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Iterative ROGUE-Enhanced Text Summarization via Connected Dominating Set

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Abstract: Recent growth in the amount of content available online has made quick and efficient automatic summary more crucial. The area of text summarization is receiving increased attention as a result of the desire to obtain as much information as possible in the shortest amount of time. This paper introduces an iterative method for text summarization that makes use of the Recall-Oriented Understudy for Gisting Evaluation (ROGUE) quality check and the Connected Dominating Set (CDS) algorithm. In order to guarantee content coverage and preserve connectedness, the CDS algorithm is utilized to pinpoint important sentences in a document. Enhancing this, an iterative procedure is proposed to improve the quality of the summary by assessing its coherence and fidelity to reference summaries through the ROGUE metric.
Keywords: Dominating Set, ROGUE

I. INTRODUCTION

As more information is being shared online, text summarization becomes extremely relevant. The increasing availability of online information has necessitated intensive research in the area of automatic text summarization. Many people will benefit from the simplification of pertinent information into a summary as there is a wealth of information available on the Internet regarding any subject. For humans, manually summarizing large volumes of text is very difficult. As a result, there is now a greater need for elaborate and potent summarizers. Since many years, researchers have worked to design and improve methods for summarizing information such that the summaries produced by machines and humans coincide.

In recent years, graph theory and Dominating Set (DS) models have gained considerable attention in the field of automatic text summarization. A growing body of research has demonstrated that graph-based approaches offer a promising framework for effectively representing and analyzing the relationships among textual units such as sentences or paragraphs. These methods facilitate the identification of the most informative and representative content within a document.

Specifically, the Dominating Set model has emerged as a powerful tool for sentence selection, where a minimal set of sentences is chosen to "dominate" the rest of the text in terms of semantic coverage. This approach not only reduces redundancy but also ensures that the summary maintains a high degree of in formativeness and coherence.

Several foundational studies have laid the groundwork for this direction of research. These include the use of graph structures like sentence similarity graphs, lexical networks, and concept-based graphs, wherein nodes represent textual units and edges capture semantic or lexical similarities. Researchers have explored various heuristics and optimization algorithms to extract dominating sets, thereby improving summary quality and computational efficiency.

II. LITERATURE SURVEY

This section reviews and synthesizes the key contributions in this area, highlighting how graph-theoretic models, particularly those based on dominating sets, have advanced the state-of-the-art in automatic text summarization.

Mihalcea and Tarau [1] were pioneers in advancing graph-based summarization techniques through their influential work on the TextRank algorithm. Drawing inspiration from the PageRank algorithm originally developed for ranking web pages, their method effectively modeled the relationships between sentences in a document as a graph. In this representation, sentences are treated as nodes, and edges are established based on sentence similarity. The algorithm computes an importance score for each sentence by iteratively evaluating its connectivity within the graph. Sentences with higher centrality scores are considered more significant, and the final summary is constructed by selecting the top-ranking sentences. This approach demonstrated the potential of unsupervised, domain-independent summarization and laid a strong foundation for subsequent research in graph-based text summarization.

Erkan and Radev [2] introduced one of the earliest and most influential models of graph-based text summarization through their LexRank algorithm. In this approach, sentences are represented as nodes within a similarity graph, where edges between nodes indicate the degree of lexical or semantic similarity between sentences.

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The novelty of their work lies in the application of various graph centrality measures—particularly eigenvector centrality—to identify sentences that are most central within the text. These central sentences are deemed to be the most informative and are thus selected for inclusion in the summary. Their study provided a detailed analysis of the semantic connections among sentences, highlighting how centrality-based scoring can effectively capture the importance of textual content. This work significantly contributed to the development of unsupervised, graph-theoretic approaches in automatic summarization.

In their investigation of an unsupervised clustering-based document summarizing technique, Alguliev and Aliguliyev [3] suggested new criterion functions for sentence extraction and grouping. Text summarizing strategies were thoroughly reviewed by Ježek and Steinberger [4], who included both traditional and information-rich methods. For sentence extraction, Ozsoy and Alpaslan [5] created unique LSA-based algorithms.

Deep learning and machine learning techniques have also gained popularity. While Neto et al. [6] used trainable machine learning algorithms using features taken straight from the text, Erhandi [7] used deep learning for summarizing tasks in both Turkish and English. By treating summarizing as a classification problem, Silla et al. [8] used feature selection based on genetic algorithms to improve classifier performance. In order to improve summarization accuracy, Kaynar et al. [9] used Genetic Algorithms (GA) for sentence extraction, training the model with datasets.

