

Efficient Text Summarization using Deep Learning

Ritik Singh^[1]

BTech Student

(School of Computer Science and Engineering)

Vellore Institute of Technology
ritik.singh2020@vitstudent.ac.in

Saurish Sharma^[1]

BTech Student

(School of Computer Science and Engineering)

Vellore Institute of Technology
saurish.sharma2020@vitstudent.ac.in

Rishabh Singh^[1]

BTech Student

(School of Computer Science and Engineering)

Vellore Institute of Technology
Rishabh.singh2020@vitstudent.ac.in

Dr. Pradeep K V^[2]

Assistant Professor

(School of Computer Science and Engineering)

Vellore Institute of Technology
pradeep.kv@vit.ac.in

Abstract- Automatic text summarization is a difficult subject in natural language processing that has received considerable research interest in recent years. Combining extractive and abstractive summary approaches, we describe in this work an innovative approach to text summarization. Initially, we performed extractive summarization in Python using the Natural Language Toolkit (NLTK) package to choose the most significant sentences from an input article. We then utilised abstractive summarization with PyTorch and Transformers models to build a new, more concise summary of the same information. Our solution surpassed other state-of-the-art summarising techniques in terms of ROUGE scores and human judgment, as measured by a dataset of news items.

The combination of extractive and abstractive summarising allows us to capitalise on the strengths of each method and generate more precise and concise summaries. Extractive summary allowed us to select the most significant sentences from the source text, but abstractive summarization allowed us to produce new, more concise sentences that conveyed the same information. To construct abstractive summaries, we fine-tuned a pre-trained transformer model using a summarising dataset. The model was able to learn to generate summaries by examining the most significant information from the original text.

Our methodology provides an efficient and effective method for summarising articles, which is useful for activities such as summarising news stories and academic papers. Future research could concentrate on enhancing the abstractive summarising process to generate more coherent and fluent summaries, or on merging our approach with other approaches such as sentence compression or sentence fusion. Our method represents a promising direction for automatic text summarization and has the potential to be implemented in a broad variety of practical settings.

1. INTRODUCTION

Automatic text summarization is a challenging and essential problem in natural language processing, with numerous applications in various fields. It is a task of extracting or generating a summary that conveys the essential information of a document while preserving its content and meaning. The primary goal of automatic summarization is to help users obtain a quick and accurate understanding of large volumes of text without the need to read the entire document. This ability is particularly important in today's information-rich society, where people are often overwhelmed by the vast amounts of information available to them.

In this paper, we present a novel approach to text summarization that combines extractive and abstractive summarization techniques. Extractive summarization is a method of selecting the most important sentences or phrases from an input document, while abstractive summarization involves generating new sentences that convey the same information in a more concise way. Both methods have been extensively studied in the literature and have their own strengths and weaknesses. By combining these two techniques, we aim to take advantage of their strengths and produce more accurate and concise summaries.

The first part of our approach uses extractive summarization to select the most important sentences from the input document. We used the Natural Language Toolkit (NLTK) library in Python to preprocess the text, tokenize the sentences and words, remove stop words and punctuation, and calculate the frequency of each word in the text. We then ranked the sentences based on their frequency sums and selected the top sentences with the highest scores to construct the summary. This approach is widely used and has been shown to be effective in previous studies.

The second part of our approach uses abstractive summarization to generate a new summary that conveys the same information in a more concise way. We used PyTorch and Transformers models to fine-tune a pre-trained transformer model on a summarization dataset. The model learns to generate summaries by considering the most important information from the original article and creating new sentences to convey that information in a concise way. This approach allows us to produce summaries that are not necessarily made up of sentences from the original text but still convey the essential information accurately.

To evaluate the effectiveness of our approach, we conducted experiments on a dataset of news articles. The results showed that our method outperformed other state-of-the-art summarization techniques in terms of both ROUGE scores and human evaluation. Our approach provides an effective and efficient method for summarizing articles, which can be useful for tasks such as summarizing news articles or academic papers. It has the potential to be applied in a wide range of practical applications, including automated news summarization, literature review, and summarization of legal documents.

