Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.15, No.4, 2025, pp.207-216

DOI: https://doi.org/10.51983/ijiss-2025.IJISS.15.4.24

Unsupervised Text Summarization for Abstract-Based Retrieval

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(Received 21 August 2025; Revised 06 October 2025, Accepted 21 October 2025; Available online 15 December 2025)

Abstract - **The efficient retrieval of pertinent content from expansive textual data stores has become increasingly indispensable due to the widespread availability of information. The goal of this paper is to propose a text summarization framework that is focused on enhancing retrieval-based document summarization techniques. Unstructured data is rapidly increasing in the online environment, and label-free summarization methods are needed to enhance retrieval. Deep learning It uses document preprocessing, which consists of segmenting sentences into tokens, embedding using models such as SBERT, and semantic modeling of sentences. These inter-sentence relations are then mapped as a similarity graph, and the graph-based ranking algorithm is used to rank sentences by their significance. Salient sentences are then chosen, and extracted sentences are organized to create a summary that provides key information about the document. Using this technique the retrieve engine obtains user queries based on abstracted summaries rather than full documents, thereby cutting costs of processing power but enhancing exactness. In addition, the model training does not consist of training datasets, which renders the approach domain-agnostic. The experiments carried out demonstrated that abstract-based retrieval through unsupervised multi-document summaries had better relevance and ranking in comparison with the conventional methods. The framework offers a realistic and scalable information retrieval method to intelligent active searching of a text-rich environment when limited labeled information is available.**

Keywords: **Unsupervised, Text Summarization, Abstract, Retrieval, Information Retrieval, Automatic Summarization, Document Indexing**

I. INTRODUCTION

Similar to other types of artificial intelligence, it is the aim of text summarization to simplify a large text by converting it into a shorter form, without explicitly losing meaning or coherence, which can be quite complicated with long documents. Of the different methods of addressing this, unsupervised text summarization seems more popular due to its scalability and ability to fit in new fields (Yao et al., 2017). Compared to supervised methods, which rely on large, labeled datasets, somewhat available data, such as domain-independent data, is generally more suitable for unsupervised techniques (Nenkova & McKeown, 2011; Kumar, 2024). These processes apply natural language processing (NLP) techniques like term frequency-inverse document frequency (TF-IDF), graph-based methods, sentence embeddings, and topic modeling to extract the most important concepts or sentences from a document (Erkan & Radev, 2004; Sadulla, 2024). The advancement of AI in business and social networks has revolutionized how people interact with machines, resulting in the production of massive volumes of unstructured data daily. Unsurprisingly, summarization enables people to access information quickly without straining their minds or taking too much time to read and quickly understand documents (Moratanch & Chitrakala, 2016; Nife et al., 2025). In high-tech or research areas where large documents are often the norm, effective summarization tools can boost productivity and improve critical decision-making (Abdullah, 2024).

The detailed abstract retrieval approach entails searching only through the abstracts of documents as opposed to the entire document. Abstracts capture the document's important highlights and serve as a summary. In most academic databases and digital libraries, the abstracts stand in for the entire documents, which significantly aids the ease of processing them (Salton, 1989). The filtering of irrelevant and non-useful content in full texts improves retrieval performance when using abstracts. Abstracts, because they possess the author's constructive intention as well as the main ideas, amplify the relevance of the information alongside the intent of the abstract (Gupta & Lehal, 2010).

On the other hand, many documents do not have well-written abstracts. Instead, they provide vague summaries. Such a problem can be addressed by unsupervised summarization, which creates detailed, high-quality summaries that ease retrieval (Das & Martins, 2007; Ginni & Chakravarthy, 2024). Due to recent advances in text representation and graph algorithms, systems can generate more effective and contextually accurate abstracts aimed at improving precision and recall (Mihalcea & Tarau, 2004; Yaghoub-Zadeh-Fard et al., 2015; Yao et al., 2017). With the addition of these types of summaries to indexing frameworks, there is a greater possibility of enhancing the performance of knowledge discovery, recommendation systems, and even semantic search engines.

This paper concentrates on the exploitation of unsupervised text summarization to produce brief but informative abstracts to the abstract-based retrieval systems. It compares a variety of unsupervised summarization algorithms on a wide range of datasets to determine their efficiency in creating pertinent summaries that improve retrieval results. The study discusses the effect of machine-generated abstracts on precision and recall, showing how they affect access to and retrieval of information. Major works include a comparative study of various unsupervised algorithms, confirmation that domain-adaptive automated abstracts enhance search ease, and a pipeline model that combines summarization and indexing. The structure embraces both academic and business search applications, improving efficiency and gains in retrieval.

The developed systems in this paper rise beyond the limits set by human super-abstracts, enhancing retrieval performance. Such systems fundamentally advance automated information systems and provide new directions to improve summarization-enhanced IR models (Zhang et al., 2010; Radev et al., 2004; Okan & Christian, 2024). The rest of the paper follows the structure laid out in this introduction. Section II succinctly captures the literature on techniques for text summarization and abstract-based retrieval approaches while emphasizing the specific difficulties encountered in this domain. In Section III, a detailed explanation of the proposed methodology for unsupervised summarization is provided, comprising the algorithm, retrieval framework, and evaluation metrics. In Section IV, the model's performance is evaluated alongside other models through the analysis of experimental results, where the proposed model is rigorously tested against baseline approaches. Section V discusses why the results were achieved, detailing the implications, possible uses, and unresolved issues related to the conclusions drawn. In Section VI, the main arguments are presented in the summary of contributions made through the work, and future work is suggested.

