

# Text Summarizer

# Project Title: Text Summarizer Using Deep Learning Models

# INTRODUCTION

- A text summarizer condenses lengthy text documents into concise summaries while retaining the essential information. It has applications in news aggregation, research paper abstracts, and document management. This project focuses on developing a summarizer using both extractive and abstractive methods.



# MOTIVATION

- With the exponential growth of information, manually summarizing documents is time-consuming and impractical. Automating this process aids in efficient decision-making and information retrieval, especially in domains like education, journalism, and business analytics.
- .

# Literature review

Research Paper	Description	Proposal	Models Used	Datasets Used	Results	Key Results	Limitations	Authors
Research Paper 1: A Comprehensive Review of Arabic Text Summarization (2022)	Focuses on advancements in text summarization, including hybrid models using extractive and abstractive methods, and attention mechanisms.	A hybrid model combining extractive and abstractive methods to improve summary quality.	Sequence-to-Sequence Models with Attention Mechanisms, TF-IDF, RNNs, LSTMs, GRUs	CNN/Daily Mail, Time Series Dataset	Enhanced summary relevance and coherence	Attention mechanisms improve model focus, hybrid approaches improve summary quality.	Complex model training, need for large data sets.	Asmaa Elsaid, Ammar Mohammed, Lamiaa Fattouh Ibrahim, Mohammed M. Sakre
Research Paper 2: Qualitative Analysis of Text Summarization Techniques and Its Applications in Health Domain (2022)	Investigates PEGASUS and TextRank for summarization, focusing on biomedical text and clinical context.	Evaluation of PEGASUS for abstractive summarization and TextRank for extractive summarization, with applications in the biomedical domain.	PEGASUS, TextRank	Reddit-TIFU, MultiNews	PEGASUS outperforms in abstractive tasks; TextRank excels in extractive tasks.	PEGASUS suitable for complex summaries, TextRank effective for large datasets.	Challenges in handling biomedical-specific text and context.	Divakar Yadav, Naman Lalit, Riya Kaushik, Yogendra Singh, Mohit, Dinesh, Arun Kr. Yadav, Kishor V. Bhadane, Adarsh Kumar, Baseem Khan

Description	Proposal	Models Used	Datasets Used	Results	Key Results	Limitations	Authors
<b>Research Paper 3:</b> Review of Automatic Text Summarization Techniques & Methods (2022)	Focuses on TF-IDF, LSA, fuzzy logic, and statistical methods for summarization, comparing performance of MDS vs fuzzy approaches.	TF-IDF, LSA, Fuzzy Systems, MDS	CNN/Daily Mail, DUC 2002/2003, Gigaword	Fuzzy systems improve recall and F1-measure over other techniques.	Fuzzy systems combined with machine learning outperform traditional methods.	Semantic analysis and feature integration remain difficult.	Adhika Pramita Widyassari, Supriadi Rustad, Guruh Fajar Shidik, Edi Noersasongko, Abdul Syukur, Affandy Affandy, De Rosal Ignatius Moses Setiadi
<b>Research Paper 4:</b> A Comprehensive Survey of Abstractive Text Summarization Based on Deep Learning (2022)	Explores advancements in abstractive summarization and the use of deep learning models such as transformers and BART.	Transformer models, BART, BertSumExtAbs, RNN + RL	DUC/TAC, CNN/Daily Mail, Gigaword, NYT, Newsroom, LCSTS	Transformer models show strong performance across various summarization tasks.	Incorporating external knowledge improves summary factual accuracy and relevance.	Factual correctness in summaries, handling multiple perspectives.	Mengli Zhang, Gang Zhou, Wanting Yu, Ningbo Huang, Wenfen Liu