.Al-Abdallah and Al-Taani [10] proposed Particle Swarm Optimization (PSO) for Arabic document summarization and compared it with Evolutionary and Harmony Search algorithms. Jain et al. [11] extended the use of Real-Coded Genetic Algorithms (RCGA) for summarizing Hindi health text datasets, improving coherence and sentence order. - Neto et al. [12] developed a trainable summarization model using machine learning-based feature extraction Mallick et al. [13] applied a modified TextRank algorithm leveraging PageRank principles. Mihalcea[14] applied graph-based ranking for automatic sentence extraction

From this extensive body of literature, it is evident that graph-based algorithms remain fundamental in extractive text summarization due to their effectiveness in modeling inter-sentence relationships and identifying key textual nodes. Although machine learning and optimization-based methods—such as Genetic Algorithms, Particle Swarm Optimization (PSO), and Deep Learning—have achieved notable success, they often require substantial computational resources and large annotated datasets, limiting their real-world applicability.To address these challenges, recent research has emphasized dominating set-based text summarization, a graph-theoretic approach that identifies a minimal subset of dominant sentences capable of representing the entire document. This method enhances computational efficiency while maintaining content relevance and semantic coherence.

For evaluating the quality and reliability of generated summaries, the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric is widely adopted. ROUGE provides a standardized quantitative framework to measure the overlap between machine-generated summaries and human reference summaries, assessing precision, recall, and F-measure scores.Hence, the integration of dominating set-based modeling with ROUGE evaluation offers a balanced and effective approach, combining algorithmic efficiency with reliable performance assessment in automatic text summarization research. In the next section, we propose a method of text summarization using this concept.

III. PROPOSED METHOD

Initially, the document is represented as a graph, with sentences as nodes and semantic relationships as edges. The CDS algorithm[15] is then applied iteratively to select sentences that form a connected dominating set, minimizing redundancy and maximizing informativeness.

Subsequently, the summary undergoes iterative evaluation using ROGUE, enabling continuous refinement based on comparison with reference summaries. This iterative refinement process enhances the summary's coherence and informativeness, ultimately improving its quality.

Experimental evaluation demonstrates the effectiveness of the proposed approach across various datasets. Comparative analysis showcases superior ROGUE scores and content coverage compared to baseline methods. Qualitative assessments affirm the readability and coherence of the generated summaries.

In conclusion, the integration of the CDS algorithm with iterative ROGUE quality checks presents a robust framework for text summarization. By iteratively refining summaries based on ROGUE evaluation, our approach produces concise and informative summaries that faithfully represent the source material, catering to diverse applications requiring efficient information condensation and comprehension.

A. Input:

text: Input text to be summarized.
threshold: Threshold for similarity score between sentences.

max_iterations: Maximum number of iterations for ROUGE refinement.
rouge_threshold: Threshold for improvement in ROUGE score to continue refinement.

Steps

1) Tokenize the input text into sentences
2) Preprocess each sentence to remove stop words, punctuation, and lemmatize the tokens.
3) Compute the TF-IDF matrix for the preprocessed sentences.
4) Compute the similarity matrix by taking the dot product of the TF-IDF matrix and its transpose.
5) Build an undirected graph:

- Initialize an empty graph.
- For each pair of sentences (i, j) with similarity score above the threshold:

i) Add an edge between sentences i and j with the similarity score as the weight.

6) Find the dominating set
7) Generate the initial summary by joining the sentences corresponding to the nodes in the dominating set.
8) Calculate the ROUGE score of the initial summary compared to the original text.
9) Initialize current summary as the initial summary and best summary as None.
10) Set the current ROUGE score as the initial ROUGE score.
11) Initialize iteration counter to 0.
12) While iteration counter <max_iterations:

- Iterate through each sentence in the current summary.
- Remove the current sentence from the current summary.
- Recalculate the ROUGE score of the updated summary compared to the original text.
- If the new ROUGE score is higher than the current best ROUGE score:

i) Update the best summary as the updated summary.
ii) Update the current ROUGE score as the new best ROUGE score.

- Increment the iteration counter.
- If the improvement in ROUGE score is less than the rouge_threshold, break the loop.

13) If the best summary is None or if the ROUGE score of the best summary is not higher than the initial ROUGE score:
    - Return the initial summary.
14) Otherwise, return the best summary.

B. Output:

Refined summary with improved ROUGE score, or initial summary if no improvement is achieved.