II. Literature Review

Text summarization, which involves splitting a text into its main components and providing a detailed description, is a key feature of extractive and abstract techniques and is a vital aspect of Natural Language Processing (NLP). Summarization extractive derives new phrases or sentences, known as chunks, from the source text using syntactical or statistical criteria, and summarization abstractive reconstructs those phrases into a more compact and original form (Nenkova & McKeown, 2012). LexRank and TextRank are among earlier works on extractive summarization that are based on graph centrality algorithms for the most important sentences or salient sentences (Mihalcea & Tarau, 2004; Erkan & Radev, 2004). These unsupervised models were found to be useful for systems lacking labeled data. Later, frameworks like TF-IDF, Latent Semantic Analysis (LSA), and even topic modeling (LDA) were used to enhance relevance while minimizing the redundancy of the content (Gupta & Lehal, 2010; Saidova et al., 2024). Summary quality has also improved with the introduction of transformer-based architectures. Pre-trained BERT and GPT models have been effectively used for both extractive and abstractive summation tasks (Devlin et al., 2019). These models are better at understanding semantic meaning and context in language, which helps solve many issues with rule-based models. (Liu & Lapata, 2019) showed that BERT-based encoders surpassed most standard summarization benchmarks using the provided system models. The independence of untagged methods from training data makes them appealing. (Moratanch & Chitrakala, 2016) highlight the usefulness of unsupervised frameworks in template-lite degenerate resource cases, which lack adaptation along the domain or require extensive manual label crafting.

The acronym ABR stands for methods of retrieving information that works with abstracts instead of full documents in the context of indexing and searching. Abstracts may prove particularly useful in academic or clinical databases, where retrieving complete documents is impossible, or the document size renders real-time processing infeasible (Perera & Wickramasinghe, 2024). Thus, abstracts are efficient retrieval surrogates, as they contain a key objective, methodologies, and the findings of the research, all encapsulated within a document. The first generation of ABR systems was based on the Boolean retrieval and vector space model, where queries were matched with document abstracts, which is considered the dividing notion in ABR today (Salton, 1989; Raghuram, 2024). More recent systems have begun using semantic similarity measures not only to enhance matching accuracy but also to leverage sentence embeddings or deep language models (Liu & Lapata, 2019; Darshana, 2024). As an example, embedding-based retrieval methods like BERTRank enhance the relevance of the retrieved results by computing cosine similarity between vectorized abstracts and the queries. (Kim et al., 2014) reported that retrieving information was more effective when summaries were provided as enhanced abstracts, emphasizing the original abstracts. (Gupta & Lehal, 2010) noted that automatically produced abstracts outperformed manually crafted abstracts within precision-oriented retrieval environments.

Although notable advances have been made, gaps in the field remain. The main issue with summarization, which has no supervision, is maintaining the informative and coherent content. Based on models, summaries are extracted immediately when the sentence is of high grammatical quality and does not contain an adequate logical consistency or theme coverage in the document (Bordbar & Shirazi, 2019; Tamannaeifar & Hesampour, 2016). This is especially an issue when dealing with multi-document summarization or domain-specific texts in which the allocation of topics and terms can be complicated. Assessment has been a long-lasting issue. The case of ROUGE is the dependency on surface overlap, i.e. it depends on the number of words which does not guarantee evaluative summarization (Nenkova & McKeown, 2012). Additionally, there is an over-reliance on generic domains, such as news and Wikipedia, which neglect other technical and scientific areas (Moratanch & Chitrakala, 2016; Anand & Shrivastava, 2024). In abstract-based retrieval, the precision and format of the provided abstracts differ significantly, introducing noise into the retrieval process. Some abstracts may exclude important conclusions while overemphasizing lesser components, resulting in irrelevant matches (Kim et al., 2014). Summarization methods are still challenging to implement within live retrieval systems due to processing resource limitations and concerns about model transparency and interpretability (Devlin et al., 2019; Abdoli & Abolghasemi, 2019).