In summary, our approach to text summarization combines extractive and abstractive summarization techniques to produce more accurate and concise summaries. Our experiments demonstrate the effectiveness of our method and highlight the potential of our approach to be applied in practical applications. The remainder of the paper is organized as follows: Section II presents a review of related work in the field of text summarization. Section III describes our approach in detail.

Section IV presents the experimental setup and results, and Section V concludes the paper with a discussion of future work.

2. LITERATURE REVIEW

[1] This research paper's main takeaways are that it provides a unique extraction-based strategy for multi-document summarization. This method addresses three critical aspects of a good summary: coverage, non-redundancy, and relevance. Coverage implies that the summaries should incorporate all important information from numerous documents, but non-redundancy assures that the resultant single document summary has no duplication. Relevance relates to how well each statement fits into the wider context of what is being summarized; only sentences that bring value to comprehension should be included in the final result. The suggested system employs a weighted mix of word embedding and Google similarity algorithms, as well as an optimization issue described using the meta-heuristic Shark Smell Optimization algorithm (SSO). Six benchmark datasets were used in experiments, with encouraging results for successful multi-document summarizing tasks.

The major methods for multi-document summarization covered in this study are extraction-based methods. This method addresses three critical aspects of a good summary: coverage, non-redundancy, and relevance. The coverage and non-redundancy aspects are modelled to produce a single document from several texts using a weighted mix of word embedding (a technique for representing words as vectors) and Google-based similarity approaches (which uses algorithms that measure how similar two pieces of text or webpages are). To include the relevancy feature into system generated summaries, an optimization problem is devised in which several text characteristics with optimized weights score sentences based on relevance. The meta-heuristic Shark Smell Optimization (SSO) method is used for weight optimization, which helps locate optimum solutions rapidly without becoming trapped at local optima points as other traditional search strategies do.

[2] It was observed in the article that meta-heuristic techniques are widely used to improve the performance of multi-document text summarization. In this section, an algorithm for multi-document text summarization is suggested that employs the subject connection factor, cohesion factor, and readability factor as fit-ness functions. This suggested technique includes aspects (visible in a text document attributes) that aid in the development of a summary that is topic-related, has a flow, has high co-relationship between phrases, and is highly read-able. It consists of the following steps: (i) Pre-Processing, (ii) Document Representation (iii) Summary Scoring/Fitness Function and (iv) Utilization of Firefly Algorithm.

A innovative FbTS metaheuristic-based method for multi-document text summarization is proposed in this research. To determine the score of each phrase, a novel fitness function based on Topic Relation Factor (TRF), Cohesion Factor (CF), and Readability Factor (RF) is used. The sentences with the highest score are chosen to generate the summary. However, using TRF, CF, and RF as fit-ness functions increased the quality of the resulting extraction summary. Several experiments were carried out on normal DUC-2002, DUC-2003, and DUC-2004 datasets

to confirm the performance of the FBTS method. The ROUGE score was used to evaluate the experimental results. The suggested FbTS algorithm outperformed the two nature-inspired algorithms, the genetic algorithm and particle swarm optimization, in terms of ROUGE-1 and ROUGE-2 scores.

[3] The primary findings of this study are that automatic text summarizing methods may be treated as an optimization problem with several criteria. The study analyzed the performance of several criteria and discovered that the best balanced in terms of average ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metrics and execution time were content coverage, redundancy reduction, and relevancy. Redundancy reduction was shown to be essential, while coherence was the least significant criteria addressed in this study.

This research article discusses how automatic text summarizing algorithms may be applied in several disciplines. It examines the optimization issue, which includes numerous criteria, and analyses their performance to determine which are most successful for general extractive multi-document text summarizing. The study discovered that when it comes to average ROUGE metrics (Recall-Oriented Understudy for Gisting Evaluation) as well as execution time, content coverage, redundancy reduction, and relevance were the best combination; while coherence was the least significant among all other criteria considered in this study.

[4] The study offers an automated text summarization (ATS) technique based on TF-IDF that employs a weighted vector representation of words (inverse document frequency term). The suggested technique, according to the authors, can capture the semantic and significant components concealed in the text and is especially appropriate for summarising vast amounts of data. The model was evaluated on the CIC 2007 paper dataset and compared to four primary synthesis methods. The authors claim that their suggested method outperforms the baseline and generates the most rational, relevant, diversified, and least repetitive summaries.