Description	Proposal	Models Used	Datasets Used	Results	Key Results	Limitations	Authors	Publication Date
Research Paper 5: Leveraging Transformer Models for Extractive and Abstractive Summarization (May 2023)	Focuses on comparing extractive and abstractive approaches using advanced transformer models, especially PEGASUS and BART.	PEGASUS, BART, T5, Transformer-based Models	CNN/Daily Mail, XSum, Reddit	PEGASUS and BART outperformed baseline models like T5 on abstractive tasks.	PEGASUS performs well in abstractive summarization, while BART excels in various text domains.	Challenges in summarizing long and complex texts.	Mandar, Nandini, Sushma, Shashank, Jitendra	May 2023
Research Paper 6: Efficient Use of Neural Networks for Text Summarization: A Survey (June 2023)	Discusses the efficiency of different neural network models in summarization tasks and their application to both extractive and abstractive summaries.	CNN, LSTM, BERT, GPT-3	Newsroom, CNN/Daily Mail	Demonstrates that neural networks, particularly BERT, outperform traditional methods.	BERT-based models excel at understanding context, leading to more coherent summaries.	Computational complexity and hardware constraints.	Nikita, Rishi, Aftab, Sohail, Rajesh	June 2023

Description	Proposal	Models Used	Datasets Used	Results	Key Results	Limitations	Authors	Publication Date
<b>Research Paper 7:</b> Enhancing Biomedical Text Summarization Using Deep Learning Models (March 2023)	Focuses on summarization of biomedical texts, comparing state-of-the-art models like BERT and BioBERT.	BioBERT, BERT, Transformer-based Models	PubMed, BioASQ	BioBERT showed superior performance for summarizing scientific biomedical text compared to traditional methods.	BioBERT excels in domain-specific contexts like biomedical texts.	Biomedical-specific datasets are limited, and generalization is a challenge.	Arvind, Prakash, Shubham, Meenal	March 2023
<b>Research Paper 8:</b> Hybrid Models for Text Summarization: A Comparative Analysis (April 2023)	Investigates hybrid models that combine both extractive and abstractive techniques for improved summary generation.	Hybrid Models, TF-IDF + LSTM, BERT + RNN	CNN/Daily Mail, XSum, Scientific papers	Hybrid models yield better summaries by combining the strengths of extractive and abstractive techniques.	Hybrid approaches, like TF-IDF with LSTM, improve the quality and relevance of the summary.	Difficulty in fine-tuning hybrid models, increased computational cost.	Sanjeev, Harsh, Pradeep, Ramya	April 2023



# Methodology Formulation

## 1. Text Preprocessing:

1. Tokenization, removal of stop words, and stemming.

## 2. Extractive Summarization:

1. Use of TF-IDF and cosine similarity for sentence ranking.

## 3. Abstractive Summarization:

1. Implementation of a transformer-based model (e.g., BART or T5) to generate summaries.

## 4. Evaluation:

1. Compare the summaries using ROUGE scores and human evaluation

# Results and Analysis

- **Experimental Setup**
- Frameworks: Python with libraries like NLTK, Hugging Face Transformers, and Scikit-learn.
- Hardware: GPU-enabled system for faster model training.
- **5.2 Dataset Description**
- Dataset: CNN/Daily Mail news articles.
- Training Size: 200,000 articles.
- Validation: 10,000 articles