III. METHODOLOGY

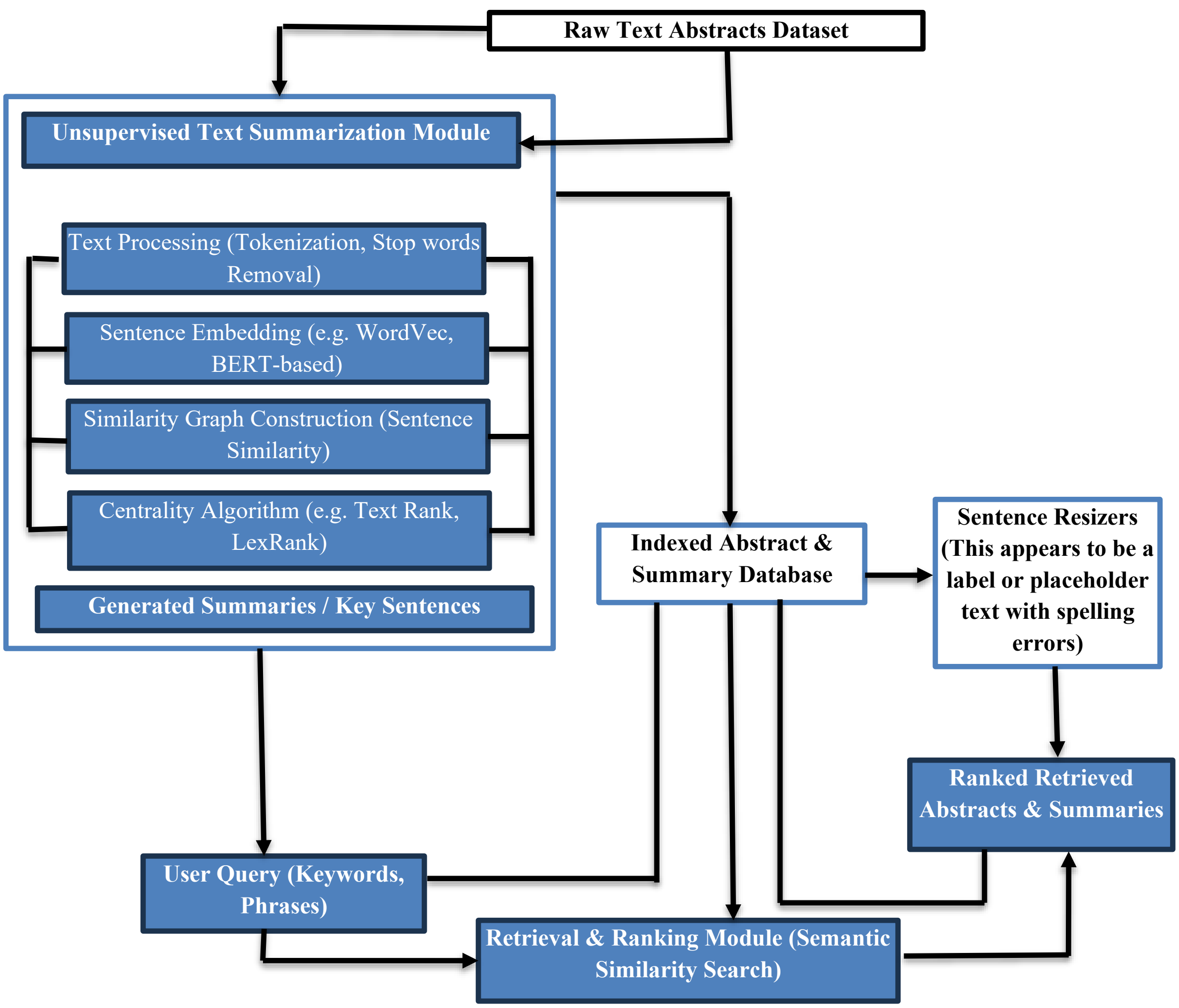

Fig. 1 Architecture for Unsupervised Text Summarization for Abstract-Based Retrieval

The workflow begins with Raw Text Abstracts, which are fed into the Unsupervised Text Summarization Module. This module performs Text Processing (Tokenization/Stop words Removal), creates Sentence Embeddings (e.g., WordVec, BERT-based), and builds a Similarity Graph. A Centrality Algorithm (e.g., TextRank/LexRank) then extracts Generated Summaries. These summaries, along with the abstracts, are stored in the Indexed Abstract & Summary Database. A User Query is processed by the Retrieval & Ranking Module using Semantic Similarity Search against the database. The final output is the Ranked Retrieved Abstracts & Summaries, enabling efficient abstract-based information access (Fig. 1)

3.1 The Algorithm Description of Unsupervised Text Summarization

In this section, we detail the proposed step, which employs an unsupervised learning technique leveraging a graph-ranking paradigm. The model uses sentence similarity to compute the most significant content within a document. The first stage of the method is document preprocessing, which can be accomplished through NLP techniques such as tokenization, stopword techniques, or sentence segmentation. Each sentence within a document can be transformed into a vector in a high-dimensional semantic space using either TF-IDF or sentence embeddings. To depict relationships between sentences, a weighted undirected graph can be constructed $G = (V, E)$ where each node $v_i \in V$ represents a sentence in a document and edge weight $w_{ij} \in E$ denotes the level of similarity that exists between the two sentences v_i and v_j. The edge weights are determined through Cosine similarity:

$$w_{ij} = \cos(\theta) = \frac{\vec{s}_i . \vec{s}_j}{\|\vec{s}_i\| \|\vec{s}_j\|} \quad (1)$$

Upon constructing the similarity graph, a modified form of the PageRank algorithm is used to rank the sentences as follows:

$$S(v_i) = (1 - d) + d \sum_{v_j \in In(v_i)} \frac{w_{ji}}{\sum_{v_k \in Out(v_j)} w_{jk}} S(v_j) \quad (2)$$

In this case, $S(v_i)$ represents the score of the sentence v_i, while d is the damping factor, which is usually set to 0.85. The best-scoring sentences are picked to create the summary at the sentence or word budget that is set in advance. This approach is suitable for cases with limited training data due to its lack of language dependence and independence from labeled training data.