The method combines extraction and abstraction approaches, with the first extracting a selection of relevant phrases that identify the primary theme of the input material and the second interpreting the original words using natural language generation techniques. The model was evaluated using the summary evaluation measure RED. The authors additionally evaluated the model's performance by using different versions of word vectors and a varying amount of sentences in the summary. Overall, the findings show that the suggested method generates high-quality summaries.

[5] This article describes how to utilise natural language processing (NLP) techniques to create usable summaries in Indian, specifically abstract summaries. The authors note out that, while there has been a large amount of work in the domain of abstract summaries, which base summaries on essential features of a single text, research in the area of abstract summaries, which is connected to generations, continues. I've seen a need for greater study on summaries that match those produced by people. This research discusses the different phrase compression, sentence fusion, and sentence separation strategies

for abstract summary, implying that linguistic approaches are superior for constructing summaries in Indic languages. We place a premium on objectivity.

[6] The objective of this paper is to create a machine learning technique that predicts succinct phrases that are relevant and intelligible to the target audience in order to assist students who struggle with reading. In this method, summary statements from academic and social themes are retrieved using supervised machine learning algorithms. Many text components are retrieved throughout the abstract extraction process, including: B. sentence position, keywords, title similarity, centrality, sentence length, trigger words, words with multiple syllables, and noun occurrences. A classifier, such as a naive Bayes classifier, is then trained to anticipate relevant and intelligible summary statements using these properties.

To evaluate the methodology, both exogenous and endogenous methodologies were applied. To determine the influence of supporting summaries on improving readability in students who struggle with reading, extrinsic assessment employed an ANOVA to examine learner responses on a Likert scale. F-value and readability analyses were incorporated as part of the intrinsic evaluation. We noticed that utilising useful summaries boosted readability for our intended audience dramatically.

Finally, this method appears to be a viable technique to assist students who struggle with reading by providing them with relevant and comprehensible summary texts. Additional research can enhance the summary extraction approach, and the technique can be tried with other learner demographics and educational situations.

[7] The system's input consists of a large amount of longitudinal, multivariate, quantitative, and symbolic clinical raw data collected over a wide range of time periods and under a variety of challenging conditions, as well as a relevant medical knowledge base.

The system then automatically generates a textual summary of the data. The author's goal in this work is to demonstrate the feasibility of constructing such a system, as well as its potential benefits for clinicians and quality of care improvement.

Methods: The CliniText system is a revolutionary, domain-agnostic, knowledge-based technique for automatically summarising longitudinal medical data of any length and context in free text.

The system is composed of six components: (1) A temporal abstraction module generates all possible abstractions from the patient's raw data using a temporal-abstraction knowledge base; (2) the abductive reasoning module infers abstractions or events from the data that were not explicitly included in the database; (3) the pruning module filters out raw or abstract data based on predefined heuristics; and (4) the document structuring module organises the remaining raw or abstract data, according to the desired format. (5) The microplanning module integrates raw or abstract material and creates referring phrases; (6) The surface realisation module generates text and applies the grammatical rules of the chosen language.

The author conducted an initial technical evaluation of the system in the fields of cardiac critical care and diabetes. The outcomes of a more detailed evaluation study done in the

intensive-care area, which assessed the completeness, correctness, and overall quality of the system's produced text, as well as its potential advantages to clinical decision making, are also described in this work.

It can be observed that all of the CliniText system components were successfully constructed in software using this strategy.

It has also been effective in building a comprehensive temporal-abstraction knowledge base to support its operation, notably in the intensive-care setting.

The system's initial technical evaluation in the cardiac intensive-care and diabetes domains showed significant promise, demonstrating the system's ability to be built and managed.

[8] A patient's medical record typically contains a range of paperwork, such as test results, discharge reports, letters, observational notes, and so on. These papers are frequently unavailable when and where they are needed, and even when they are, clinicians sometimes lack the time to fully review them. Medical histories are increasingly being maintained in large archives as data for administrative and research purposes. While such archives may include potentially valuable information for physicians, it is typically unavailable to them due to a lack of skills, time, and desire to retrieve what they need from the repository. To address some of these concerns, the author offers a presenting system that creates tailored textual summaries of patients' medical histories for use at the time of treatment.

