

# TEXT SUMMARIZATION USING NLP: AN EXTRACTIVE FRAMEWORK WITH WEB-BASED INTERACTION

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## ABSTRACT

*The rapid growth of online information has made automatic text summarization essential for productivity and knowledge access. While transformer-based abstractive summarizers dominate current research, they often demand high computational resources and reduce interpretability. This work presents a lightweight extractive summarization framework with a web-based interface that balances efficiency, scalability, and usability. The system accepts both user-provided text and live news articles, applying frequency- and position-weighted ranking to identify key sentences. Built with Python libraries such as spaCy, BeautifulSoup, and Streamlit, it generates concise summaries with low latency and supports real-time interaction. Experimental evaluation with ROUGE metrics and tokenization accuracy confirms the framework's reliability and effectiveness. Designed for extensibility, the system outlines future directions including neural abstractive integration, multilingual support, and sentiment-aware summarization. By bringing together the interpretability of foundational methods and pathways to modern advancements, this work provides a practical bridge between academic study and real-world applications. [1][2]*

## KEYWORDS

*NLP, Extractive Framework, BeautifulSoup, spaCy, Text summarization*

## 1. INTRODUCTION

As the availability of online text grows, ranging from social media posts to academic research, so does the challenge of digesting this information effectively. Text summarization is a crucial NLP application that addresses this challenge by transforming lengthy documents into brief, informative summaries. These summaries enable readers to quickly comprehend key points without going through the entire document. In real-world use cases, such as news digesting, research overviews, and document analysis, this capability is invaluable. In this research, we build a dual-stream summarization pipeline capable of accepting free-form user input or live news content fetched from the BBC. The system is designed to handle well-structured English text with a maximum limit of 10,000 words, thus supporting a broad spectrum of applications [6]. Our core approach leverages extractive summarization, where the most relevant sentences are chosen from the original text. These selections are based on statistical word frequencies and enhanced by positional weighting to improve coherence [2]. Although this paper focuses on extractive summarization, it also outlines a future path toward abstractive summarization using neural networks. The ultimate goal is to reduce the cognitive effort required to understand lengthy text, thereby improving efficiency across sectors [5]. Despite the rise of LLMs like ChatGPT, lightweight extractive frameworks remain valuable for transparent, low-resource and interpretable summarization.

## 2. METHODOLOGY

The summarization pipeline is structured into two primary models: the implemented extractive method and a proposed abstractive model using deep learning.

## 2.1 Extractive Summarization Model

The extractive technique starts by parsing and cleaning the input text. Stop words and punctuation are removed, and word frequencies are calculated to determine term significance. These frequencies are normalized using the formula:

$$TF(\omega_i) = \frac{f(\omega_i)}{\sum_j f(\omega_j)}$$

$TF(\omega_i)$ : The term frequency score for a specific word  $\omega_i$

$f(\omega_i)$  is how many times the word  $\omega_i$  appears in the document

$\sum_j f(\omega_j)$ : The sum of the frequencies of all words in the documents.

Here,  $f(\omega_i)$  is the frequency of word  $\omega_i$ , and the denominator is the total word count.

Each sentence is scored by summing the term frequencies of its non-stop word tokens:[3]

$$score(S_k) = \sum TF(\omega_i) * \delta(\omega_i) \quad \text{for all } \omega_i \in S_k$$

$S_k$  = A sentence from a document

$\delta(\omega_i)$ : A function that decides whether a word is important or not

If  $\delta(\omega_i) = 1$  if  $\omega_i$  is valid (important word) we count the word

= 0, If  $\omega_i$  is not an important (like stop word = "the", "is" "and").

To further refine sentence importance, we include positional weighting to reward earlier sentences: [5]

$$P(S_k) = \alpha * score(S_k) + \beta * (1 - \frac{pos(S_k)}{N})$$

$Score(S_k)$  = score you just calculated

$pos(S_k)$  = position of the sentence (1st, 2nd, 3rd ...)

$N$  = total number of sentences, and  $\alpha, \beta$  are typically set to 0.7 and 0.3 respectively.