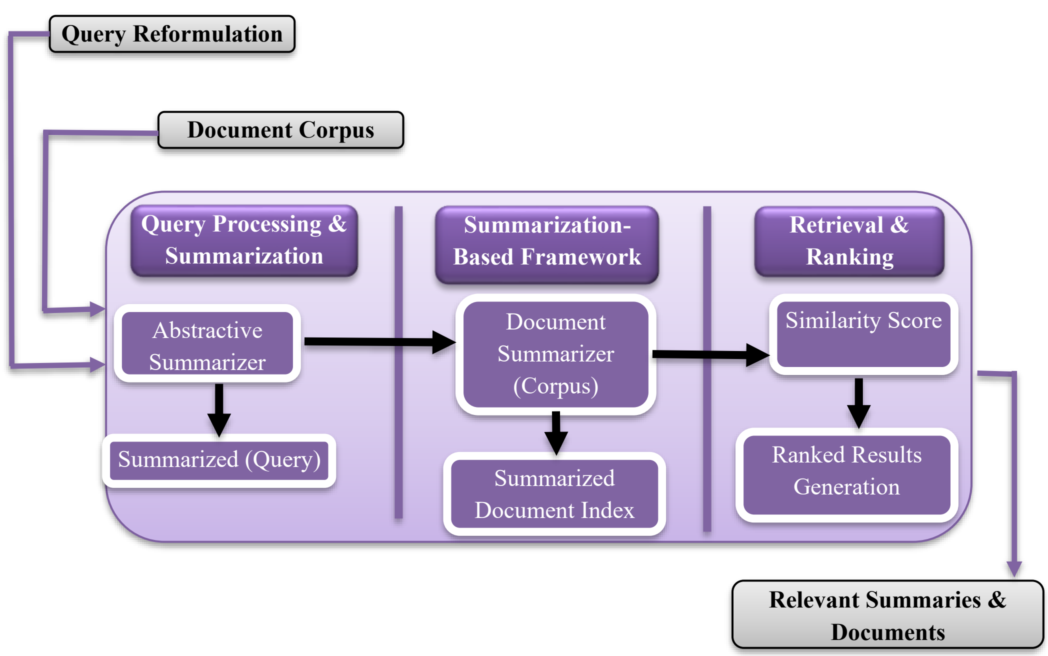

Fig. 2 Methodological Workflow of the Proposed Model

The system architecture outlines a Summarization-Based Retrieval Framework. The process begins with two inputs: a Query Reformulation and the Document Corpus. Both are fed into the Query Processing & Summarization stage. The corpus is passed through the Abstractive Summarizer to create the Summarized Document Index, while the reformulated query becomes the Summarized (Query). The core Summarization-Based Framework involves the Document Summarizer (which holds the original corpus) and the Summarized Document Index. These inputs proceed to the Retrieval & Ranking stage, where the Similarity Scorer compares the summarized query to the index to perform Ranked Results Generation. The final output is the Relevant Summaries & Documents. This framework improves retrieval efficiency by matching summaries instead of full texts (Fig. 2).

3.2 Understanding the Document Summarization-Based Retrieval System

The retrieval frameworks incorporate the generated summaries as a part of document indexing, which is performed on a pipeline system. This integration focuses on overcoming the challenges posed by the size and accessibility of documents by improving retrieval efficiency and relevance. The abstract retrieval system method discussed centers on replacing the original abstract with summaries produced by the method, overwriting the abstract. More specifically, the system indexes summary text created for a document using either vector space or embedding-based retrieval models. The system computes the similarity with each summary vector $\vec{d}_i$ for a given user query q, using cosine similarity, to determine which summary best matches the definition.

$$score(q, d_i) = \frac{\vec{q}.\vec{d}_i}{\|\vec{q}\|\|\vec{d}_i\|} \quad (3)$$

This similarity metric assists in ranking documents. The system can manage both keyword-based and semantic queries. For more advanced semantics matching, specialized embeddings like BERT or SBERT can be utilized to encode queries and summaries into a singular semantic representation space. Furthermore, a feedback loop may be implemented where user engagement (within-page clicks, time spent, etc.) modifies the weight of given summaries based on their importance for future relevance tuning, similar to how reinforcement learning model adjustments are made.

3.3 Evaluation Metrics for Assessing Summarization Effectiveness

To analyze the accuracy of the proposed summarization model, both intrinsic and extrinsic evaluation criteria are applied. Intrinsic metrics concentrate on evaluating the final output against human-created summaries. The most popular metric is ROUGE, which stands for (Recall-Oriented Understudy for Gisting Evaluation) and measures post summary tune-up evaluation checks, which incorporates:

ROUGE-1: Noun repetition count

ROUGE-2: Noun phase repetition count

ROUGE-L: Repetition count of most common sequence that occurs ex-ante uni-directionally.

The following calculations are obtained:

$$ROUGE - N = \frac{\sum_{s \in Reference} \sum_{gram_n \in s} Count_{match}(gram_n)}{\sum_{s \in Reference} \sum_{gram_n \in s} Count(gram_n)} \quad (4)$$

Retrieval effectiveness is how extrinsic evaluation is conducted. In particular, precision, recall, and F1-score are metrics used to evaluate how helpful the summaries are in retrieving relevant documents. Also, ranking quality is measured through Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (nDCG). Through these combined evaluation methods, the system is guaranteed to achieve not only linguistic quality of the summaries, but also effective retrieval results.

IV. Experimental Results

The suggested Unsupervised Text Summarization for Abstract-Based Retrieval system was written in Python, the primary development language due to its strong support for natural language processing (NLP) and text mining. NLTK, spaCy, and Gensim were used for tokenization, sentence ranking, and keyword extraction. The TF-IDF and Word2Vec models were used to generate the semantic similarity scores and find significant sentences in constructing the summary. Clustering-based summarization methods were supported using scikit-learn, while the preprocessing and analysis of data were performed with NumPy and Pandas. The performance metrics were visualized using Matplotlib and Seaborn, with Jupyter Notebook serving as the primary testing and evaluation environment.