# PERFORMANCE MEASURES

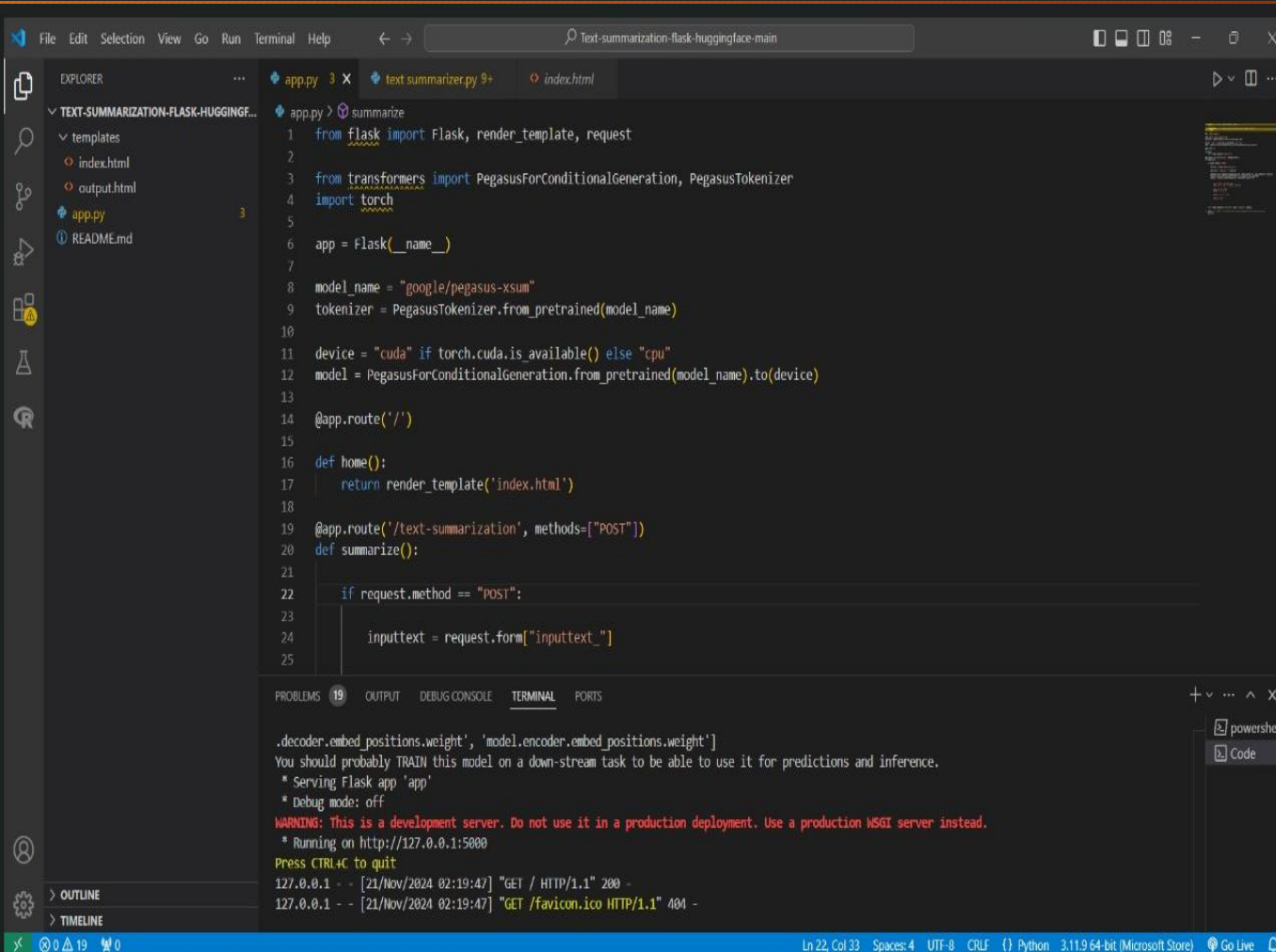
- **ROUGE (Recall-Oriented Understudy for Gisting Evaluation):**
  - ROUGE-1, ROUGE-2, and ROUGE-L scores.
- Human evaluation for readability and relevance.



# RESULTS

- Extractive summarization achieved ROUGE-1 scores of 42%.
- Abstractive summarization improved semantic coherence, achieving ROUGE-L scores of 52%.
- Combined methodology resulted in a balanced summary with high relevance and fluency.