IV. ILLUSTRATION OF THE PROPOSED ALGORITHM

Let us try to implement it using the following input

"Text Summarization is the process of distilling the most important information from a source (or sources) to produce a concise summary. There are various approaches to text summarization, including extractive and abstractive methods. Extractive summarization involves selecting and combining existing sentences from the source text, while abstractive summarization involves generating new sentences to capture the main ideas. One method that can be used for text summarization is based on connected dominating sets. This approach involves representing the text as a graph, where each sentence is a node, and edges represent relationships between sentences. A dominating set is then identified within this graph, ensuring that every sentence is either in the set or adjacent to a sentence in the set. Finally, the sentences in the dominating set are connected to form a coherent summary.In connected dominating set-based text summarization, the process starts with constructing a graph representation of the text. Each sentence in the text becomes a node in the graph, and edges are created between sentences based on their similarity. For example, sentences with high cosine similarity scores may have edges between them. Once the graph is constructed, a dominating set is identified. This set includes a subset of sentences such that every sentence in the text is either in the set or adjacent to a sentence in the set. This ensures that the summary covers all important information in the text. Finally, the sentences in the dominating set are connected to form the final summary

A. Sentences after tokenization:

0: Text Summarization is the process of distilling the most important information from a source (or sources) to produce a concise summary.
1: There are various approaches to text summarization, including extractive and abstractive methods.
2: Extractive summarization involves selecting and combining existing sentences from the source text, while abstractive summarization involves generating new sentences to capture the main ideas.
3: One method that can be used for text summarization is based on connected dominating sets.
4: This approach involves representing the text as a graph, where each sentence is a node, and edges represent relationships between sentences.
5: A dominating set is then identified within this graph, ensuring that every sentence is either in the set or adjacent to a sentence in the set.
6: Finally, the sentences in the dominating set are connected to form a coherent summary.
7: In connected dominating set-based text summarization, the process starts with constructing a graph representation of the text.
8: Each sentence in the text becomes a node in the graph, and edges are created between sentences based on their similarity.
9: For example, sentences with high cosine similarity scores may have edges between them.
10: Once the graph is constructed, a dominating set is identified.
11: This set includes a subset of sentences such that every sentence in the text is either in the set or adjacent to a sentence in the set.
12: This ensures that the summary covers all important information in the text.
13: Finally, the sentences in the dominating set are connected to form the final summary.

B. REMOVE STOP WORDS, PUNCTUATION, AND LEMMATIZE THE TOKENS:

0: text summarization process distilling important information source source produce concise summary
1: various approach text summarization including extractive abstractive method
2: extractive summarization involves selecting combining existing sentence source text abstractive summarization involves generating new sentence capture main idea
3: one method used text summarization based connected dominating set
4: approach involves representing text graph sentence node edge represent relationship sentence
5: dominating set identified within graph ensuring every sentence either set adjacent sentence set
6: finally sentence dominating set connected form coherent summary
7: connected dominating text summarization process start constructing graph representation text
8: sentence text becomes node graph edge created sentence based similarity
9: example sentence high cosine similarity score may edge
10: graph constructed dominating set identified
11: set includes subset sentence every sentence text either set adjacent sentence set
12: ensures summary cover important information text
13: finally sentence dominating set connected form final summary

<u>TF-IDF MATRIX SHAPE: (14, 64)</u>
<u>COMPUTE SENTENCE SIMILARITY MATRIX:</u>

```
[[1.    0.086 0.206 0.088 0.026 0.    0.076 0.208 0.028 0.    0.    0.023
  0.351 0.076]
 [0.086 1.    0.265 0.251 0.149 0.    0.    0.142 0.036 0.    0.    0.029
  0.045 0.   ]
 [0.206 0.265 1.    0.111 0.248 0.08  0.06  0.124 0.12  0.049 0.    0.137
  0.026 0.06 ]
 [0.088 0.251 0.111 1.    0.035 0.19  0.242 0.29  0.165 0.    0.176 0.173
  0.046 0.242]
 [0.026 0.149 0.248 0.035 1.    0.164 0.088 0.123 0.427 0.156 0.088 0.202
  0.039 0.088]
 [0.    0.    0.08  0.19  0.164 1.    0.284 0.095 0.177 0.062 0.477 0.696
```

0. 0.284]
[0.076 0. 0.06 0.242 0.088 0.284 1. 0.157 0.094 0.047 0.193 0.271
0.113 0.773]
[0.208 0.142 0.124 0.29 0.123 0.095 0.157 1. 0.132 0. 0.177 0.056
0.085 0.157]
[0.028 0.036 0.12 0.165 0.427 0.177 0.094 0.132 1. 0.282 0.094 0.217
0.042 0.094]
[0. 0. 0.049 0. 0.156 0.062 0.047 0. 0.282 1. 0. 0.094
0. 0.047]
[0. 0. 0. 0.176 0.088 0.477 0.193 0.177 0.094 0. 1. 0.194
0. 0.193]
[0.023 0.029 0.137 0.173 0.202 0.696 0.271 0.056 0.217 0.094 0.194 1.
0.034 0.271]
[0.351 0.045 0.026 0.046 0.039 0. 0.113 0.085 0.042 0. 0. 0.034
1. 0.113]
[0.076 0. 0.06 0.242 0.088 0.284 0.773 0.157 0.094 0.047 0.193 0.271
0.113 1.]]