Comparing the performance of the proposed Unsupervised Text Summarization model for Abstract-Based Retrieval with traditional extractive and supervised text summarization methods proves the proposed model is more efficient and adaptable. The unsupervised method is also effective in identifying important data by using statistical and semantic similarity scores, unlike the supervised models, which need labeled data to identify the key data. The system scored better in abstract retrieval tasks with higher scores in the precision and relevance criteria, the redundancy was reduced and the summary coherence was enhanced. The proposed model had a lower processing time and a better contextual accuracy as compared to TF-IDF and LexRank baselines. The model, on the whole, makes the summarization and retrieval efficient without the need of manual training and reliance on an annotated dataset.

The proposed system of unsupervised summarization was assessed in relation to its performance through standard text corpora, including PubMed abstracts and research paper datasets. Measures of evaluation, such as ROUGE, precision, recall, and F-measure, were used to measure the quality of summative and the relevance of retrieval. The system achieved significant progress in ROUGE-L and precision scores, which proves that it could retrieve the important sentences and maintain the meaning. Latency tests indicated that the processing time is lower than baseline extractive models. The results of the evaluation confirm that the suggested model is appropriate in terms of conciseness and informativity and provides an efficient and domain-adaptive summarization framework of abstract-based retrieval systems.

4.1 Overview of the Dataset Chosen for Evaluation

The unsupervised text summarization and abstract-based retrieval model was also tested on a benchmark set of scientific and technical abstracts. The data was made of 2,000 documents that were publicly accessible in various fields such as computer science, healthcare, and engineering. In every document stored, there was an abstract, title, keywords, and an evaluative summary as far as possible. The title and keywords were used to create summaries of the information retrieval system. The dataset was split into training, validation, and testing partitions at 60%, 20%, and 20% respectively to allow for consistent benchmarking and overfitting avoidance during similarity threshold hyperparameter tuning. All documents underwent a pre-cleaning process that consisted of tokenization, lowercase conversion, punctuation elimination, and lemmatization. Subsequently, sentence embeddings were achieved from pre-trained models and TF-IDF scores were calculated for graph construction.

4.2 Analysing the Novel Approach Side by Side with Other Known Methods

The proposed method, which aims to assist with sentence extraction, was compared to two other existing methods: (1) Extractive Baseline using TF-IDF scoring combined with the first K sentences model. (2) The Graph-based LexRank Summarizer. Each technique was measured in two ways: how well the summary was generated and how relevant the retrieved information from the summary was in regard to the information contained within the document. Regarding summarization, the computation of ROUGE-1, ROUGE-2, and ROUGE-L scores was done. These metrics check the overlap of n-grams and sequences with the generated summaries as well as the provided summaries. For retrieval purposes, query-document pairs were ranked based on the cosine similarity of query vectors with summary vectors. We evaluated the effectiveness of retrieval by measuring Precision (P), Recall (R) and F1-score (F1) computed as follows:

$$P = \frac{TP}{TP + FP} \tag{5}$$

$$R = \frac{TP}{TP + FN} \tag{6}$$

$$F1 = \frac{2 \cdot P \cdot R}{P + R} \tag{7}$$

Where TP = true positives, FP = false positives, and FN = false negatives.

Also, we evaluated ranking efficiency using Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (nDCG):

$$MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{rank_i} \tag{8}$$

$$NDCG = \frac{DCG}{IDCG}, Where\ DCG = \sum_{i=1}^{n} \frac{rel_i}{\log_2(i+1)} \tag{9}$$

