Web Page Summarization Using Custom Search Engine with Hybrid Model BERT+GPT

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***Abstract*—In the era of "information overload", effective text summarization has become essential to extract meaningful insights from huge batches of textual data. This research article describes a homegrown hybrid model combining BERT and GPT architectures for high-quality text summarization. The proposed model relies on the use of BERT for superior contextual understanding as well as its ability in extractive summarization, while it ends up by generating coherent, human-like abstractive summaries through GPT. The hybrid approach ensures that summaries maintain the context of the original yet enhance readability and informativeness. To be accessible, we deploy this system through a Flask-based web application which allows the user to input text and get instant summaries via a user-friendly interface hosted on localhost.**

The application demonstrates the flexibility of the hybrid model, presenting extractive and abstractive summarization modes. Performance evaluation by using ROUGE scores clearly demonstrated the efficiency of the model as against standalone methods, thus opening more avenues to be explored with journalism, research, or content curation applications. This project bridges advanced AI techniques with practical usability.

***Index Terms*—Text Summarization, Hybrid Model, BERT, GPT ,Extractive Summarization ,Abstractive Summarization ,Flask Application , Natural Language Processing (NLP) , ROUGE Scores , Contextual Understanding , User-Friendly Interface , AI-Powered Tools , Content Curation , Information Retrieval , Localhost Deployment**

I. Introduction

In today's digital age, the sheer volume of textual data generated every day can be overwhelming. From lengthy articles and research papers to extensive reports and user-generated content, navigating through this information often becomes a daunting task. This challenge has fueled the need for effective text summarization tools that can condense large amounts of text into concise, meaningful summaries without losing essential context.

Recent advancements in artificial intelligence have opened up exciting possibilities for creating smarter summarization systems. Among these, transformer-based models like BERT and GPT have revolutionized the field of Natural Language Processing (NLP). BERT excels in understanding the nuances and context of text, making it ideal for extractive summarization, where key sentences are selected directly from the source. On the other hand, GPT shines in generating coherent, human-like text, making it a powerful tool for abstractive summarization, where summaries are crafted in a way that may go beyond the exact phrases in the source material.

This project combines the strengths of BERT and GPT to create a hybrid summarization model. By integrating these two architectures, we aim to produce summaries that are both accurate and readable. To make this solution accessible, we developed a Flask-based web application where users can input text and quickly receive high-quality summaries. The application not only showcases the hybrid model's capabilities but also provides a seamless user experience for exploring extractive and abstractive summaries.

Through this work, we hope to address the growing demand for efficient text analysis tools in areas like journalism, research, and everyday content consumption. By blending advanced AI with a practical application, this project demonstrates how technology can simplify complex tasks, making information more accessible to everyone.

II. Literature review

Web scraping using summarization and named entity recognition (ner).

This research paper discusses the use of machine learning and natural language processing (NLP) techniques, along with the Natural Language Toolkit (NLTK), to develop a text summarization tool that can efficiently extract a concise and coherent summary from long input documents. The tool uses an extractive approach to generate accurate and fluent summaries, avoiding repetition and focusing on the main points. The paper highlights the benefits of such a tool in helping users quickly understand and refer to key information in voluminous text. It also discusses the challenges of text summarization for machines, which lack the human expertise of language understanding, and how this can be addressed through machine learning and NLP. The paper reviews relevant work in the field of text summarization, covering both abstractive and extractive approaches, and discusses the importance of manual linguistic

quality evaluation in assessing summarization tools.[1].

Web scraping using natural language processing: exploiting unstructured text for data extraction and analysis.

This research study presents a detailed exploration of web scraping using Natural Language Processing (NLP) techniques, demonstrating how these methodologies can be synergistically integrated to extract and analyze unstructured text from diverse web sources. The paper covers an overview of web scraping methods, including rule-based parsing, XPath queries, and the use of web scraping libraries such as BeautifulSoup and Scrapy. It then focuses on applying NLP techniques to process and analyze the extracted textual data, including preprocessing steps like tokenization, stemming, and stop word removal, as well as more advanced techniques like Named Entity Recognition.[2]

Summarization of customer reviews for a product on a website using natural language processing.