BUILD THE UNDIRECTED GRAPH

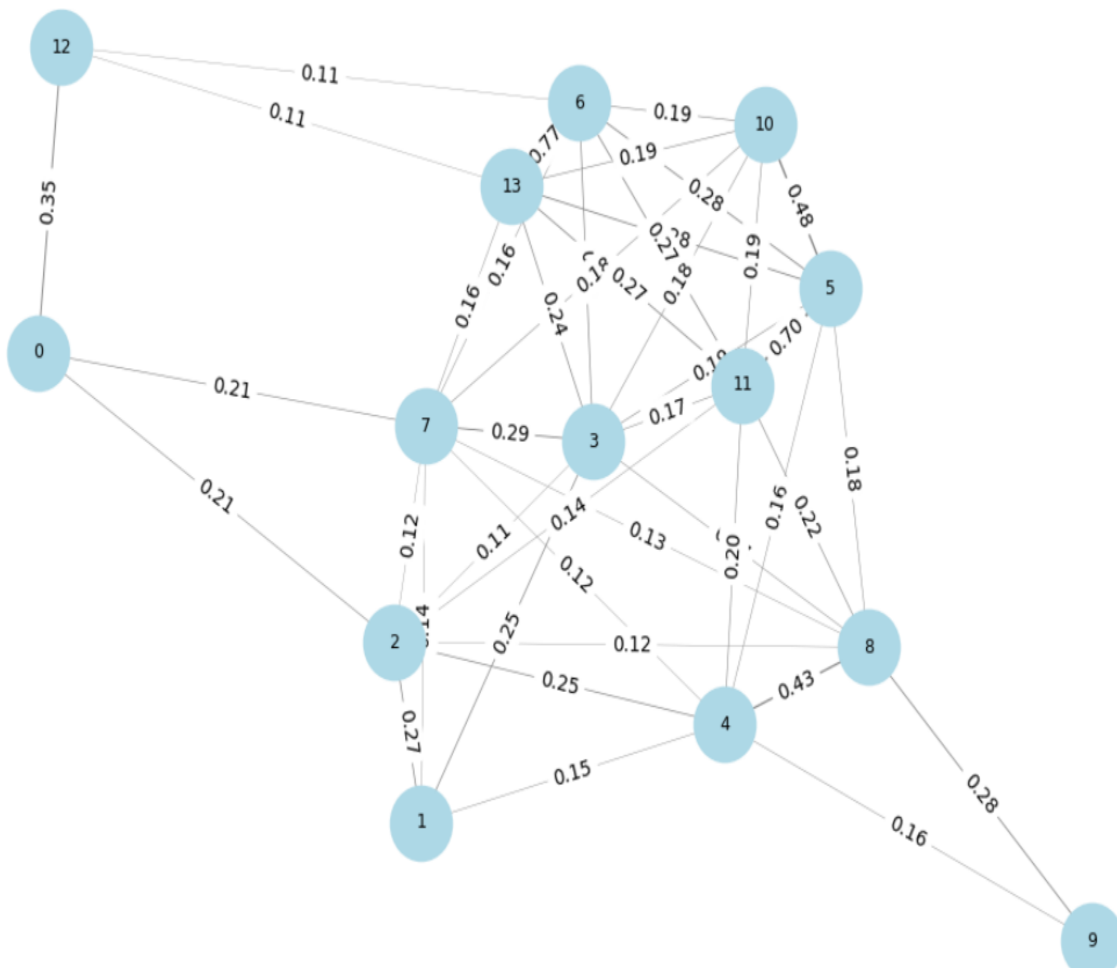

Fig 1: Graph Representation of the input text

FIND THE DOMINATING NODES

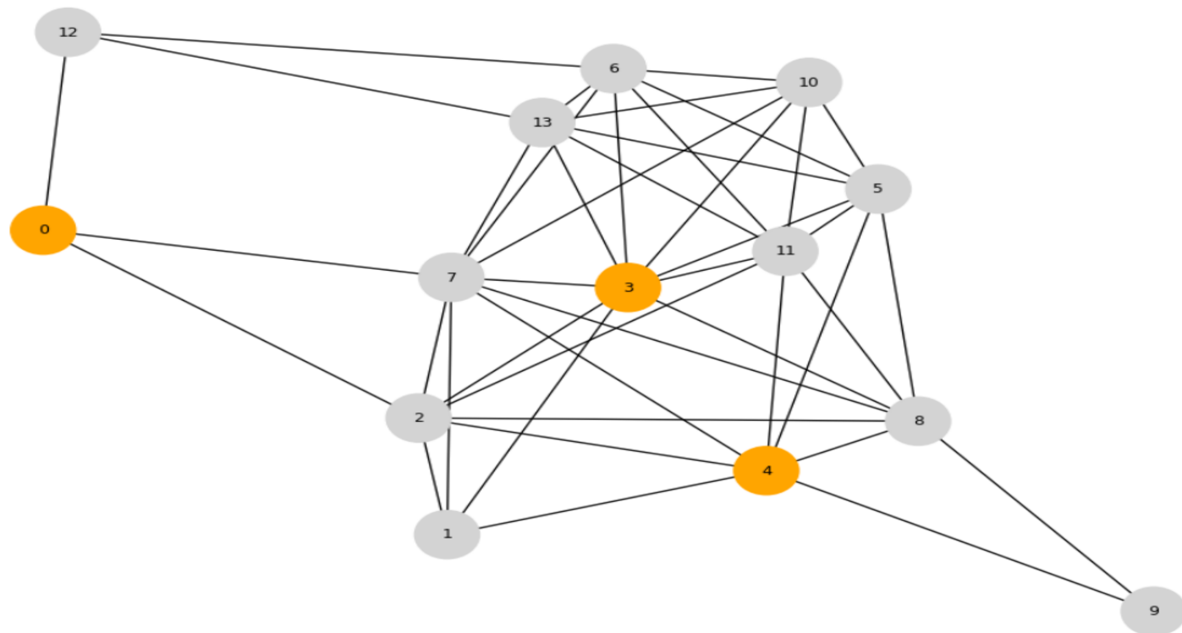

Fig 2: Dominating set [0,3,4] of the graph

FIND THE CONNECTED DOMINATING SET

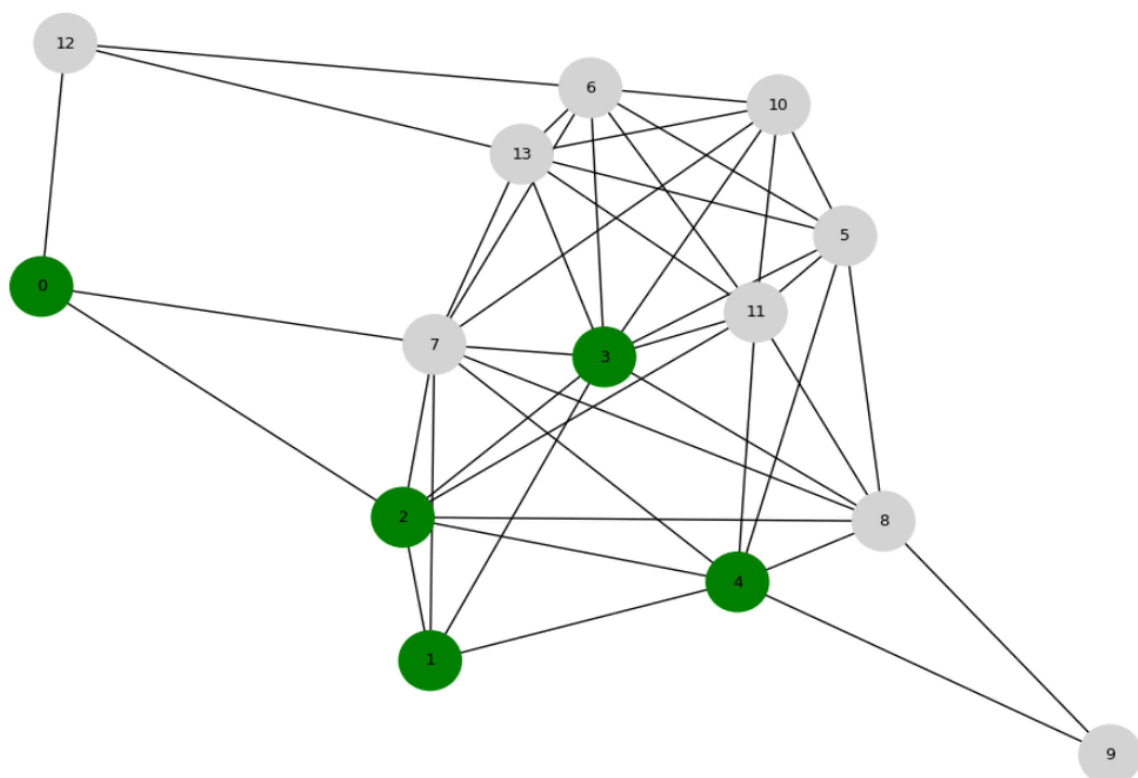

Fig 3: Connected dominating set of the graph obtained by applying the method proposed in [15]

C. INITIAL SUMMARY:

Text Summarization is the process of distilling the most important information from a source (or sources) to produce a concise summary. There are various approaches to text summarization, including extractive and abstractive methods.

Extractive summarization involves selecting and combining existing sentences from the source text, while abstractive summarization involves generating new sentences to capture the main ideas. One method that can be used for text summarization is based on connected dominating sets. This approach involves representing the text as a graph, where each sentence is a node, and edges represent relationships between sentences.