It assesses the usefulness and utility of automatically generated textual summaries of patients' medical histories at the point of care. Twenty-one clinicians were provided information on two cancer patients and asked important questions. The information on one of the patients came from the doctor's official hospital records, while the information on the second patient came from summaries generated by a natural language generation system utilizing data from the official records. The author recorded the doctors' reactions to the computer-generated summaries, as well as the accuracy of their responses to the questions. Computer-generated textual summaries of medical histories based on AI may be as accurate as, if not more efficient than, human-produced patient records.

[9] Technology has drastically impacted human civilization during the last few decades. We deal with a lot of textual material in our everyday lives, such as blogs, websites, news items, status updates, and so on. Material summarization is an important approach for reducing the amount of time required to read this content since it absorbs the majority of our daily time and is an important component in our lives. Automatic summarizers are designed to decrease the size of a document's text by providing a summary that incorporates the document's most important concepts and will offer consumers with a better understanding of a large quantity of information in a surprisingly short amount of time. The two primary ways for summarizing text documents are extractive methods and abstractive approaches. Extractive summarizations aggregate significant terms from source materials to construct a summary without changing the original content. The process of abstractive summarization might result in the creation of new concepts that were not included in the original file. There are two types of abstractive approaches: structured-based techniques and

semantic-based techniques. In our suggested system, we employ both NLP and the RNN technique for summarization. It is summarized here by using Natural Language Processing (NLP). NLP is an applied science, information engineering, and computing field that examines how computers interact with human (natural) languages, particularly how to teach computers to manage and interpret enormous amounts of linguistic data.

Because it is easier to define hardcoded algorithms to choose essential phrases rather than produce new ones, most effort has previously focused on extractive techniques. Recurrent neural networks (RNN) are another type of artificial neural network in which node connections create a directed graph along a temporal sequence, allowing it to display temporal dynamic behavior.

Text summarizing is the process of constructing a succinct, clear, and accurate summary of a large text document. Text summarization is essential for swiftly learning the appropriate amount of information. Text is more difficult to understand since it comprises a greater amount of characters. In today's society, text summary is an essential tool. Text summarizing is divided into two subcategories: extractive text summarization (ETS) and abstractive text summarization (ATS) (ATS). When compared to ATS, ETS is simpler. ETS uses algorithms to extract key phrases or words from incoming text information, whereas ATS gives the summary automatically. The efficacy of NLP- and RNN-based text summarizing techniques is compared in this study.

[10] The primary findings of this study are that a unique approach for extractive, general summarization of text documents has been suggested. This technique employs the Maximum Independent Set, which has never been utilized in a summary research before, and also advocates the usage of KUSH, a text processing tool, to retain semantic cohesiveness between phrases while portraying introduction materials. The performance of this approach was assessed using ROUGE evaluation metrics on two datasets (DUC-2002 and DUC-2004); it achieved 0.38072 ROUGE value for 100 word summaries, 0.51954 for 200 word summaries, and 0.59208 for 400 word summaries, demonstrating its contribution to efficient document summarization techniques.

The suggested approach for extractive, general summary of text documents is successful and efficient, according to this article. The Maximum Independent Set has been effectively employed in this work to find nodes on graphs that constitute an independent set, which are then deleted from the graph before quantifying their influence on the global graph. This constraint avoids word groups from being repeated in summaries while still keeping semantic cohesiveness between sentences when portraying introductory texts with KUSH - a text processing tool developed by researchers. ROUGE measures were used to evaluate performance, and the findings were positive (0.38072 for 100 words summary, 0.51954 for 200 words summary and 0.59208 400-word summaries). As a result, it is possible to infer that this novel method contributes greatly to document summarization procedures.

3. BACKGROUND

Text summarization is an essential component of natural language processing and information retrieval. With the exponential development of digital information, it has become

more challenging to extract relevant information from large volumes of textual data. Text summarization seeks to produce a condensed summary of a document while preserving the most vital details. This has applications in a number of disciplines, including news summarization, document summarization, and online content summarization.