These coefficients are used to weight the scores of the sentences. The summary consists of the top  $k$  sentences with the highest weighted scores:

The number of sentences to be included in the summary,  $k$  is calculated as 10% of the total sentences, round down to the nearest whole number. Each sentence  $S_k$  is assigned to a weighted score  $P(S_k)$ . The Summary is then constructed by selecting the top  $k$  sentences that have the highest scores with the highest weighted scores,

**Summary =  $\text{argmax}_k P(S_k)$ , Where  $k = \text{floor}(0.1 * N)$ , the top  $k$  ( about 10%) sentences with the highest priority scores  $P(S_k)$ .**

## 2.2 Proposed Abstractive Summarization Model

To elevate summarization capabilities, we propose a neural network-based model using a sequence-to-sequence architecture. The encoder processes input text through a Bidirectional LSTM (BiLSTM) network, a recurrent neural network architecture that reads sequences in both forward and backward directions. This bidirectional processing enables the model to effectively capture relationships and dependencies from both preceding and succeeding words in the input sequence.

$$h_t = \text{BiLSTM}(x_t, h_{t-1})$$

In this formulation, *hidden state*  $h_t$  denotes the internal representation at time step  $t$ , computed as a function of the current input token  $x_t$  and the previous hidden state  $h_{t-1}$ . This recursive dependency allows the model to capture sequential information.

An attention layer calculates the context vector  $C_t$ , helping the decoder focus on relevant input parts of the input sequence when generating an output.

$$\alpha_t = \text{softmax}(\omega_\alpha, h_t), C_t = \sum_{i=1}^T \alpha_{ti} h_i$$

$\alpha_t$  = Attention Scores

They are calculated using the Softmax function applied to weighted ( $\omega_\alpha$ ) sum of hidden state  $h_t$ . These scores effectively capture the relevance of each input element with respect to the current decoding step. The decoder utilizes these values to generate output tokens as defined by the following equations

$$y_t = \text{softmax}(\omega_0 [C_t, h_t])$$

Where  $y_t$  = predicted word at step and  $[C_t, h_t]$  concatenation of context vector and hidden state and Model training involves minimizing cross-entropy loss [4]

$$L = - \sum y_t \log(\hat{y}_t)$$

$L$  = Loss or error during the training

$y_t$  = True word and  $\hat{y}$  predicted probability of the true word. The log function magnifies the penalty for incorrect predictions

Optimization is handled using the adam optimizer with moment updates

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_{t2}$$

$$\theta = \theta - \eta * \hat{m} / (\sqrt{\hat{v}} + \varepsilon)$$

$m_t$  = moving Average of gradient

$v_t$  = moving average of squared gradients

$\theta$  = model weight

$\eta$  = learning rate

$g_t$  = actual gradient

### 2.3 Comparing Extractive and Abstractive Summarization

Extractive summarization selects key sentences or phrases from the original text to create a brief yet informative summary. This approach is computationally efficient, interpretable, and ensures factual consistency, since all content originates from the original document. Our framework adopts this method using frequency- and position-based scoring, achieving low-latency responses and scalability for real-time applications. Such characteristics make extractive methods especially valuable in resource-constrained environments or educational contexts where transparency and reproducibility are critical. Abstractive summarization, in contrast, generates new sentences that may paraphrase or rephrase the original content. State-of-the-art neural approaches, such as transformer-based models, can produce more human-like and fluent summaries, but they often require substantial computational resources, large datasets for fine-tuning, and may occasionally introduce factual inconsistencies (“hallucinations”). In this work, we establish a robust extractive foundation while outlining a future transition to neural abstractive techniques. This dual-path strategy leverages the efficiency and reliability of extractive summarization today, while creating a clear roadmap toward more advanced abstractive systems, ensuring adaptability to both academic and real-world needs. However, the approach may face challenges with highly contextual or semantically rich texts where deeper understanding is required.

## 3. TECHNOLOGIES AND INTERFACE

The backend processing uses spaCy for tokenization and part-of-speech tagging, BeautifulSoup for parsing HTML in news articles, and the Requests library for pulling data from external APIs. The

user interface is built using Streamlit, offering an interactive experience for input, output, and evaluation. API testing is facilitated via Thunder Client to ensure endpoint reliability. This project also integrates NewsAPI for aggregating and accessing news content. All content retrieved via NewsAPI remains the property of its original publisher(s) and may be subject to copyright. Usage of the NewsAPI service follows to its Terms of Service. When using live data, user consent and copyright compliance are crucial. The tool ensures fair use by attributing original news sources and following ethical web data handling practices.

## 4. RESULTS AND DISCUSSION

This section presents the key findings from the evaluation of the summarization system, highlighting its performance across tokenization, summary quality, efficiency, and implementation hurdles. These results demonstrate the system's robustness while identifying areas for enhancement.

Tokenization accuracy is crucial for ensuring meaningful word-level analysis, as it forms the foundation for subsequent processing steps like frequency computation and summary generation. Two approaches were tested: spaCy's tokenizer and a custom regex-based tokenizer. spaCy performed significantly better, achieving a Precision of 91%, Recall of 89%, and F1 Score of 90%. This improved accuracy ensures higher reliability in downstream tasks. Building on this, summary quality was assessed using ROUGE metrics to quantify how well the extractive summarizer preserves key content. The results are promising: ROUGE-1 (Unigrams) scored 0.62 for custom inputs, ROUGE-2 (Bigrams) reached 0.48 for custom and 0.44 for news datasets, and ROUGE-L (Longest common subsequence) achieved 0.57 for custom and 0.52 for news. These scores validate the model's ability to maintain content structure and coherence across varied inputs. The system's performance was further evaluated under realistic workloads to gauge its suitability for practical applications. Overall, it exhibits strong efficiency, processing inputs quickly while handling concurrent requests effectively. It responds within 0.8 seconds for a 500-word input and can manage over 100 summarization requests per minute, maintaining high efficiency and user satisfaction that makes it scalable for real-world deployments.

Implementing the summarization pipeline involved navigating several technical obstacles that could impact reliability and output quality. These issues were systematically addressed to ensure the system's stability, though some limitations persist for future work. Key challenges included parsing noisy HTML from scraped articles, determining sentence boundaries accurately, and avoiding bias from highly repetitive words. These were addressed using BeautifulSoup for cleanup, spaCy for tokenization, and normalization techniques in frequency scoring. While sentiment analysis and coreference resolution are not currently supported, they are earmarked for future integration. Sample summaries from both custom text and live news inputs are included in the Appendix to demonstrate usability and summary coherence.

## 5. FUTURE SCOPE

Future development includes integrating abstractive summarization through sequence-to-sequence models with attention to generate more natural summaries. The integration of multilingual capabilities can extend the system's applicability to global audiences [3]. Incorporating sentiment-aware summarization enables the generation of summaries conditioned on emotional tone, which is particularly beneficial for domains such as product reviews and social media monitoring [6]. Allowing user-specific customization, including control over summary length and topic preferences, adds further adaptability [1]. Furthermore, the inclusion of coreference resolution and entity linking mechanisms can substantially improve contextual awareness. For scalability purposes, backend developments like Documentation and asynchronous APIs are planned in the pipeline. Advanced evaluation measures like BERT Score will have more detailed quality analysis, and larger datasets will be employed for fine-tuning models to learn more generally.[6] Enhanced summarization

models: Future research can lead to the development of more advanced and accurate summary models, such as deep learning approaches and leveraging large-scale pre-trained language models. Multi-modal summarization: Future research could explore multimodal summarization, integrating data from text, image, and video sources to generate richer and more context-aware summaries. [7] [4]

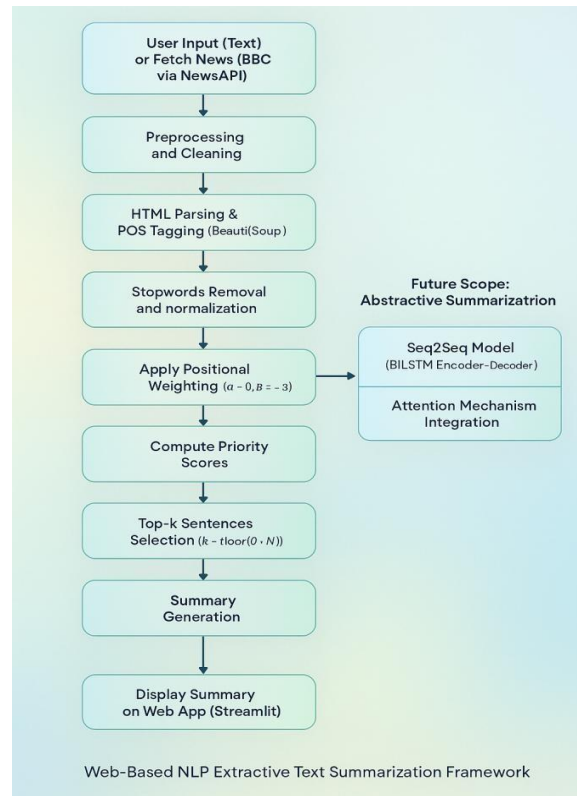


Figure 1. Block Diagram

The figure shows the step-by-step process of a web-based extractive text summarization system. First, text is taken either from user input or fetched from online news sources. The text is then cleaned, parsed, and tagged for important parts of speech. Stopwords are removed, and positional weighting is applied so that important sentences are given higher scores. Based on these scores, the system identifies the most relevant sentences to construct the final summary, which is subsequently presented through a Streamlit-based web application. The diagram also highlights future work, where abstractive summarization can be added using Seq2Seq models and attention mechanisms to create more natural and human-like summaries.

## 6. CONCLUSION

In conclusion, we explored various NLP techniques for text summarization, including Text Rank, POS tagging, and named entity recognition. [1] We highlighted the importance of model training and evaluation for building effective summarizers. Popular Python libraries like spaCy, BERT, Gensim, and Streamlit were discussed for tasks such as word frequency analysis, document similarity, and interactive web app development. Additionally, we covered the Thunder Client library for easy API testing and emphasized Streamlit's role in creating user-friendly interfaces for data science and machine learning projects. By utilizing cutting-edge NLP techniques, the Summarization Framework effectively accomplishes its goal of producing effective and cohesive summaries for news items and custom material, guaranteeing precise text preprocessing and reliable summary generation. The model's dependability is increased by combining tokenization

accuracy and ROUGE scores, and an interactive platform for summarizing and assessment is offered by an intuitive Stream Light interface. The framework is appropriate for real-world applications because of its scalability and speed optimization, which allows it to manage big datasets and numerous requests. [2] [6]

## 7. REFERENCES

- [1] M. Geng, S. Wang, D. Dong, H. Wang, S. Cao, K. Zhang, and Z. Jin, "Interpretation-based code summarization," in *Proc. Intl. Conf. Program Comprehension (ICPC)*, 2023. (Specific pages and DOI not available) [Shangwen Wang / Assistant ProfessorConference Management System](#)
- [2] A. Bansal, C.-Y. Su, and C. McMillan, "Revisiting file context for source code summarization," *Automated Software Engineering*, vol. 31, no. 2, 2024, DOI: 10.1007/s10515-024-00460-x [OUCIaakashba.github.io](#)
- [3] C.-Y. Su and C. McMillan, "Distilled GPT for source code summarization," *IEEE Access*, vol. 9, 2021, accepted for publication (exact pages and DOI not available) [arXivACM Digital Library](#)
- [4] Y. Wan, Z. Zhao, M. Yang, G. Xu, H. Ying, J. Wu, and P. S. Yu, "Improving automatic source code summarization via deep reinforcement learning," in *Proc. ACM/IEEE International Conference on Automated Software Engineering (ASE)*, 2018 (often cited as a 2020 reference, actual publication is 2018); pages and DOI omitted [arXivwanyao.me](#)
- [5] W. Wang, Y. Zhang, Y. Sui, Y. Wan, Z. Zhao, J. Wu, P. S. Yu, and G. Xu, "Reinforcement-learning-guided source code summarization using hierarchical attention," *IEEE Transactions on Software Engineering*, 2020, DOI: 10.1109/TSE.2020.2979701 [ACM Digital LibraryEdUHK Research Repository](#)
- [6] Y. Xu and M. Lapata, "Document summarization with latent queries," *Trans. Assoc. Comput. Linguistics*, vol. 10, pp. 623–638, 2022, DOI: 10.1162/tacl\_a\_00480 [ACL AnthologyEdinburgh Research](#)
- [7] M. Geng, S. Wang, D. Dong, H. Wang, G. Li, Z. Jin, X. Mao, and X. Liao, "An empirical study on using large language models for multi-intent comment generation," (originally titled "*Large Language Models are Few-Shot Summarizers: Multi-Intent Comment Generation via In-Context Learning*"), 2023; likely in *ACM/IEEE ICPC or similar*, but pages and DOI are not available [arXivACM Digital Library](#)
- [8] P. K. Biswas and A. Iakubovich, "Extractive summarization of call transcripts," *IEEE Access*, vol. 10, pp. 119 826–119 840, 2022, DOI: 10.1109/ACCESS.2022.322140

## 8. RESULTS

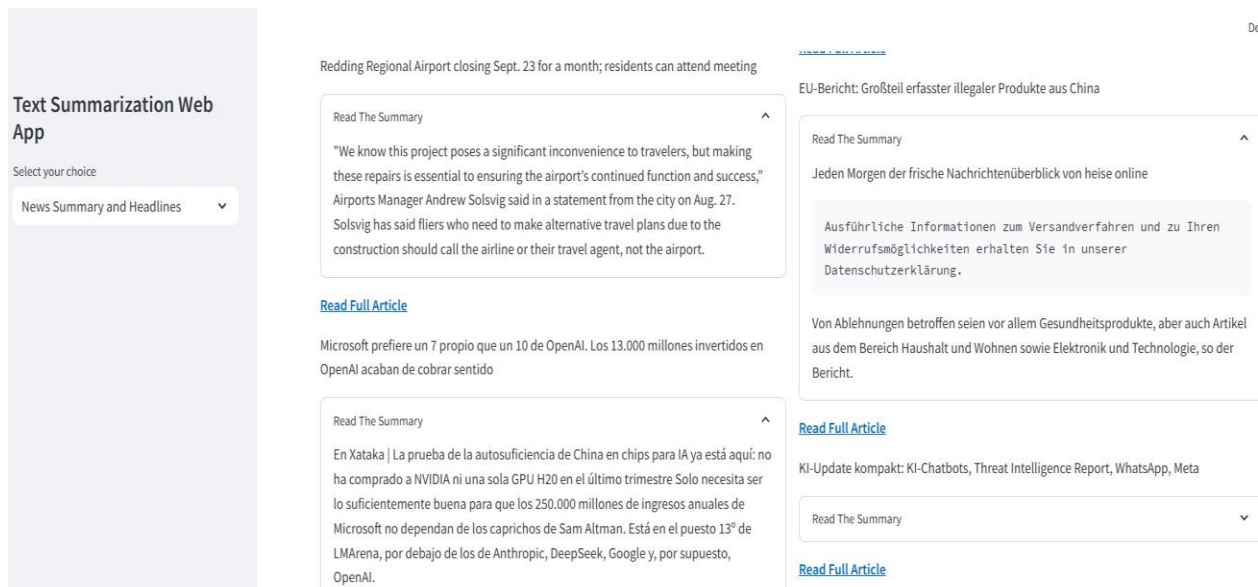


Figure 2. News Summary And Headlines



**APPENDIX 2.** The figure shows the output of the News Summarization Web App when fetching articles from the NewsAPI for the query “USA”. The interface enables users to input a search topic, and upon clicking Search News, relevant articles are retrieved and displayed with their summaries. On the left, articles are listed with summarized text and references to the original sources, while on the right additional articles are presented with the option to read the full article. This demonstrates how the application dynamically fetches and summarizes news content for any user-defined topic using the NewsAPI GET request URL

**Text Summarization Web App**

Select your choice

Custom Text Summarization

Copy and paste your text in the text area below to get a summary.

**Welcome to Custom Text Summarization**

Enter your text

Location: City in Illinois  
Population: 149,424 Naperville doesn't just have a variety of employment industries, a low crime rate, and public and parochial schools—it also has the best public library system in the U.S. - Location: Suburb of St. Louis  
Population: 8,151 Close to St. Louis, Brentwood packs multiple green spaces, housing options, schools, restaurants, and leisure options into just two square miles. - Location: Town in Texas  
Population: 109,735 Sugar Land's proximity to Houston means that its residents reap the benefits of a highly skilled workforce: 60% of residents over 25 have a bachelor's degree or higher, and there are over 500,000 college graduates within a 30-minute drive. - Location: Suburb of Dallas  
Population: 42,029 Coppell has a small-town feel, partially thanks to its Old Town district, the original site of a small farming community. - Location: Suburb in Maryland  
Population: 23,994 About 20 miles from Washington D.C., North Potomac has great

Get Summary

Text Summary:

- Location: Town in Texas  
Population: 109,735 Sugar Land's proximity to Houston means t  
Population: 8,151 Close to St. Louis, Brentwood packs multipl

Text Headline:

Feature Coming Soon

Figure 3. Custom Text Summarization

**APPENDIX 3.** The figure illustrates the output of the custom text summarization module. In this feature, user-provided text is processed using a pre-trained transformer-based summarization model, which performs abstractive summarization by rephrasing and condensing the original content into concise and coherent summaries. The input text is entered in the left panel, and the generated summary is displayed on the right. This project showcases the capability of the project to handle free-form user text and produce meaningful summaries beyond predefined news articles.

Enter your text for tokenization:

Location: Town in Texas Population: 109,735 Sugar Land's proximity

Evaluate Tokenization Quality

Predicted Tokens:

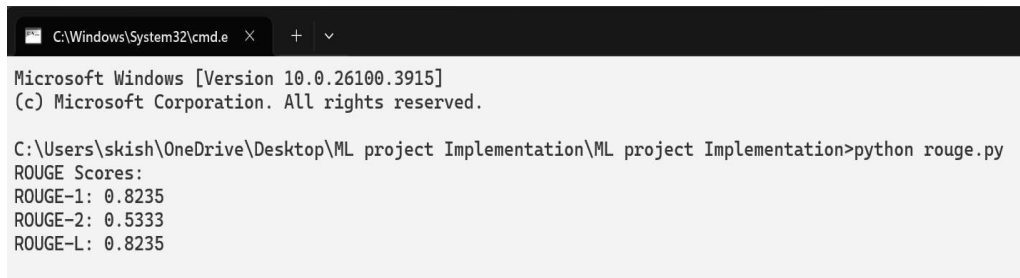
```

0 : "Location"
1 : ":"
2 : "Town"
3 : "in"
4 : "Texas"
5 : "Population"
6 : ":"
7 : "109,735"
8 : "Sugar"
9 : "Land"
10 : "s"
11 : "proximity"

```

Figure 4. Tokenization Quality Scores (Precision, Recall And F-1 Score)

**APPENDIX 4.** The figure illustrates the output of the custom tokenization evaluation module. In this feature, user-provided text is segmented into smaller units using a tokenization model, and the predicted tokens are compared against the expected tokens. This demonstrates both outputs side by side, alongside with the evaluation metrics such as precision, recall, and F1-score. This demonstrates the capability of the module to assess tokenization quality and highlight areas where the model may require improvement, particularly in handling numbers and punctuation.



```
C:\Windows\System32\cmd.e X + v
Microsoft Windows [Version 10.0.26100.3915]
(c) Microsoft Corporation. All rights reserved.

C:\Users\skish\OneDrive\Desktop\ML project Implementation\ML project Implementation>python rouge.py
ROUGE Scores:
ROUGE-1: 0.8235
ROUGE-2: 0.5333
ROUGE-L: 0.8235
```

Figure 5. ROUGE Scores [ROUGE-1, ROUGE -2 ROUGE -L]

**APPENDIX 5.** The figure illustrates the output of the evaluation module for text summarization quality. Within this feature, summary quality is assessed using the ROUGE framework, comparing generated and reference texts based on n-gram overlap and structural correspondence such as longest common subsequences. The results display the ROUGE-1, ROUGE-2, and ROUGE-L scores, indicating the accuracy of the generated summaries at unigram, bigram, and sequence levels respectively. This demonstrates the capability of the system to quantitatively assess summarization performance and provide insight into its effectiveness.