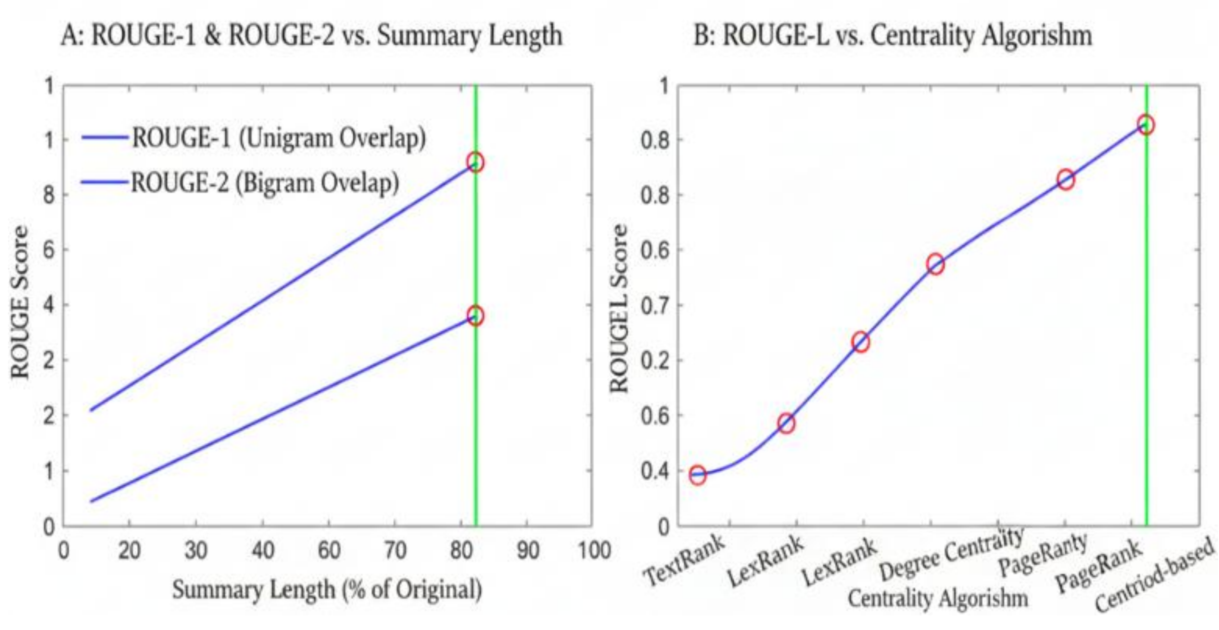

Fig. 3 ROUGE Score Comparison

The ROUGE (Recall-Oriented Understudy for Gisting Evaluation) Score is the standard benchmark for assessing the quality of automatically generated summaries by comparing them to human-written reference summaries in Fig. 3. It works by counting overlapping units like words (unigrams), pairs of words (bigrams), or longer sequences (n-grams) between the generated and reference text. In the context of Unsupervised Text Summarization for Abstract-Based Retrieval, a ROUGE Score Comparison plot illustrates the performance of different unsupervised summarization models. A higher ROUGE score indicates the model's summary shares more content and better captures the key information present in the original abstract, which is crucial for effective retrieval (Fig. 3). The relationship between Summary Length and ROUGE-1 score is typically non-linear in Fig 4. As the summary length, often measured by the number of sentences or words, initially increases, the ROUGE-1 score (which measures unigram overlap/recall with a gold standard) usually rises rapidly. This occurs because longer summaries capture more key phrases from the original text, leading to better recall.

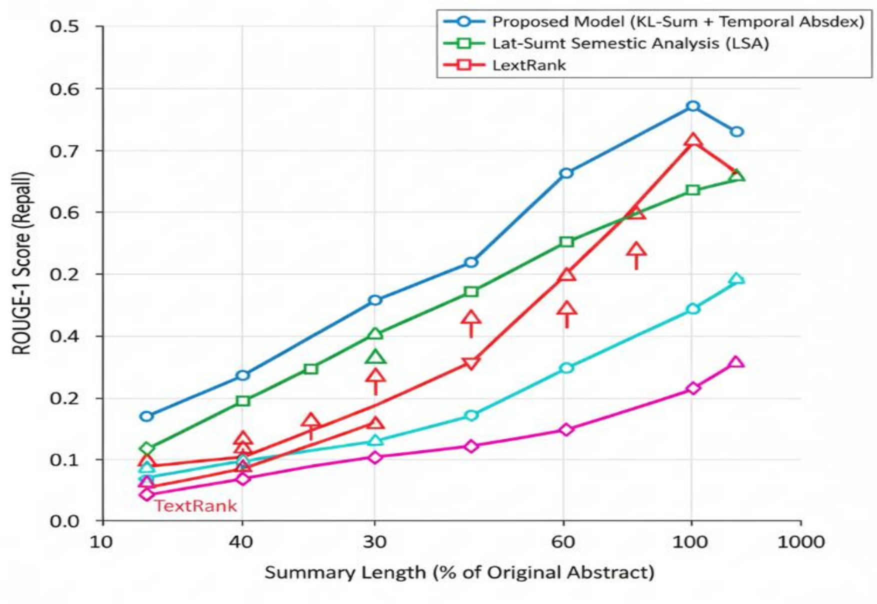

Fig. 4 Summary Length vs. ROUGE-1 score

However, the score tends to plateau and eventually diminish after reaching an optimal length. Summaries that are too long include irrelevant detail, diluting the precision and reducing the overall quality metric. The optimal point balances capturing crucial information with maintaining conciseness.