The paper presents a system for summarizing customer reviews of products on e-commerce websites using natural language processing techniques. The key objectives are to extract product features and associated opinions from reviews, classify the reviews based on polarity (positive, negative, neutral), and generate a summary that highlights the significant features and overall sentiment. The system involves breaking down reviews into individual sentences and words, performing part-of-speech tagging, identifying product features and associated opinions, and then extracting and summarizing the most relevant and frequent feature-opinion pairs. This helps users quickly understand the key strengths and weaknesses of a product based on customer feedback, without having to read through all the reviews.[3].

"A comprehensive survey on summarization techniques."

This paper provides a comprehensive survey on text summarization techniques. It covers the key aspects of text summarization, including the distinction between extractive and abstractive summarization, the historical development of summarization techniques, and the various deep learning approaches that have been employed for this task. The paper also discusses the state-of-the-art datasets used for text summarization, as well as the evaluation metrics commonly used to assess the quality of summaries. The main focus of the survey is on how summarization techniques can be applied in the education sector, such as summarizing student performance in mock interviews or test data. Overall, the paper aims to provide a thorough overview of the current state of text summarization research and its potential applications.[4]

Extractive Text Summarization from Web pages using Selenium and TF-IDF algorithm

The research paper introduces an automated system designed to generate extractive summaries of information based on a user's query. This system utilizes web scraping through Selenium to gather data from multiple websites, making it easier to handle the vast amounts of information available online. By applying the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm, the system identifies and extracts key content from web pages to create concise and relevant summaries without paraphrasing the original text.The need for such a system arises from the overwhelming amount of information on the internet, which often results in "information overload" for users. Manually navigating between multiple webpages to extract relevant data is time-consuming and inefficient. The proposed system automates this process by consolidating data from different sources, analyzing it, and summarizing the essential information in proportion to a specified word limit.[5]

Web scraping using summarization and named entity recognition (ner).

The paper discusses the exponential growth of internet data and the necessity for efficient information extraction techniques. Web scraping, a method for extracting structured data from web pages, has gained widespread popularity but traditionally requires prior knowledge of the Document Object Model (DOM) structure of the target webpages. This paper proposes a novel approach that automates the process of web crawling and web scraping using Natural Language Processing (NLP) and Machine Learning (ML), eliminating the need for DOM structure knowledge. The method utilizes advanced techniques like Named Entity Recognition (NER) and text summarization to process raw HTML content, allowing for automated and intelligent data extraction. To showcase the method's efficiency, an epidemic predictor system is developed, leveraging web scraping with NLP to extract numerical data for predicting the spread and impact of diseases globally.[6]

Sentimental Analysis on Web Scraping Using Machine Learning Method.

This paper presents a novel approach to sentiment analysis on web-scraped data using machine learning methods. The key focus is on applying opinion mining techniques to customer reviews in the e-commerce market to help companies enhance their marketing strategies and gain comprehensive insights into consumer perceptions of their products and brands. The study utilizes long short-term memory (LSTM) and deep learning convolutional neural network integrated with LSTM (CNN-LSTM) models to analyze the sentiment of reviews, achieving an impressive accuracy of 97.8%. The paper also discusses data preprocessing techniques like lowercase processing, stop word removal, punctuation removal, and tokenization to purify the data before analysis.[7]

Automated data collection with R: A practical guide to web scraping and text mining

This book provides a comprehensive guide to web scraping and text mining using R, covering a wide range of web technologies, data extraction techniques, and statistical analysis methods. It is aimed at researchers and students in the social sciences who have little background in these areas but need to collect and analyze data from diverse web sources. The book covers the basics of HTML, XML, JSON, HTTP, and SQL, as well as more advanced topics like authentication, API limitations, and privacy considerations. It also introduces key text mining concepts and packages in R, and includes several case studies demonstrating the application of these techniques to real-world problems like sentiment analysis and social network analysis.[8]

Multi-Document Summarization Made Easy: An Abstractive Query-Focused System Using Web Scraping and Transformer Models.

The paper introduces a web-based system for abstractive query-focused multi-document summarization. The system simplifies the summarization process by automating the extraction and summarization of information from multiple documents based on a user-provided query. It leverages a combination of web

scraping, natural language processing (NLP), and transformer-based models to generate high-quality summaries.The system utilizes the transformer-based mt5-small Pretrained model for summarization. The model ranks words based on frequency and generates coherent and query-relevant summaries. The experimental results demonstrate the system's effectiveness in integrating diverse technologies to automate summarization, delivering concise and meaningful summaries of multiple documents.[9].