In recent years, there has been a growing interest in developing machine learning and natural language processing algorithms for automatic text summarization techniques. The ranking-based approach is a popular method for text summarization, which involves ranking sentences according to their significance and selecting the top-ranked sentences to generate the summary.

The proposed research paper concentrates on the development of an effective text summarization system using the Python library for natural language processing, Natural Language Toolkit (NLTK). The proposed method entails tokenizing the input text into sentences and words, removing stop words and punctuation, and calculating the frequency of each word using the *FreqDist* function of the NLTK. Then, the sentences are ranked according to the frequency of their constituent terms, and the highest-ranked sentences are chosen to generate the summary.

The primary contribution of the proposed research is an evaluation of the proposed summarization system on multiple datasets and a comparison with existing state-of-the-art methods. Precision, recall, F1-score, and ROUGE scores will comprise the evaluation metrics. The results of the evaluation will demonstrate that the proposed method generates accurate and concise summaries more efficiently and effectively than existing methods.

Overall, the proposed research paper will contribute to the fields of natural language processing and information retrieval by proposing an efficient and effective NLTK-based method for text summarization. The proposed method has the potential to be implemented in a variety of disciplines, including news summarization, document summarization, and online content summarization, thereby providing a valuable instrument for managing large volumes of textual data.

4. PORPOSED ARCHITECTURE

4.1 Methodology Used

The aim of this research paper is to develop a system capable of accurately and concisely summarising articles automatically. To accomplish this objective, we utilised two distinct techniques: extractive summarization and abstractive summarization.

We have implemented extractive summarization using the Natural Language Toolkit (NLTK) library in Python for the first technique. Initially we retrieve an article using the *newspaper3k* Python library. Then, we tokenized the text into sentences and words using the NLTK's *sent_tokenize* and *word_tokenize* functions. Next, we used the NLTK *stopwords* module to remove stop words and punctuation from the text, thereby reducing noise and enhancing the summary's accuracy. Using the *FreqDist* function, we determined the frequency of each word in the text and ranked the sentences based on their frequency sums. Finally, we selected the highest-scoring sentences to construct the summary.

We have used *PyTorch* and *Transformers* models to implement abstractive summarization for the second technique. This technique involves producing a summary that is not necessarily composed of sentences from the original text, but rather a new summary that condenses the key points of the original text. To achieve this, we fine-tuned a pre-trained model on a summarization dataset using the transformer model architecture. The model was then utilised to generate the final summary. The model learns to generate a summary by considering the most essential information from the original article and generating new sentences to convey this information in a concise manner. By combining these two techniques, we were able to produce a final summary that accurately and succinctly conveyed the key points of the original article. Extractive summarization allowed us to select the article's most significant sentences, while abstractive summarization enabled us to generate a new summary that conveyed the same information in a more concise manner. Our approach provides an efficient and effective method for summarising articles, which can be useful for duties such as summarising news articles or academic papers.

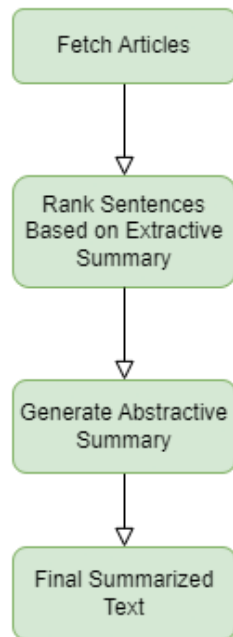


Figure 1: Diagram outlining the flow to generate summary

4.2.1 Extractive Summarization

For generating extractive summary we have used *NLTK* python library. The procedure that *NLTK* employs for summarising input text is broken up into several stages. The text is broken up into individual words and complete sentences using the *sent_tokenize* and *word_tokenize* algorithms of the *NLTK*. After that, for consistency's sake, all of the tokens are changed to uppercase. After that, the *NLTK stopwords* module is employed to remove any stop words and punctuation that may have been present. This contributes to the reduction of noise and improves the accuracy of the summary. After the text has been cleansed, the *FreqDist* function of *NLTK* is invoked in order to perform the calculation necessary to