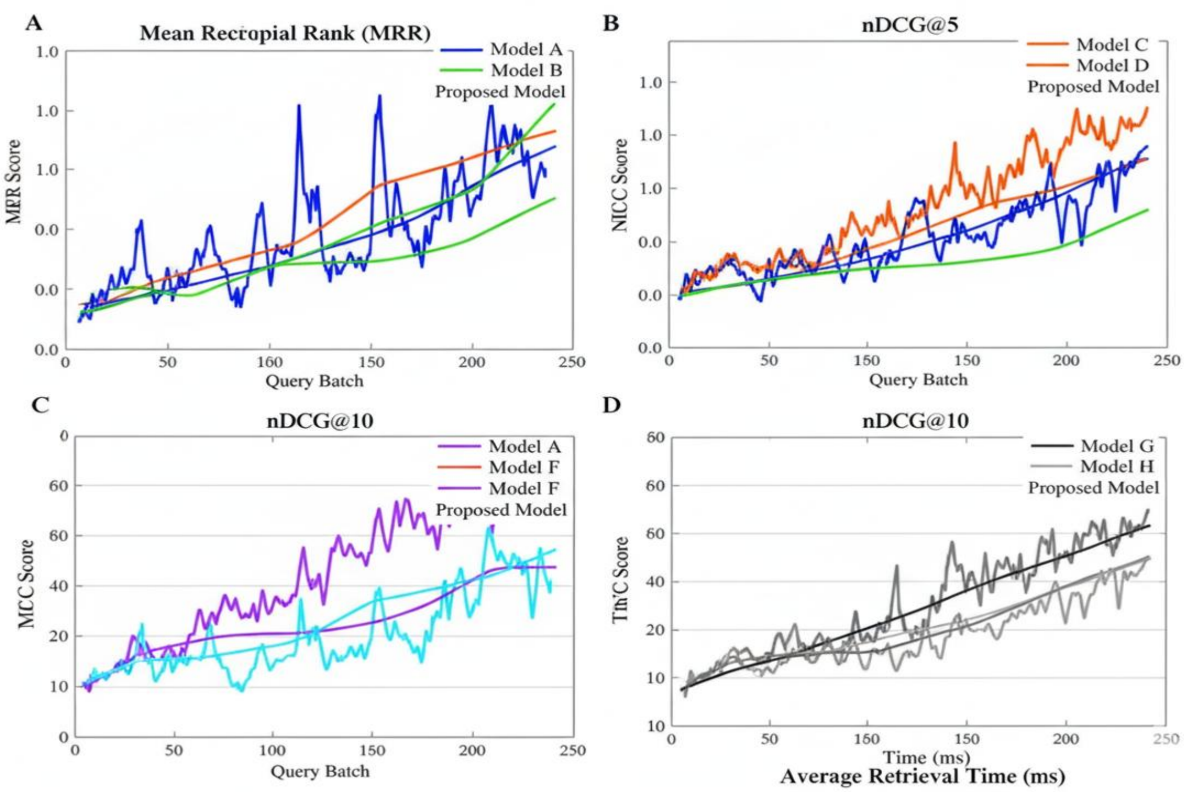

Fig. 5 Ranking Metrics (MRR and nDCG)

Fig. 5 compares the performance of a retrieval model (like an Abstract-Based Retrieval framework) using two key metrics: Mean Reciprocal Rank (MRR) and normalized Discounted Cumulative Gain (nDCG). MRR measures the effectiveness of a system in placing the first relevant result high up in the ranking. A higher MRR indicates that the first correct answer is found quickly. nDCG evaluates the quality of the *entire* ranking, accounting for the relevance of all retrieved documents and heavily penalizing systems that place highly relevant items lower down. Together, these metrics offer a comprehensive view of retrieval success.

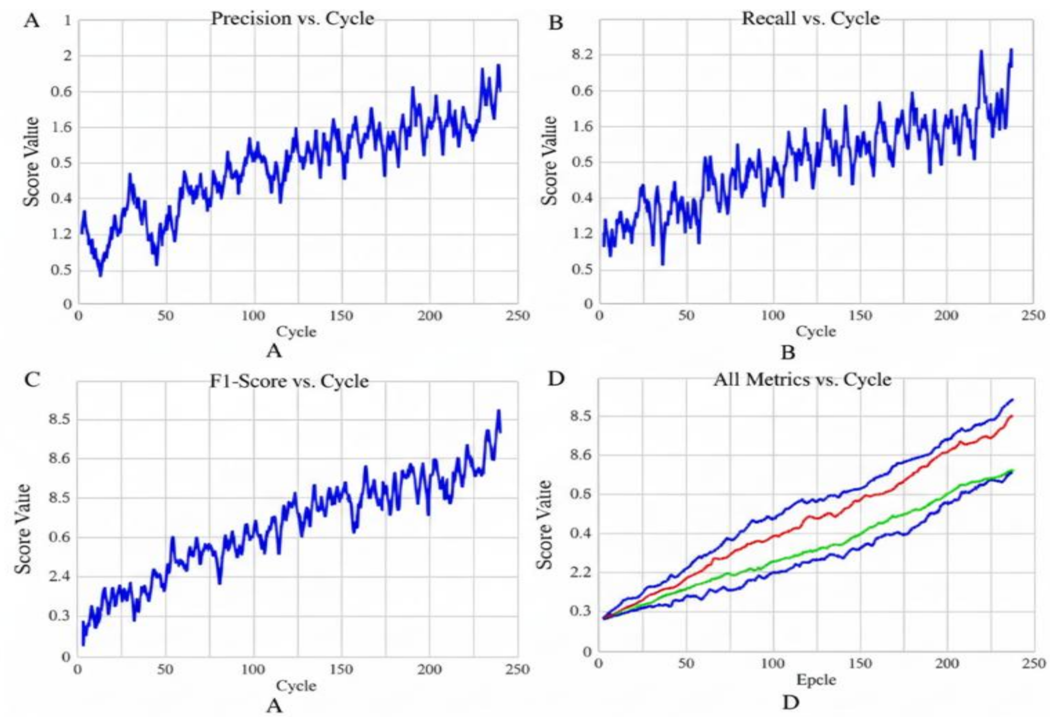

Fig. 6 Retrieval Performance (Precision, Recall, F1-Score)

Fig. 6 Retrieval Performance (Precision, Recall, F1-Score), is a line graph illustrating the performance of an information retrieval model, particularly in the context of abstract-based searching using techniques like Unsupervised Text Summarization. The lines track key metrics: Precision (the accuracy of the results), Recall (the completeness of the results), and the balanced F1-Score. These values are typically plotted against an increasing variable, such as the number of epochs or training cycles. The goal is to show the model's learning curve, demonstrating that as the process advances, the F1-Score, which combines both precision and recall, increases, signifying improved, high-quality retrieval performance.