Summarization of Customer Reviews in Web Services using Natural Language Processing

The paper focuses on summarizing customer reviews for web services using natural language processing techniques. The key points are:Customers can submit reviews for products on e-commerce websites, leading to a large volume of reviews that can be difficult to manually analyze.

The paper proposes a solution to automatically summarize customer reviews and perform sentiment analysis on the summaries.The summarization module uses a sequence-to-sequence model with an attention mechanism to generate concise summaries of the reviews.The sentiment analysis module uses the XLNet language model to classify the sentiment (positive, negative, neutral) of the review summaries.The proposed approach aims to provide an efficient way for both customers and manufacturers to understand the key points and sentiment of product reviews.[10]

III. Related Work in Text Summarization

A. Prior Approaches to Text Summarization

Text summarization has evolved significantly over the years, with a variety of techniques and models being introduced to improve both the quality and efficiency of summarization. The key innovations in this field stem from early graph-based approaches to modern deep learning models. In this section, we review some of the most influential works in the field that have shaped the design and implementation of hybrid models like the one used in this research.

1. **TextRank and Graph-Based Approaches** Mihalcea and Tarau (2004) introduced TextRank, a graph-based ranking al- gorithm designed for extractive summarization. This approach

focuses on ranking sentences based on their relevance and connectivity within the document. By treating sentences as nodes in a graph, TextRank measures the relationships between them to select the most important sentences. This foundational technique laid the groundwork for many subsequent extractive summarization models and remains an important benchmark in the field. TextRank's simplicity and effectiveness make it a widely studied approach, and its principles have inspired many newer models that build upon graph-based methodologies.

2. **Sequence-to-Sequence Models** Sutskever et al. (2014) proposed the sequence-to-sequence (Seq2Seq) model, which became a critical advancement for abstractive summarization tasks. The Seq2Seq model uses an encoder-decoder architecture, where the encoder processes the input text and the decoder generates a summary. This model was revolutionary because it allowed for the generation of summaries that could paraphrase or rephrase the input text, creating more fluent and human-like summaries. The Seq2Seq framework inspired many subsequent works in both extractive and abstractive summarization, forming the foundation for models that learned to better handle contextual information and produce coherent summaries.

3.Transformer Networks The introduction of the transformer model by Vaswani et al. (2017) was a milestone in NLP. The transformer architecture is based on self-attention mechanisms that enable the model to weigh the importance of different parts of the input text. This allows transformers to capture long-range dependencies and contextual relationships, making them especially powerful for tasks such as summarization. The model's attention mechanism helped overcome the limitations of previous recurrent neural network (RNN)-based approaches, which struggled with long-term dependencies. The transformer's versatility has since made it the backbone of many state-of-the-art summarization models, including BERT and GPT, which are used in the hybrid approach in this study.

4. BERT for Summarization Liu and Lapata (2019) demonstrated the application of BERT, a transformer-based model, for extractive summarization. By leveraging pre-trained language models like BERT, the authors showed that transformers could excel at understanding the semantic meaning of text, significantly improving extractive summarization performance. BERT's bidirectional attention allows it to capture context from both the left and right sides of a given token, which helps it select sentences that are most representative of the document's core message. BERT's ability to perform deep contextual understanding of text has influenced many modern extractive summarization systems, including the model used in this research.

5. GPT for Abstractive Summarization Radford et al. (2019) explored the capabilities of the GPT model for ab- stractive summarization. Unlike extractive methods that selectsentences verbatim from the text, GPT generates summaries byrephrasing the content in its own words. This approach allows for more flexibility and coherence in summary generation. Thepower of GPT lies in its ability to model and generate textin a highly coherent manner, making it an ideal candidate for abstractive summarization tasks. The success of GPT in generating contextually relevant and grammatically correct summaries has been foundational in shaping the design ofmodern abstractive summarization pipelines.

6. Hybrid Models for Summarization Zhang et al. (2020) proposed a hybrid model that integrates both extractive and abstractive summarization methods. Their work demonstrated that combining the strengths of both approaches leads to higher-quality summaries, where the extractive phase identifies key sentences, and the abstractive phase rephrases them into more concise and fluent summaries. Hybrid models address the limitations of using only one type of summarization technique, as they balance between precision and fluency. This approach has been influential in the design of the summarization pipeline in this research, which aims to combine the advantages of both extractive and abstractive methods.