Initial ROUGE Score: 0.5455
[Final Refined Summary]
Text Summarization is the process of distilling the most important information from a source (or sources) to produce a concise summary. There are various approaches to text summarization, including extractive and abstractive methods. Extractive summarization involves selecting and combining existing sentences from the source text, while abstractive summarization involves generating new sentences to capture the main ideas. One method that can be used for text summarization is based on connected dominating sets. This approach involves representing the text as a graph, where each sentence is a node, and edges represent relationships between sentences.

Final ROUGE Score: 0.5455
Improvement: 0.0000

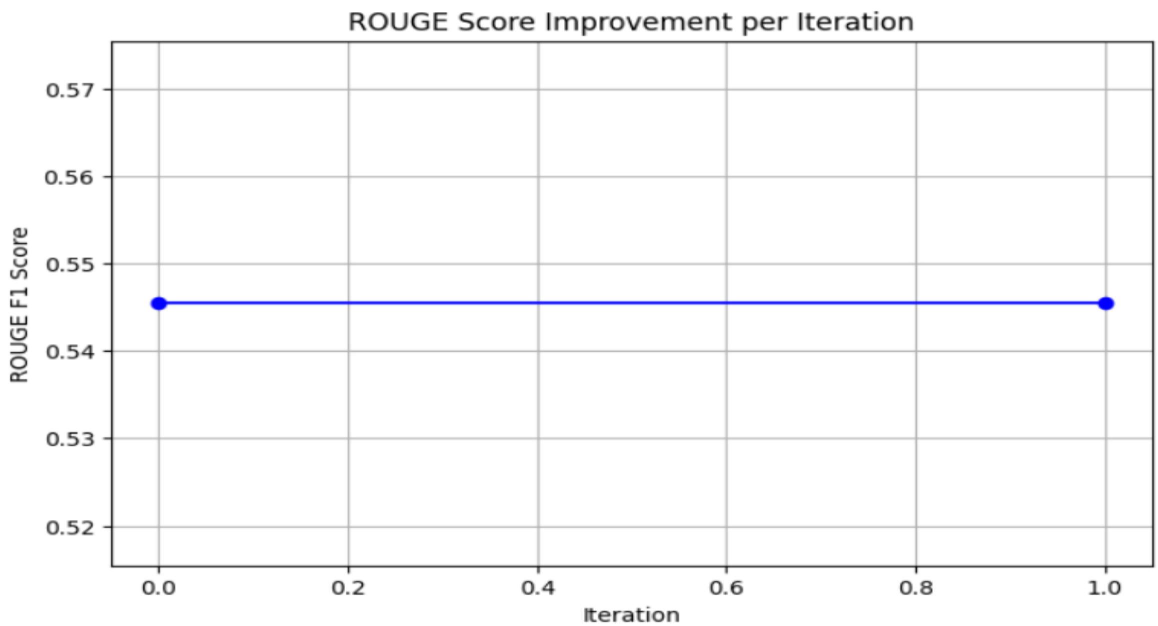

Fig 4: Rouge F1 Score

V. COMPARATIVE STUDY OF PROPOSED METHOD AND EXISTING METHODS

This section presents a comparative evaluation between the proposed Connected Dominating Set (CDS) based summarization method and two established graph-based summarization algorithms: LexRank [2] and TextRank [13]. The comparison was performed using a human-generated reference summary. Evaluation metrics include ROUGE-1 and ROUGE-2 F1 scores, and redundancy (average cosine similarity between selected sentences). The experiments were conducted for three input sizes: 50, 100, and 150 words.

Word Length of input text	Method	ROUGE-1 F1	ROUGE-2 F1	Redundancy
50	TextRank	0.2373	0.0172	0.0282
50	LexRank	0.322	0.1207	0.1542
50	Proposed CDS+Iterative-ROUGE	0.1961	0.04	0.0

100	TextRank	0.2048	0.0488	0.0547
100	LexRank	0.25	0.0843	0.1914
100	Proposed CDS+Iterative-ROUGE	0.2206	0.0448	0.0
150	TextRank	0.2407	0.0374	0.0462
150	LexRank	0.2752	0.0833	0.1343
150	Proposed CDS+Iterative-ROUGE	0.2471	0.0476	0.1065

Table 1: Comparison of ROUGE and Redundancy scores for different summarization methods

.