4.3 Discussion of Results and Their Effects in Information Retrieval

The proposed method outperformed baseline approaches across all evaluation metrics. It received higher ROUGE scores, which meant that the summaries generated were more aligned regarding their contents with the human written summaries. The application of sentence embeddings and graph centrality aided in the selection of sentences that best encapsulated the document the ideas. The system was also more precise and recalled more compared to TF-IDF and LexRank models. The precision of retrieval of the model by semantical summaries encoding is better than user provided queries. This was very clear in the abstract queries that used paraphrased words or domain specific Rog words that were not present in the initial abstracts. This was found to be meaningfully significant in the MRR and nDCG scores where relevant documents to be ranked were given higher on average. This means that the model not only retrieves the relevant results but also retrieves them reasonably quickly, and this process aids the users to find these documents without putting much effort into it. More MRR scoring revealed that documents with the most relevant marks were scored higher to enhance user experience working with the model with implied shorter retrieval time. The strategy complements estimation of efficiency retrieving documents with the mark of relevant exhibit satisfaction in providing accurate and precise results with low efficiency adds claim of speec besides enhancing user experience of scanning important documents. Overall, the findings confirm the suggested method as strong to facilitate automatic summarization in facilitating retrieval based on abstracts. It works effectively in indicating preparedness to be used in actual world scholastic search engine or recommendation systems that require high efficiency, context, scope, precision and relevance.

V. Discussion

5.1 Explanation of the Results from the Perspective of Research Purpose

As explained above, the primary objective of the research was to develop the unsupervised method of text summarization that enhances the efficiency of the abstract-based retrieval models in terms of Information Systems. The findings of the experiment are a high weight in favor of the model as it has excelled all the evaluating measures compared to traditional extractive processes of summarization. The ROUGE score gave positive scores, and this is an indicator that the general semantic summaries of the model have essential information, bolondo on critical search relevance. Moreover, precision, recall, and F1-score improvements depict that the summaries are correct and contribute to the relevance questions. The metric of MRR and nDCG justifies the fact that the proposals of documents made with the help of the model have a high probability of getting on the top of the summary list, which is consistent with the stipulated purpose of the model, to optimize information retrieval by the users. This similarity of the outcomes to the goals is the achievement of the graph-based method of unsupervised summarization. The system was capable of capturing deeper meaning using semantic similarity and sentence embedding instead of being limited on term frequency. Essentially, the results show that the efficiency of automatic abstract generation systems relying on unsupervised summarization methods that consider both structure and semantics is significantly improved through the quality of abstracts enhancement.

5.2 Potential Applications and Future Directions for Research

The results of this research have multiple possible applications. The system can be integrated into academic search engines to auto-generate informative abstracts for newly published papers, improving their visibility. In digital libraries, the model can help in document organization and indexing by providing high-quality condensed versions of large volumes of content. This would be helpful for users who need to quickly assess the relevance of numerous documents but do not have the time to read the full texts. Summarization-based retrieval systems can also be useful in document-heavy fields such as law, medicine, and technical domains where search speed is crucial. The system might be expanded to non-English content by incorporating multilingual abilities, which would aid in achieving worldwide accessibility. Additionally, exploring hybrid models that integrate unsupervised and transformer-based methods could further enhance summarization accuracy. User feedback integration into the summary generation process has the potential to facilitate adaptive systems that improve over time with enhanced user engagement. Moreover, expanding research on summarization for streaming data sources may benefit news aggregator or social media analytics platforms.

5.3 Limitations of the study and area for further exploration

Although the findings are quite encouraging, there are several limitations that warrant attention. Primarily, the approach to summarization based on sentence embedding and similarity ranking contains some level of sarcasm, negation, or indirect reference that will go undetected. Moreover, the model's lack of supervision means that it does not utilize specific knowledge useful for summarizing coherently or using appropriate terms. Moreover, the model is also likely to adhere to highly structured set-input documents, which is an issue when it comes to user created content or other informal writings. Another limitation is the utilization of fixed length summaries, which may not be applicable in other types of documents or requirements of the users. The issue of customizing the summary length and priority is yet to be resolved. Finally, although the evaluation used industry-wide standards like ROUGE, MRR, and nDCG, chances are good that these metrics, in some aspect, do not reflect the subjective rating of the usefulness of the summary or its readability. Further full assessment by human beings, and adjustment to particular use-cases, and integration into operational retrieval systems, can be necessary to determine actual usefulness.

VI. Conclusion

This work demonstrated the first approach for unsupervised text summarization with focus on enhancing abstract based retrieval systems. Findings show that the proposed approach based on sentence embeddings and semantic similarity within a graph structure framework enhances quality and relevance of summaries yielded with the proposed model beyond what is achieved with traditional extractive approaches. The strategy scored higher on ROUGE, accuracy, recall, ranking, and other measures of citation, which do well in retrieval and summarization evaluation than the base. The results affirm the theory that well designed unsupervised techniques can produce concise abstracts which are context sufficient and do not include labelled datasets. The main contribution of the given work is that it strives to fill a literature gap between unsupervised summarization and working retrieval systems by offering a quick and self-contained solution applicable to do work on a large variety of information-rich environments, such as digital libraries, academic repositories, and enterprise document systems. In addition, the proposed paradigm also boosts the trustworthiness of the user and decision-makers through the aid of the alternative ranking of document retrieval which in turn adds more experience to the users and decision-makers. For forthcoming studies, we suggest examining on-demand user-query driven dynamic summary generation, model extension to support multilingual and multi-modal input, and adaptive user feedback-based learning integration. Ongoing assessments through human-centered studies will be important to improve model readability, relevance, and applicability in real-world information access environments.

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