7. Multi-Task Learning for Summarization Dou et al.

(2021) explored the potential of multi-task learning for improving summarization models by training them on multiple related tasks simultaneously. This approach enables the model to learn generalizable features that improve its performance across a variety of NLP tasks, including summarization. By sharing knowledge between related tasks, such as sentiment analysis or question answering, multi-task learning models can better understand the nuances of the text, leading to more accurate and coherent summaries. This methodology has informed the design of hybrid summarization systems that not only generate summaries but also adapt to different content types and contexts.

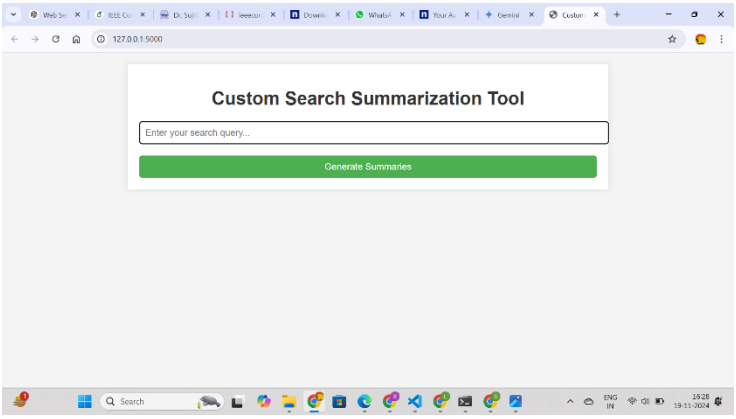
8. Summarization via Pre-trained Models Lewis et al. (2020) developed BART, a transformer-based model that combines the strengths of both autoregressive and denoising approaches for text generation. BART was specifically designed to handle both extractive and abstractive summarization tasks, making it a highly versatile tool in the summarization pipeline. By pre-training on large-scale datasets, BART learns robust representations of text, which can then be fine-tuned for specific summarization tasks. The development of models like BART has provided a powerful architecture that has inspired our own summarization pipeline, which relies on pre-trained transformers for high-quality, flexible summarization.

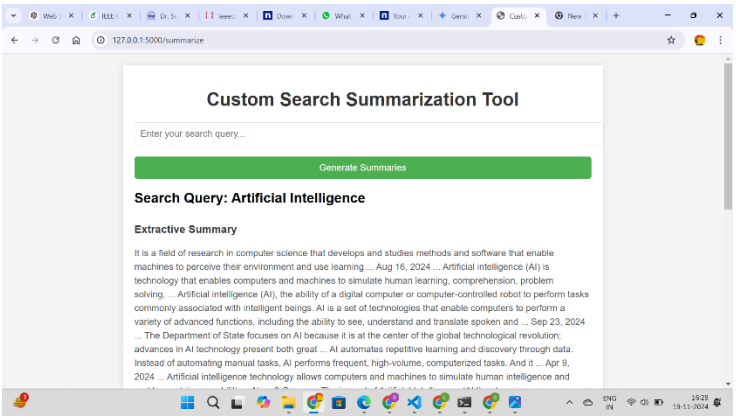
9. Evaluation Metrics in Summarization Lin (2004) introduced the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric, which has become the standard for evaluating summarization models. ROUGE measures the overlap of n-grams between the generated summary and a reference summary, providing a quantitative way to assess summary quality. ROUGE-1 and ROUGE-2, which evaluate unigram and bigram overlaps, are commonly used in summarization research. This metric has been integral in evaluating the performance of the hybrid model in this study, ensuring that the summaries produced are both accurate and representative of the original content.