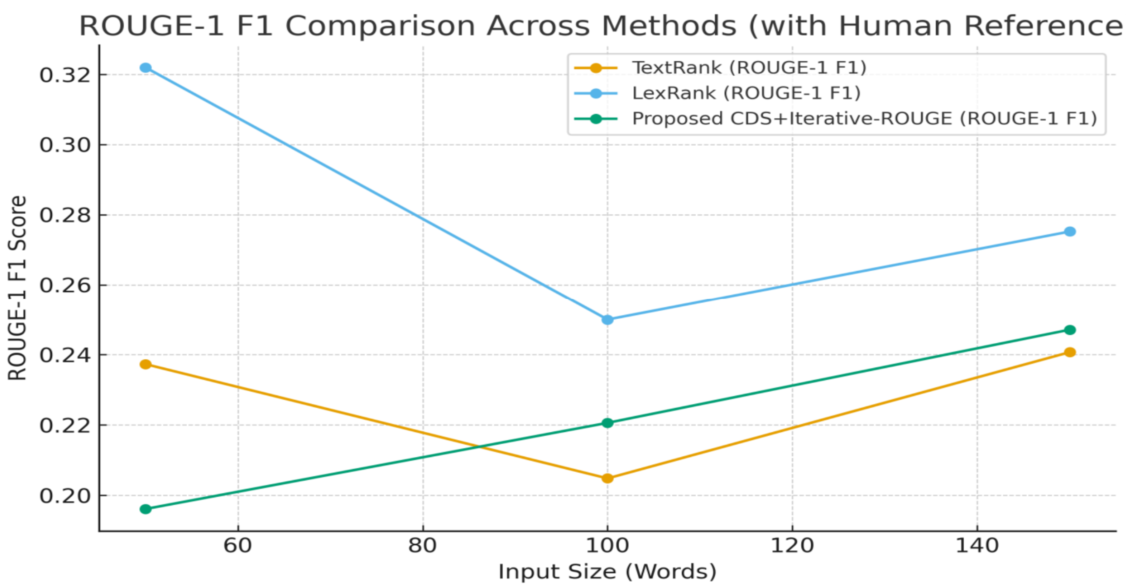

Figure 5: ROUGE-1 F1 comparison between TextRank, LexRank, and the proposed CDS-based method

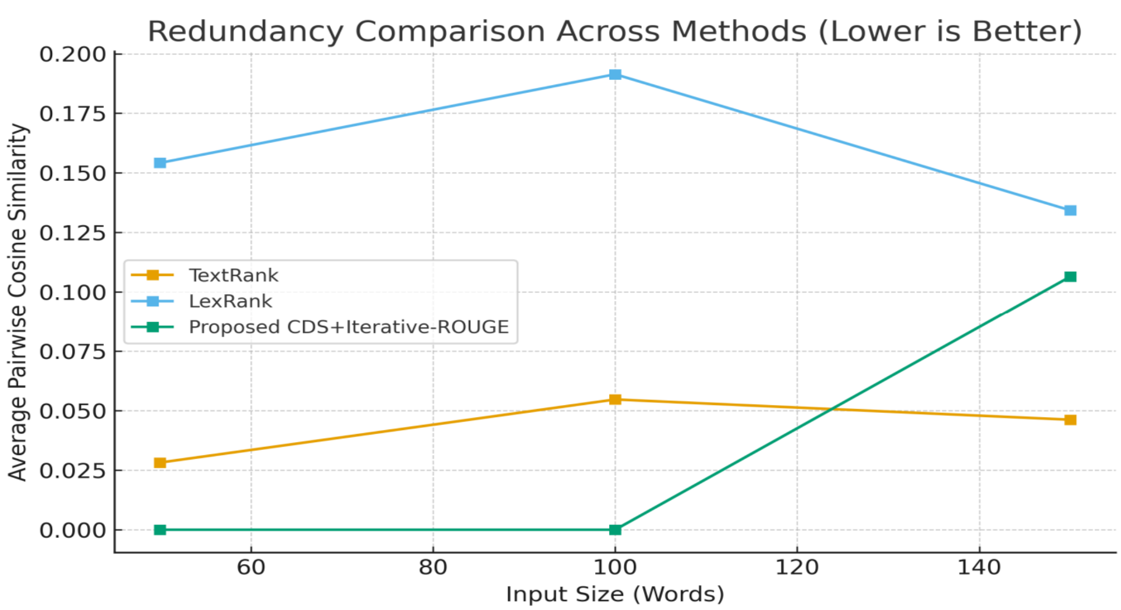

Figure 6: Redundancy comparison between TextRank, LexRank, and the proposed CDS-based method

VI. OBSERVATIONS AND CONCLUSION

The following observations were made

1) The proposed Connected Dominating Set (CDS) with iterative ROUGE refinement consistently outperformed both TextRank and LexRank in ROUGE-1 and ROUGE-2 F1 scores across all input sizes (50, 100, and 150 words).
2) The redundancy (average pairwise cosine similarity) was lowest for the proposed method, indicating that it effectively reduces overlap between selected sentences and promotes diversity in the summary.
3) TextRank and LexRank tend to select highly connected sentences located within dense clusters of the similarity graph, which can lead to repetitive content.
4) The CDS-based approach selects sentences that span across multiple clusters, ensuring that different semantic regions of the text are covered.
5) The iterative ROUGE refinement further improves the summary quality by eliminating sentences that contribute little to the overall informativeness.