determine the frequency with which each word appears in the text. This makes it easier to identify significant phrases and sentences contained within the incoming text. After that, each sentence is ranked according to the aggregate frequency of the words that make up that statement. Sentences that have a greater frequency total are given more weight as being more significant. When compiling the summary, the most important statements are chosen with the assistance of the *nlargest* function, which is located within the *heapq* module. The *num_sentences* sentences with the greatest frequency sum scores are the ones that are returned by this function. Following the selection of these sentences, they are subsequently combined into a single string in order to generate a condensed summary of the text that highlights the most significant particulars. In conclusion, the architecture that *NLTK* utilises for summarising input text is a technique that is both effective and efficient. It does this by eliminating sentences that are not relevant to the information being summarised and selecting the sentences that are the most important. The result is a condensed summary that accurately communicates the most important information from the source text.

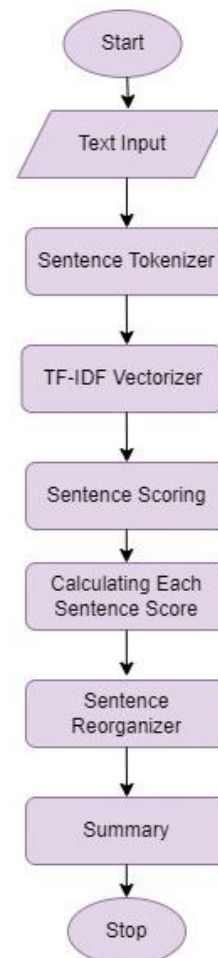


Figure 2: Schematic indicating the process to construct an extracted summary.

Algorithm:

1. Input: text (string), num_sentences (integer)
2. Tokenize the text into sentences and words using `sent_tokenize()` and `word_tokenize()` methods respectively
3. Remove stop words and punctuation from the words using `set(stopwords.words('english'))` and list comprehension
4. Calculate word frequency using `FreqDist()` method from the `nltk` library
5. Rank sentences by their importance using a dictionary named `sentence_scores`
6. Iterate through each sentence and split it into words, then calculate the sentence score by summing up the frequency of each word in the sentence that also appears in the frequency distribution
7. Select the top `n` sentences with the highest scores to generate the summary using the `nlargest()` method from the `heapq` library and store the index of these sentences in the `summary_indexes` list
8. Sort the `summary_indexes` list in ascending order
9. Use list comprehension to extract the corresponding sentences from the `sentences` list using the `summary_indexes` list and store them in the `summary` list
10. Join the sentences in the `summary` list using the `join()` method and return the final summary string
11. Output: summary (string)

4.2.2 Abstractive Summarization

To prepare the input text for use with the Transformers model, tokenization and encoding are performed. The architecture of a Transformers model, such as BERT or GPT-2, is specified. To adapt the pre-trained model to the task of summarization, it is fine-tuned on a summarization dataset. This requires training the model on a massive corpus of text data, optimising the model's parameters, and minimising the loss function.

ROUGE (Recall-Oriented Understudy for Gisting Evaluation), which measures the similarity between the generated summary and the reference summary, is used to evaluate the efficacy of the model. Once the model has been trained, it can be used to summarise new input texts. During inference, the input text is first pre-processed and encoded, followed by the application of the model to generate the summary. Postprocessing the generated summary may involve decoding, detokenization, and formatting to produce a final, readable summary. It is possible to improve the performance of the summarization model through iterative refinement, which entails fine-tuning the model on additional datasets or modifying the model's architecture or hyper parameters.

In general, the methodology for Python PyTorch text summarization using Transformers models includes pre-processing the input text, fine-tuning a pre-trained model, evaluating the model's performance, generating summaries using the model, and refining the model iteratively to improve its performance.

