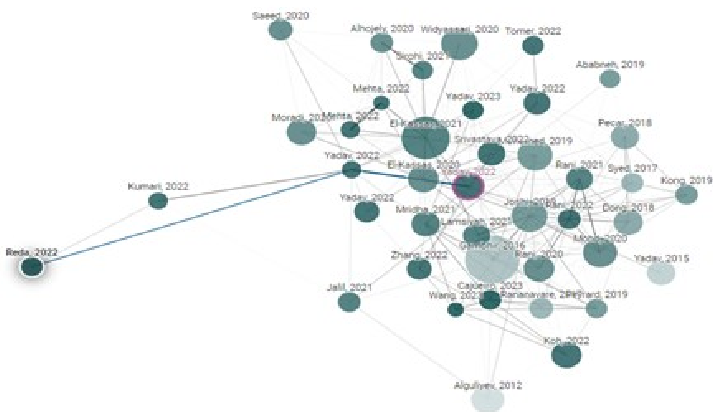

Figure 9: shows the connected graph for literature survey.

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model's performance. The selection of summarization methods depends directly on the intended application. The most accurate summarization quality assessments stem from human evaluation methods, yet different evaluation methods currently exist, and their choice determines summarization quality results. Evaluation measures need development to include human-based evaluation techniques. Researchers have accomplished substantial progress with single-document summaries, yet multi-document summarization remains underdeveloped. The research reveals little work has been dedicated to developing hybrid summarization models. Research needs to unite extractive and abstractive approaches to create abstract summaries that carry essential information.

## References

[1] S. Raza and C. Ding. News recommender system: a review of recent progress, challenges, and opportunities. *Artificial Intelligence Review*, 1:1–52, 2022.

[2] A. A. Selçuk. A guide for systematic reviews: Prisma. *Turkish archives of otorhinolaryngology*, 57(1):57, 2019.

[3] M. Umadevi. Document comparison based on tf-idf metric. *International Research Journal of Engineering and Technology (IRJET)*, 7(02):1546–1550, 2020.

[4] S. Antony and D. S. Pankaj. Automatic text summarization using word embeddings. In *International Conference on Data Management, Analytics & Innovation*, pages 489–509, Singapore, 2023. Springer Nature Singapore.

[5] A. Grover and J. Leskovec. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 855–864, 2016.

[6] M. Tomer and M. Kumar. Improving text summarization using ensembled approach based on fuzzy with lstm. *Arabian Journal for Science and Engineering*, 45:10743–10754, 2020.

[7] V. Uc-Cetina, N. Navarro-Guerrero, A. Martin-Gonzalez, C. Weber, and S. Wermter. Survey on reinforcement learning for language processing. *Artificial Intelligence Review*, 56(2):1543–1575, 2023.

[8] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[9] A. K. Yadav, A. Singh, M. Dhiman, R. Kaundal, A. Verma, and D. Yadav. Extractive text summarization using deep learning approach. *International Journal of Information Technology*, 14(5):2407–2415, 2022.

[10] T. Walkowiak, S. Datko, and H. Maciejewski. Bag-of-words, bag-of-topics and word-to-vec based subject classification of text documents in polish-a comparative study. In *Contemporary Complex Systems and Their Dependability: Proceedings of the Thirteenth International Conference on Dependability and Complex Systems DepCoS-RELCOMEX*, volume 13, pages 526–535. Springer International Publishing, Brunów, Poland, 2019.

[11] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. *Advances in neural information processing systems*, 32, 2019.

[12] D. Bhartiya and A. Singh. A semantic approach to summarization. *arXiv preprint arXiv:1406.1203*, 2014.

[13] M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, and L. Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*, 2019.

[14] J. Zhang, Y. Zhao, M. Saleh, and P. Liu. Pegasus: Pre-training with extracted gap-sentences for abstractive summarization. In *International Conference on Machine Learning*, pages 11328–11339. PMLR, 2020.

DOI: https://doi.org/10.54216/FPA.200114

Received: January 01, 2025 Revised: February 05, 2025 Accepted: April 02, 2025

[15] A. Radford, K. Narasimhan, T. Salimans, and I. Sutskever. Improving language understanding by generative pre-training. 2018.

[16] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, and P. J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21(1):5485–5551, 2020.

[17] Q. Wang, P. Liu, Z. Zhu, H. Yin, Q. Zhang, and L. Zhang. A text abstraction summary model based on bert word embedding and reinforcement learning. *Applied Sciences*, 9(21):4701, 2019.

[18] I. K. Bhat, M. Mohd, and R. Hashmy. Sumitup: A hybrid single-document text summarizer. In *Soft Computing: Theories and Applications: Proceedings of SoCTA 2016, Volume 1*, pages 619–634. Springer Singapore, 2018.

[19] M. Song, L. Jing, Y. Feng, Z. Sun, and L. Xiao. Hybrid summarization with semantic weighting reward and latent structure detector. In *Asian Conference on Machine Learning*, pages 1739–1754. PMLR, 2021.

[20] C. Y. Lin. Rouge: A package for automatic evaluation of summaries. *Text summarization branches out*, pages 74–81, 2004.

[21] T. Zhang, V. Kishore, F. Wu, K. Q. Weinberger, and Y. Artzi. Bertscore: Evaluating text generation with bert. *arXiv preprint arXiv:1904.09675*, 2019.

[22] M. Cao. A survey on neural abstractive summarization methods and factual consistency of summarization. *arXiv preprint arXiv:2204.09519*, 2022.

[23] F. Nan, C. N. D. Santos, H. Zhu, P. Ng, K. McKeown, R. Nallapati, and B. Xiang. Improving factual consistency of abstractive summarization via question answering. *arXiv preprint arXiv:2105.04623*, 2021.

[24] Summeval: Re-evaluating summarization evaluation. *Transactions of the Association for Computational Linguistics*, 9:391–409, 2021.

[25] A. Ghadimi and H. Beigy. Hybrid multi-document summarization using pre-trained language models. *Expert Systems with Applications*, 192:116292, 2022.

[26] D. O. Cajueiro, A. G. Nery, I. Tavares, M. K. De Melo, S. A. D. Reis, L. Weigang, and V. R. Celestino. A comprehensive review of automatic text summarization techniques: method, data, evaluation and coding. *arXiv preprint arXiv:2301.03403*, 2023.

[27] Intel. Distribution for python. `https://www.intel.com/content/www/us/en/developer/tools/oneapi/distribution-for-python.html`. Accessed: 2023-05-06.

[28] Intel. Machine learning using oneapi. `https://www.intel.com/content/www/us/en/developer/tools/oneapi/training/machine-learning-using-oneapi.html`. Accessed: 2023-05-06.

[29] Huggingface. Huggingface and github repositories. `www.huggingface.comandGithubrepositories`. Accessed: 2023-05-06.

[30] Intel. Term set expansion based nlp architect by intel ai lab. `arXiv:1808.08953`. Accessed: 2023-05-06.


Received: January 01, 2025 Revised: February 05, 2025 Accepted: April 02, 2025