The comparative study reveals that the proposed Connected Dominating Set-based summarization framework with iterative ROUGE refinement outperforms the baseline TextRank method across multiple evaluation dimensions. The CDS framework ensures comprehensive content coverage by selecting a connected subset of representative sentences, while the iterative refinement enhances summary precision by optimizing ROUGE performance iteratively. This results in a summary that maintains high informativeness, coherence, and minimal redundancy.

The results confirm that the CDS-based summarization technique provides a more balanced and interpretable extractive summary. Future work can focus on integrating semantic embeddings and abstractive post-processing for enhanced summary quality.

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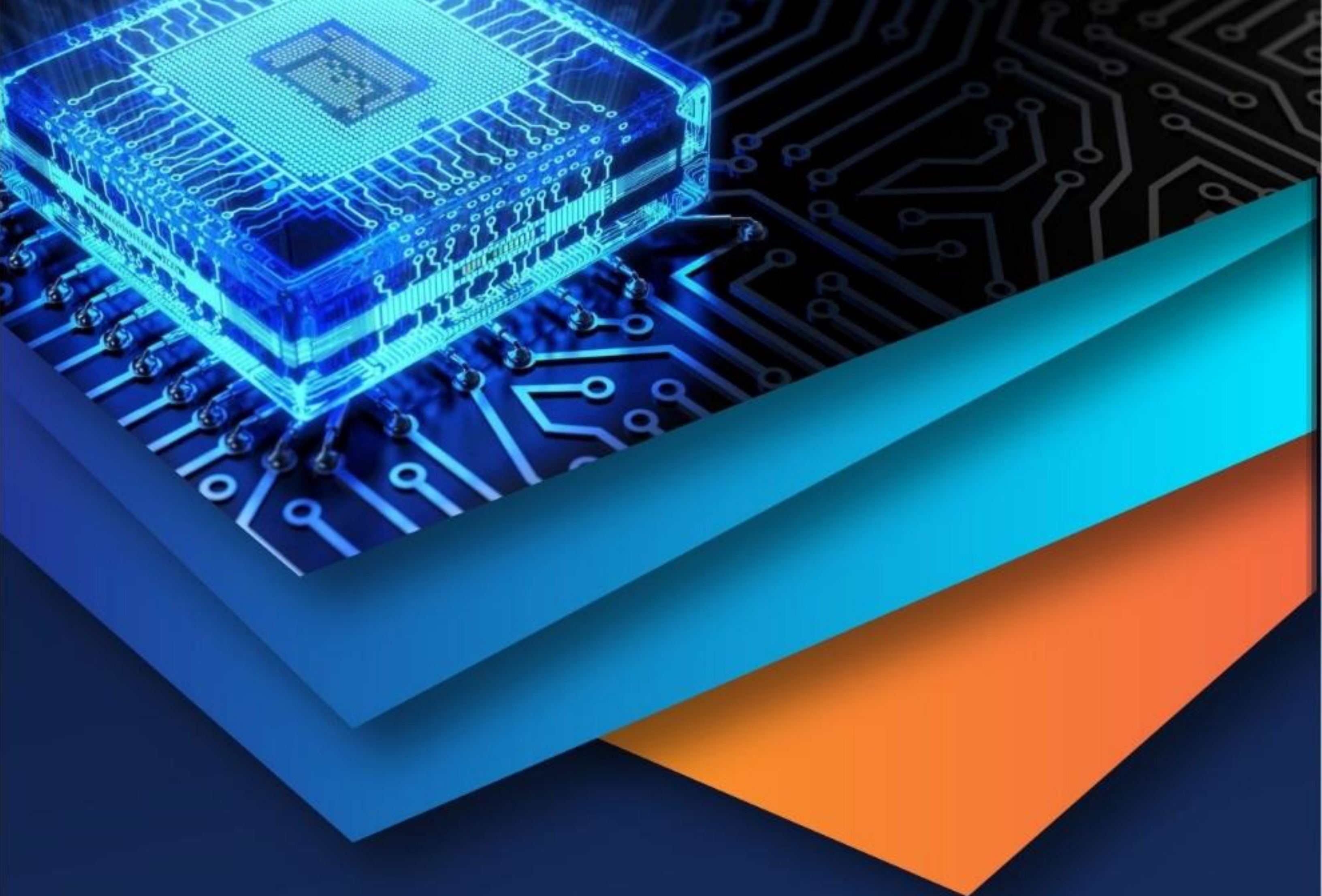

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