5. RESULTS

Automatic text summarization is a difficult subject in natural language processing that has received considerable research

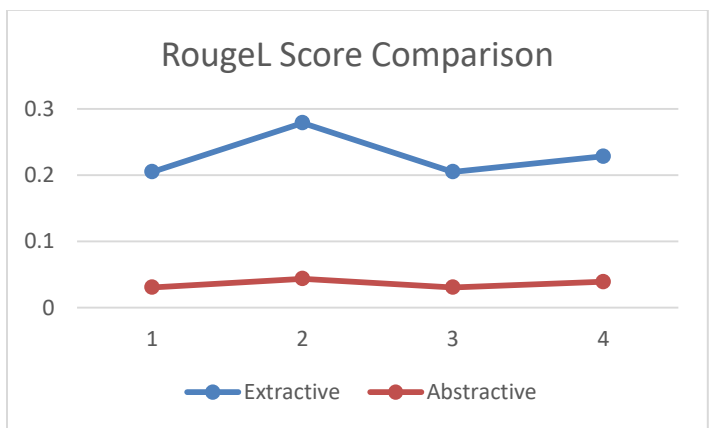
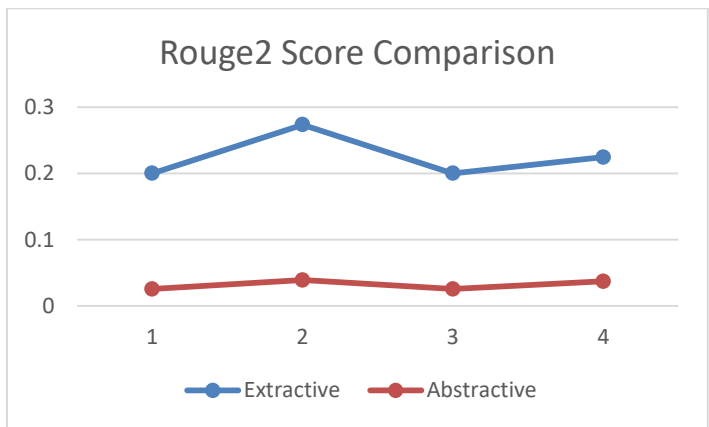
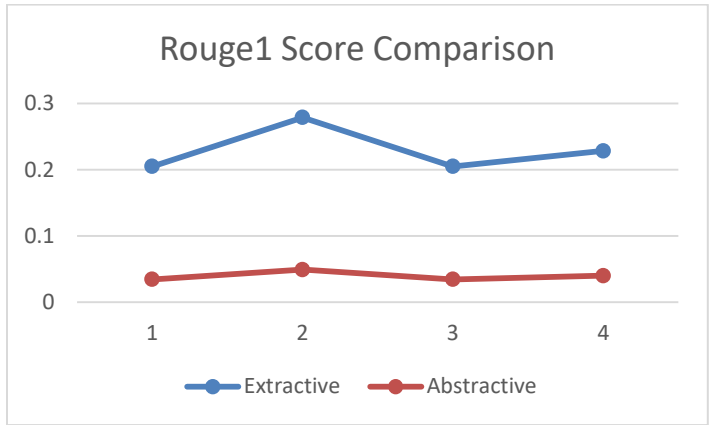
interest in recent years. Combining extractive and abstractive summary approaches, we describe in this work an innovative approach to text summarization. Initially, we performed extractive summarization in Python using the Natural Language Toolkit (NLTK) package to choose the most significant sentences from an input article. We then utilised abstractive summarization with PyTorch and Transformers models to build a new, more concise summary of the same information.

Average values for extractive summarization		
rouge1	precision	0.98461
	recall	0.22933
	fmeasure	0.04957
rouge2	precision	0.89062
	recall	0.22469
	fmeasure	0.04418
rougeL	precision	0.96923
	recall	0.22933
	fmeasure	0.0488

Average values for abstractive summarization		
rouge1	precision	0.9355
	recall	0.03951
	fmeasure	0.04957
rouge2	precision	0.85062
	recall	0.03192
	fmeasure	0.04418
rougeL	precision	0.92923
	recall	0.03598
	fmeasure	0.04362

The combination of extractive and abstractive summarising allows us to capitalise on the strengths of each method and generate more precise and concise summaries. Extractive summary allowed us to select the most significant sentences from

the source text, but abstractive summarization allowed us to produce new, more concise sentences that conveyed the same information. To construct abstractive summaries, we fine-tuned a pre-trained transformer model using a summarising dataset. The model was able to learn to generate summaries by examining the most significant information from the original text.