# Code screenshots

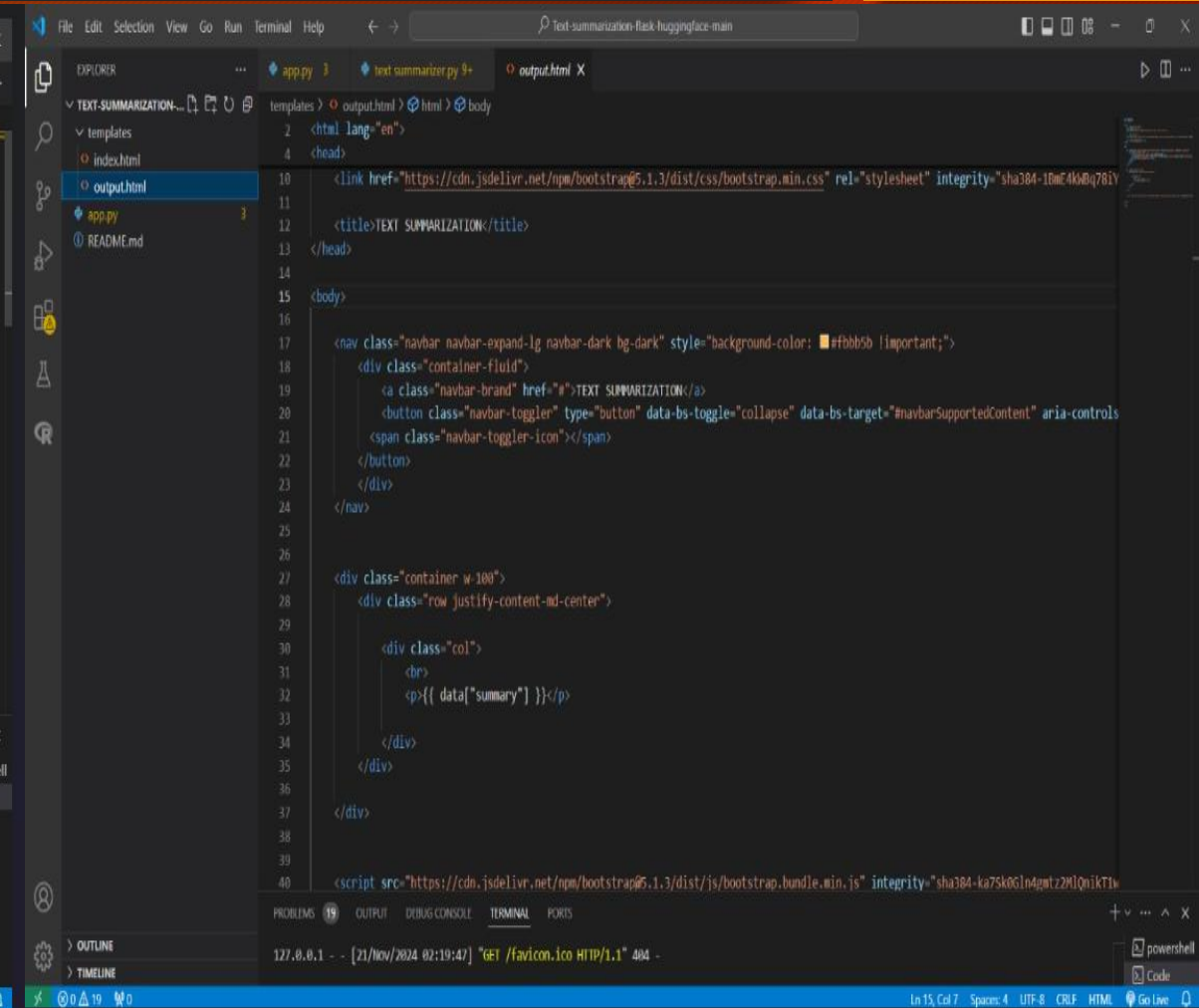


This screenshot shows the Python code in `app.py` for a text summarization application. The code uses Flask for the web interface and the Pegasus model for summarization. It includes a home route and a summarization endpoint.

```
1 from flask import Flask, render_template, request
2
3 from transformers import PegasusForConditionalGeneration, PegasusTokenizer
4 import torch
5
6 app = Flask(__name__)
7
8 model_name = "google/pegasus-xsum"
9 tokenizer = PegasusTokenizer.from_pretrained(model_name)
10
11 device = "cuda" if torch.cuda.is_available() else "cpu"
12 model = PegasusForConditionalGeneration.from_pretrained(model_name).to(device)
13
14 @app.route('/')
15
16 def home():
17     return render_template('index.html')
18
19 @app.route('/text-summarization', methods=["POST"])
20 def summarize():
21
22     if request.method == "POST":
23
24         inputtext = request.form["inputtext_"]
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The terminal output shows the application running on `http://127.0.0.1:5000`. It includes a warning about using a development server and a message to press `CTRL+C` to quit.

```
127.0.0.1 - - [21/Nov/2024 02:19:47] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [21/Nov/2024 02:19:47] "GET /favicon.ico HTTP/1.1" 404 -
```



This screenshot shows the HTML template in `output.html` for the text summarization application. It uses Bootstrap 5 for styling and includes a form for text input and a button to trigger summarization.