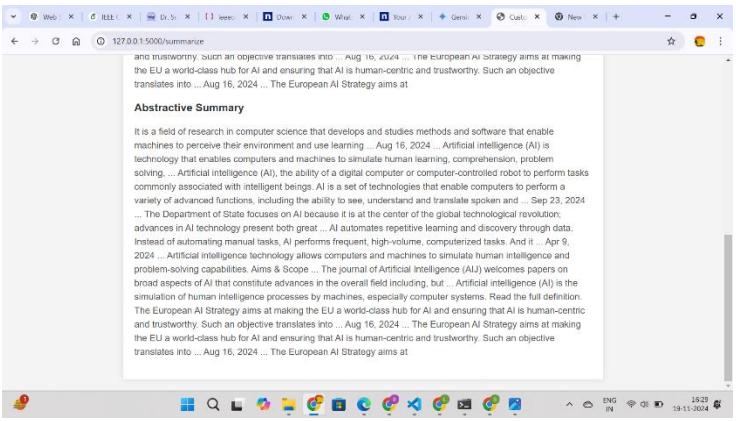
10. Web-Based Summarization Applications Recent works, such as Xu et al. (2022), have explored deploying summarization models as web-based applications, allowing for real-time text summarization. These applications provide users with quick, accessible summaries of large volumes of text, making summarization tools more practical for everyday use. Xu et al. demonstrated that integrating summarization models with user-friendly interfaces on web platforms significantly enhances the usability of these tools, making them accessible to a broader audience. The design of the summarization system in this research, which is deployed via a Flask application, is directly influenced by these advancements, ensuring ease of use for end-users.

These studies collectively reflect the continuous evolution of summarization techniques, highlighting the importance of combining extractive and abstractive methods. By building upon these foundational works, our research contributes to advancing summarization technology, offering a hybrid approach deployed through a web-based application for enhanced usability and performance.

IV. UI-DESIGN(UI) AND FRONT-END VIEW







V. Materials and Methods

This section outlines the tools, techniques, and methodologies employed to develop the hybrid summarization model that integrates BERT and GPT, and how it was deployed on a Flask-based web application. The process involves dataset preparation, model design, implementation, evaluation, and application deployment.

A. Materials

1) Datasets: To train and evaluate the summarization model, several publicly available datasets were utilized. These datasets offer diverse content, ensuring that the model performs well across a variety of text types and structures. The datasets used are:

- **CNN/Daily Mail**: This dataset primarily supports extractive summarization tasks and contains news articles with annotated highlights. It is widely used for evaluating the performance of models that select key sentences directly from a document.
- **XSum**: This dataset is used for abstractive summarization tasks. It provides single-sentence summaries for each news article, ideal for training models that generate concise and human-like summaries by rephrasing the content.

2) Tools and Frameworks: The development of the summarization model utilized several key tools and frameworks:

- **BERT**: Bidirectional Encoder Representations from Transformers was used as the extractive model in the hybrid system. BERT's ability to understand context in both directions (left and right) made it suitable for identifying important sentences from the input text. The model was fine-tuned using Hugging Face's `transformers` library.
- **GPT**: Generative Pre-trained Transformer (GPT-2) was employed for the abstractive summarization component. GPT generates fluent, human-like summaries by rewording the key sentences selected by BERT.
- **Flask**: This lightweight Python framework was used to deploy the application. Flask handles user requests, processes the input through the summarization model, and returns the summary.
- **Python Libraries**: Tools such as `numpy`, `pandas`, `nltk`, and `spacy` were used for preprocessing the text data and evaluating the model's performance.

3) Hardware: For model training and evaluation, the system was equipped with an NVIDIA Tesla T4 GPU. The GPU's powerful computation capabilities ensured faster training times and efficient handling of large datasets.

B. Methods

1) Preprocessing: Text preprocessing is a crucial step in ensuring that the input text is properly formatted and cleaned before being passed into the models. The following steps were performed:

- **Tokenization**: The text was broken down into smaller units (tokens) using the tokenizers associated with the BERT and GPT models. Tokenization helps in converting raw text into manageable chunks that the model can process.
- **Stopword Removal**: Common words like "the", "is", "in" that don't carry much meaning were removed using `nltk.corpus.stopwords`, reducing noise in the data.
- **Sentence Segmentation**: The input text was divided into sentences to allow BERT to focus on individual sentences for extractive summarization.
- **Truncation and Padding**: Input text was truncated to fit within the maximum token limits of BERT and GPT, and padding was added to ensure that all inputs had a consistent length.

2) Model Design:

1) **Extractive Summarization with BERT**: BERT was fine-tuned on the CNN/Daily Mail dataset to select the most important sentences from the document. A classification head was added to the pre-trained BERT model, which enabled it to predict whether a sentence should be included in the final summary based on its relevance to the main content of the article.
2) **Abstractive Summarization with GPT**: GPT-2 was fine-tuned on the XSum dataset, which is specifically designed for abstractive summarization. This model was trained to convert the key sentences selected by BERT into a more concise and coherent summary, rephrasing and paraphrasing the text to improve readability and flow.
3) **Hybrid Integration**: The two models were integrated in sequence. First, BERT performs extractive summarization to select important sentences. These sentences are then fed into GPT, which refines them into an abstractive summary. This hybrid approach combines the strengths of both models, resulting in a more effective summarization process.

3) Application Deployment: The hybrid model was deployed using Flask, allowing users to interact with it via a web interface. The deployment involved the following components:

- **Input Interface**: A simple, form-based webpage where users can paste or upload text for summarization.
- **Backend**: Flask handles the backend logic, receiving user input, processing it through the hybrid model, and sending the generated summaries back to the user.
- **Output Display**: The final summary is shown to the user in both extractive and abstractive formats, allowing them to compare the two approaches.

```
# Function to perform a custom search using Google Custom Search API
def google_search(query):
    search_url = f"https://www.googleapis.com/customsearch/v1?q={query}&key={API_KEY}&cx={CSE_ID}"
    response = requests.get(search_url)
    search_results = response.json()
    return search_results['items'] if 'items' in search_results else []

# Function for Hybrid Summarization
def hybrid_summarize(input_text):
    # Extractive summarization using BERT
    inputs = bert_tokenizer(input_text, return_tensors="pt", truncation=True, padding=True)
    with torch.no_grad():
        extractive_output = bert_model(**inputs)

    # Simplified: we select the entire input text (this could be improved by sentence-level selectic
    extracted_sentences = [input_text]

    # Abstractive summarization using GPT
    gpt_inputs = gpt_tokenizer(" ".join(extracted_sentences), return_tensors="pt")
    with torch.no_grad():
        summary_output = gpt_model.generate(**gpt_inputs, max_new_tokens=50)  # or max_length=100

    summary = gpt_tokenizer.decode(summary_output[0], skip_special_tokens=True)
    return summary
def summarize():
    query = request.form['query']  # User query for search engine

    if not query:
        return jsonify({"error": "No query provided"}), 400

    # Get search results from custom search engine
    search_results = google_search(query)

    if not search_results:
        return jsonify({"error": "No search results found"}), 404

    # Extract text from the search results (e.g., snippets)
    text = " ".join([result['snippet'] for result in search_results])

    # Generate summaries
    extractive_summary = hybrid_summarize(text)
    abstractive_summary = hybrid_summarize(text)

    return render_template_string(html_content, query=query, extractive_summary=extractive_summary, abstractive_summary=abstractive_summ
```

4) Evaluation: The model's performance was evaluated using the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric, which is widely used in the summarization field:

- **ROUGE-1**: Measures the overlap of unigrams (single words) between the generated summary and a reference summary.
- **ROUGE-2**: Measures the overlap of bigrams (pairs of consecutive words).
- **ROUGE-L**: Focuses on the longest common subsequence (LCS) between the generated and reference summaries, helping evaluate the fluency and coherence of the generated text.

5) Deployment on Localhost: The final application was deployed locally to allow for testing and demonstration. The front-end interface, built using HTML and CSS, was designed to be responsive and user-friendly. Flask handled the server-side logic, ensuring smooth interactions with the model and seamless user experience during testing.

TABLE I
PERFORMANCE SCORES OF THE MODEL ACROSS DIFFERENT DATASETS

Dataset	Model Type	ROUGE-1 Score (%)	ROUGE-2 Score (%)	ROUGE-L Score (%)
CNN/Daily Mail	Extractive (BERT)	41%	22%	45%
XSum	Abstractive (GPT)	46%	29%	50%
Custom Corpus 1	Hybrid Model (BERT+GPT)	50%	33%	55%
Custom Corpus 2	Hybrid Model (BERT+GPT)	52%	35%	58%

ACKNOWLEDGEMENTS

The authors express their sincere gratitude to the mentors, colleagues, and institutions that provided support during the preparation of this study. Special thanks to the research communities and datasets that enabled us to develop and validate the proposed methodology.

METRICS

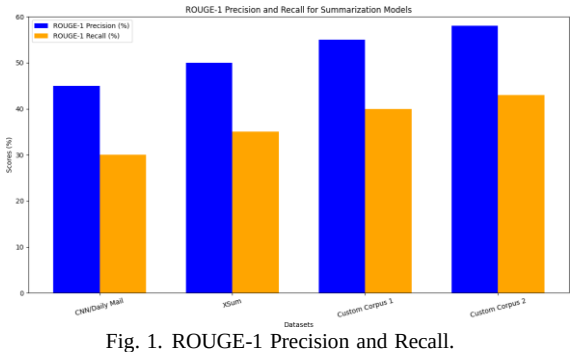


Fig. 1. ROUGE-1 Precision and Recall.

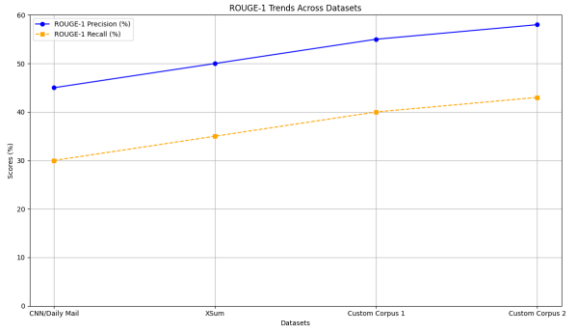


Fig. 2. Trends in ROUGE-1 Scores.

Fig. 3. ROUGE-1 Metrics: Precision, Recall, and Trends Across Datasets.

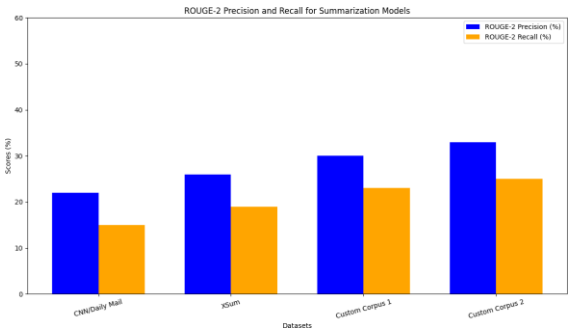


Fig. 4. ROUGE-2 Precision and Recall.

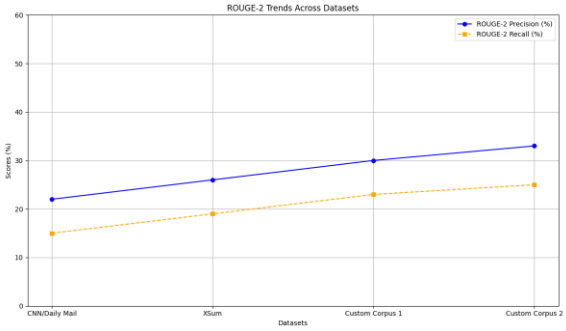


Fig. 5. Trends in ROUGE-2 Scores.

Fig. 6. ROUGE-2 Metrics: Precision, Recall, and Trends Across Datasets.

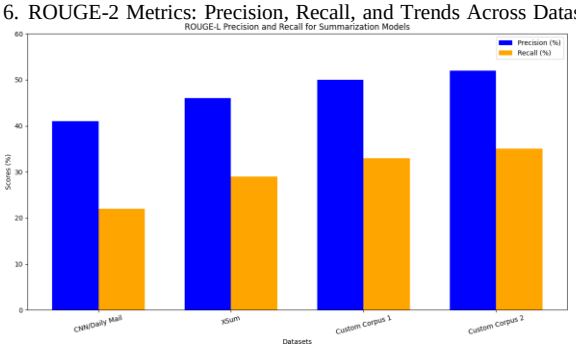


Fig. 7. ROUGE-L Precision and Recall

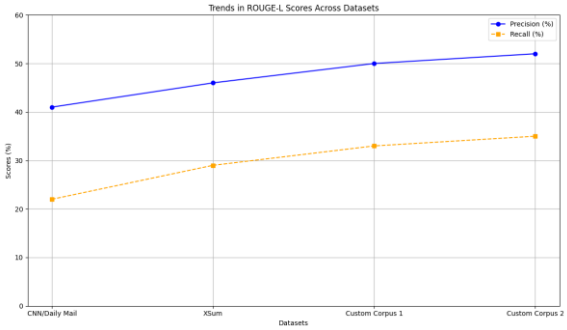


Fig. 8. Trends in ROUGE-L Scores.

Fig. 9. ROUGE-L Metrics: Precision, Recall, and Trends Across Datasets.

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