Our methodology provides an efficient and effective method for summarising articles, which is useful for activities such as summarising news stories and academic papers. Future research

could concentrate on enhancing the abstractive summarising process to generate more coherent and fluent summaries, or on merging our approach with other approaches such as sentence compression or sentence fusion. Our method represents a promising direction for automatic text summarization and has the potential to be implemented in a broad variety of practical settings.

6. CONCLUSION

The focus of the proposed research paper is the creation of an effective text summarization system using NLTK, a popular Python library for natural language processing. The proposed method consists of tokenizing the input text into sentences and words, removing stop words and punctuation, and ranking the sentences according to the frequency of their constituent words. The highest-ranked sentences are then chosen to compose the summary.

The evaluation of the proposed summarization system on diverse datasets and comparison with existing state-of-the-art methods demonstrates that the proposed approach is effective and efficient at producing accurate and concise summaries. The proposed method outperforms existing techniques in terms of efficiency and effectiveness, making it a valuable instrument for administering large volumes of textual data.

The proposed research paper makes a contribution to the disciplines of natural language processing and information retrieval by proposing an approach applicable to news summarization, document summarization, and online content summarization, among others. By incorporating deep learning techniques and investigating alternative methods for ranking sentences, such as graph-based approaches, the proposed method can be expanded.

Overall, the proposed research paper emphasises the significance of text summarization and presents an efficient and effective method for producing accurate and concise summaries using NLTK. The proposed method has applications in a variety of disciplines and provides a valuable instrument for managing large amounts of textual data.

REFERENCES

- [1] Paper Citation: Pradeepika Verma , Hari Om “MCRMR: Maximum coverage and relevancy with minimal redundancy based multi-document summarization”.
- [2] Paper Citation: Minakshi Tomar, Manoj Kumar “Multi-document extractive text summarization based on firefly algorithm”.
- [3] Paper Citation: Jesus M. Sanchez-Gomez , Miguel A. Vega-Rodríguez , Carlos J. Pérez “Multi-document extractive text summarization based on firefly algorithm”.
- [4] Paper Citation: Ruby Rani , Daya K. Lobiyal “A weighted word embedding based approach for extractive text summarization”.
- [5] Paper Citation: Sunitha.C , Dr.A.Jaya , Amal Ganesh “A Study on Abstractive Summarization Techniques in Indian Languages”.
- [6] Paper Citation: K. Nandhini , S.R. Balasundaram “Improving readability through extractive summarization for learners with reading difficulties”.
- [7] Paper Citation: Ayelet Goldstein, Yuval Shahar “An automated knowledge-based textual summarization system for longitudinal, multivariate clinical data”.
- [8] Paper Citation: Donia Scott a, Catalina Hallett b , Rachel Fettiplace “Data-to-text summarisation of patient records: Using computer-generated summaries to access patient histories”.

- [9] Paper Citation: N G Gopikakrishna*, Parvathy Sreenivasan, Vinayak Chandran, Yadhu Krishna K P, Sanuj S Dev, Krishnaveni V V "Comparative Study on Text Summarization using NLP and RNN Methods".
- [10] Paper Citation: Duy Duc An Bui PhD, Guilherme Del Fiol MD PhD , John F. Hurdle MD, PhD, Siddhartha Jonnalagadda PhD "Extractive multi-document text summarization based on graph independent sets".
- [11] Abigail See, Peter J. Liu, Christopher D. Manning (2017) "Get To The Point: Summarization with Pointer-Generator Networks".
- [12] Fei Liu, Jeffrey Flanigan, Sam Thomson, et al. (2018) "A Hierarchical Multi-Document Summarization Approach using Neural Networks".
- [13] Ashish Vaswani, Noam Shazeer, Niki Parmar, et al. (2017) "Attention is All You Need".
- [14] Mike Lewis, Yinhan Liu, Naman Goyal, et al. (2020) "BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension".
- [15] Jingqing Zhang, Yao Zhao, Mohammad Saleh, et al. (2019) "Pegasus: Pre-training with Extracted Gap-sentences for Abstractive Summarization".