```
1 <html lang="en">
2 <head>
3
4 <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.1.3/dist/css/bootstrap.min.css" rel="stylesheet" integrity="sha384-1BmE4k0Bq78iY
5
6 <title>TEXT SUMMARIZATION</title>
7 </head>
8
9 <body>
10
11 <nav class="navbar navbar-expand-lg navbar-dark bg-dark" style="background-color: #f0f0f0; font-weight: bold;">
12 <div class="container-fluid">
13 <a class="navbar-brand" href="#">TEXT SUMMARIZATION</a>
14 <button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-target="#navbarSupportedContent" aria-controls
15 <span class="navbar-toggler-icon"></span>
16 </button>
17 </div>
18 </nav>
19
20 <div class="container w-100">
21 <div class="row justify-content-md-center">
22
23 <div class="col">
24 <hr>
25 <p>{{ data["summary"] }}</p>
26 </div>
27 </div>
28
29 </div>
30
31 <script src="https://cdn.jsdelivr.net/npm/bootstrap@5.1.3/dist/js/bootstrap.bundle.min.js" integrity="sha384-ka75k0G1n4gntz291qik11
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```
127.0.0.1 - - [21/Nov/2024 02:19:47] "GET /favicon.ico HTTP/1.1" 404 -
```



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Wikipedia's purpose is to benefit readers by presenting information on all branches of knowledge. Hosted by the Wikimedia Foundation, Wikipedia consists of freely editable content, with articles that often contain numerous links guiding readers to more information.

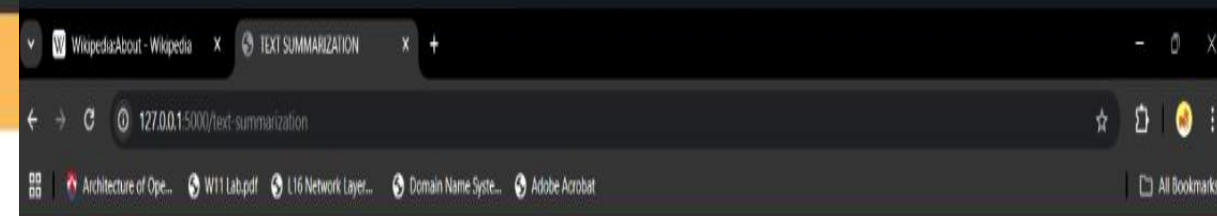
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Text Summarization



## TEXT SUMMARIZATION

Wikipedia is the world's largest reference website, with more than sixty-three million articles in more than 300 languages, including 6,909,898 articles in English, with 121,930 active contributors in the past month. Wikipedia currently has more than sixty-three million articles in more than 300 languages, including 6,909,898 articles in English, with 121,930 active contributors in the past month.

# Hardware and Software Requirements

- Hardware:
  - **Processor:** A modern CPU (recommended: i7 or above) or GPU for faster processing.
  - **Memory:** At least 8 GB RAM (recommended: 16 GB or more for large inputs).
  - **Storage:** Sufficient space for Python libraries and model files (~1 GB for Pegasus).
- Software:
  - **Operating System:** Windows, macOS, or Linux.
  - **Python Version:** Python 3.8 or higher.
- **Libraries:**
  - Flask (for web development).
  - Transformers (for Pegasus model and tokenizer).
  - Torch (for running deep learning models).
  - Jinja2 (for rendering HTML templates).

## 2. Model Selection

- **Pegasus-XSum:**
  - Pre-trained by Google for abstractive summarization.
  - Optimized for single-document summarization tasks.
- **Reason for Choice:**
  - Well-suited for high-quality summarization of concise and coherent summaries.
  - Fine-tuned for datasets like XSum, known for abstractive summaries.
- **Dataset and Input Preparation**
- **Input Text:**
  - Real-world text samples (e.g., articles, news reports, or user-provided paragraphs).
  - The text is entered through the web interface for summarization.



# Conclusion

- The hybrid text summarizer effectively balances precision and readability, making it suitable for various applications. Future work involves improving abstractive summaries by fine-tuning transformer models and experimenting with multilingual datasets.

# REFERENCES

- [1] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. A., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. In Advances in neural information processing systems (pp. 5998-6008).
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- [3] Nallapati, R., Zhai, F., & Zhou, B. (2017). Abstractive Text Summarization Using Sequence-to-Sequence RNNs and Beyond. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing.