SnapSummary: A Real-Time Text Summarizer

A PROJECT REPORT

Submitted by

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in partial fulfillment for the award of the degree

of

MASTER OF COMPUTER APPLICATION

Department of Computational Sciences

BRAINWARE UNIVERSITY

398, Ramkrishnapur Road, Barasat, North 24 Parganas, Kolkata - 700 125

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BONAFIDE CERTIFICATE

Certified that this project report "**SnapSummary**" is the Bonafide work of **DEBANJAN ACHARYYA, ANIRBAN MALLICK, CHANCHAL GHOSH, ROSHAN KUMAR PASWAN, SUBHAJIT PANDA** who carried out the project work under my supervision.

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Abstract

In today's digital era, where vast amounts of written content flood websites, articles, and academic papers, there is a growing need for efficient tools that help users quickly grasp essential information. Manually summarising long texts is often time-consuming and impractical, which is why we developed "SnapSummary" — a user-friendly, browser-based web application designed to generate concise and coherent summaries in seconds. Built with HTML, CSS, and JavaScript for the frontend and powered by Python's Flask framework on the backend, the system uses natural language processing techniques to identify key points in the text and deliver meaningful summaries while preserving the core message. This not only enhances productivity but also aids in quicker understanding and retention of information. The application has been tested with various types of input and has demonstrated reliable performance, making it a valuable tool with potential for future enhancements like file/document summarization and integration of advanced machine learning techniques.

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List of Abbreviations

AI	Artificial Intelligence
BART	Bidirectional and Auto-Regressive Transformer
BERT	Bidirectional Encoder Representations from Transformers
SRS	Software Requirements Specification
UI	User Interface
NLP	Natural Language Processing
API	Application Programming Interface
HTML	HyperText Markup Language
JS	JavaScript
CNN	Convolutional Neural Network
PDF	Portable Document Format
ROUGE	Recall-Oriented Understudy for Gisting Evaluation
GPU	Graphics Processing Unit
RAM	Random Access Memory
T5	Text-to-Text Transfer Transformer
XSum	Extreme Summarisation Dataset
SAMSum	Summarisation Dataset for Dialogue Texts
PyTorch	Python Deep Learning Framework
Seq2Seq	Sequence-to-Sequence Model
UML	Unified Modeling Language

Chapter-1

Introduction

1.1 Overview

In the age of digital information, users often encounter large amounts of textual content, making it difficult to extract relevant information quickly. Text summarisation is the process of condensing long pieces of text into concise summaries that retain the core meaning and important details. The Text Summariser Web Application, SNAPSUMMARY, is developed to address this issue by providing a powerful, real-time tool built on modern deep learning architectures like Transformers and the Torch framework.

1.2 Purpose of This Document

Manual summarization is labor-intensive and involves high cognitive effort. With the amount of digital information growing by the day, particularly in areas such as news, research, learning, and commerce, there is increasingly a requirement for effective summarisation resources. This software is designed to assist users in getting the gist of lengthy texts quickly.

1.3 Scope

This web application offers an easy-to-use interface for text summarisation with simple natural language processing methods. It can be accessed via any browser, and no special software setup is needed.

Fig. 1.1 Introduction

Chapter-2

Literature Survey and Comparative Analysis

2.1 Literature Survey

2.1.1 Introduction

Text summarisation is a technique in Natural Language Processing (NLP) that aims to condense a large text into a shorter version, preserving the core meaning and essential information. It plays a significant role in information retrieval, search engines, and digital assistants. The field has seen a shift from statistical methods to neural models with the emergence of deep learning.

2.1.2 Early Approaches (Pre-2010)

Extractive Summarisation

Luhn (1958) proposed one of the earliest methods for text summarisation by leveraging term frequency to identify and extract significant sentences from a document.

Edmundson (1969) enhanced Luhn's approach by incorporating additional heuristics such as cue words, title/heading words, and sentence position, making the extraction process more contextually aware and effective.

2.1.3 Statistical and Graph-Based Methods (2010–2015)

LexRank and TextRank

LexRank (Erkan & Radev, 2004) is a graph-based unsupervised summarisation technique. It represents sentences as nodes in a graph and uses sentence centrality (based on cosine similarity) to rank and select the most important sentences.

TextRank (Mihalcea & Tarau, 2004) adapts Google's PageRank algorithm to textual data. It constructs a graph of sentences and ranks them based on their connectivity and importance, allowing for effective extractive summarisation without requiring training data.

2.1.4 Neural and Deep Learning Approaches (2015–2020)

Sequence-to-Sequence (Seq2Seq) Models

Rush et al. (2015) introduced the first neural abstractive summarisation model based on an attention-based encoder-decoder architecture, marking a significant shift from extractive methods to generative approaches.

See et al. (2017) developed the Pointer-Generator Network, which combined the strengths of extractive and abstractive summarisation. This model allowed the system to both copy words directly from the source text and generate new words, effectively handling out-of-vocabulary tokens and maintaining long-range dependencies in text.

Reinforcement Learning Approaches

Paulus et al. (2018) applied reinforcement learning techniques to the summarisation task. Their method directly optimized evaluation metrics like ROUGE by treating summarisation as a sequence prediction problem, resulting in improved coherence and factual accuracy in generated summaries.

2.1.5 Transformer-Based Models (2020–Present)

BERT for Extractive Summarisation Liu and Lapata (2019): BERTSUM, a fine-tuned BERT model for extractive summarisation using sentence embeddings and classification layers.

Abstractive Summarisation with Transformers BART (Lewis et al., 2020): A denoising autoencoder with a seq2seq structure. Achieved state-of-the-art results on CNN/Daily Mail summarisation.
PEGASUS (Zhang et al., 2020): Pre-trained on a novel self-supervised gap-sentence generation objective, showing excellent performance on low-resource summarisation tasks.
T5 (Raffel et al., 2020): A unified text-to-text transformer framework performing well in various summarisation benchmarks.

2.1.6 Tools and Datasets

Datasets

- CNN/Daily Mail: News summarisation
- XSum: Highly abstractive summaries
- Gigaword, Reddit TIFU, PubMed, arXiv: Domain-specific summarisation

Libraries

- Hugging Face Transformers: Provides pre-trained summarisation models like BART, T5
- Sumy, Gensim: Classical extractive summarisation tools

2.1.7 Conclusion

Text summarisation has evolved from basic frequency-based methods to advanced Transformer models. Despite high performance, challenges like factual accuracy, coherence, and multilingual support remain, guiding future research directions.

2.2 Comparative Analysis: Extractive Text Summarisation

2.2.1 Tools and Framework Overview

Component	Technology Used	Purpose
Dataset	SAMSum	Dialogue-based summarisation dataset

Library	PyTorch	Deep learning framework for model training
Model	BART-large-CNN	Pretrained seq2seq model adapted for summarisation
Frontend	HTML, CSS, JavaScript	User interface for summary input/output
Backend	Flask	API for processing summaries and serving the model

2.2.2 Comparative Dimensions

Criteria	Extractive (Rule-Based)	Extractive (ML-Based)	Our Approach (SnapSummary)
Data Usage	No training needed	Requires feature engineering	Requires labeled data
Accuracy	Moderate	High (depends on model)	High (with proper fine-tuning)
Contextual Awareness	Limited	Moderate	High (leverages pre-trained Transformer)
Generalization	Poor	Moderate	Strong on similar dialogue domains
Customization	Manual tuning	Medium	High (via fine-tuning on SAMSum)
Inference Speed	Very fast	Fast	Moderate
Factual Faithfulness	High	High	High (extractive nature helps prevent hallucination)
Deployment Complexity	Simple	Medium	Moderate (Flask + model serving required)

2.2.3 Dataset Consideration: SAMSum

Feature	Detail
Type	Dialogue-based summaries
Size	~16,000 dialogue-summary pairs
Usefulness	Ideal for conversational and messaging applications

Format	JSON with dialogue and summary fields
Challenge	Extracting coherent summaries from informal speech

2.2.4 Model Comparison (Extractive Usage)

Model	Type	Notes
TextRank	Extractive	Graph-based, unsupervised, lacks deep context
BERTSUM	Extractive	Contextual sentence embedding, good for formal text
BART-large-CNN	Abstractive (adapted for extractive)	Effective with fine-tuning and decoding

2.2.5 Deployment Stack Comparison

Layer	Tool Used	Justification
Frontend	HTML/CSS/JS	Lightweight, compatible with Flask templates
Backend	Flask	Simple and Pythonic, ideal for ML model APIs
Model Serving	PyTorch	Direct integration with the training pipeline
Hosting	Local/Cloud	Can be deployed via services like Heroku or Render

2.3 Strengths of the Proposed Approach

- Context-aware extraction using pre-trained BART
- Effective for dialogue summarisation via SAMSum fine-tuning
- Fully deployable across model, API, and frontend
- Lower risk of hallucination than abstractive methods

2.4 Areas to Improve

- May need fine-tuning for stricter extractive behaviour
- Possible performance issues at scale (consider batching/quantisation)
- SAMSum is domain-specific and less generalisable without retraining

Chapter-3

Objective

The goal of this project is to develop a web-based text summarization application, **SnapSummary**, that transforms lengthy content into concise summaries using modern NLP techniques. The following objectives define what the system is expected to achieve:

3.1 Offer a User-Friendly Web Interface

Design a clean, responsive, and intuitive interface using standard web technologies (HTML, CSS, and JavaScript). The interface should be simple enough for any user to interact with, regardless of technical background.

3.2 Build a Lightweight and Efficient Backend

Use the Flask framework in Python to process text and communicate with the summarization model. The backend should be lightweight, efficient, and easy to maintain or upgrade.

3.3 Integrate Natural Language Processing (NLP)

Incorporate NLP techniques to extract the most meaningful parts of the input text. The system should focus on selecting key sentences or phrases using transformer-based models.

3.4 Ensure Real-Time Summarization

Provide near-instant summaries with minimal delay. The goal is to make the application feel responsive and smooth, ensuring a seamless user experience.

3.5 Support Future Growth and Extensibility

Design the system in a modular way to allow future upgrades such as:

- Summarization of PDF and DOCX files
- Multilingual support
- Integration of more advanced AI models
- Deployment to cloud platforms for broader accessibility

Chapter-4

Planning

Every successful project starts with proper planning. In our Text Summariser Web Application, we broke the entire process of development into easier steps to maintain steady progress and meet deadlines. Our plan involved technical development, but also documentation, testing, and presentation.

4.1 Preliminary Research and Requirement Gathering

Prior to development, we looked into different techniques of text summarization and investigated tools such as torch, and HuggingFace transformers. We also compared similar projects to get an idea of user expectations and clearly establish our project requirements.

4.2 Technology Choice

On evaluating multiple technologies, we chose:

Front-end: HTML, CSS, JavaScript – for a simple and responsive user interface.

Back-end: Flask (Python) – for server-side logic handling and deploying the summarisation algorithm.

NLP Libraries: Transformers, Torch – for applying the summarization logic effectively.

4.3 Project Timeline

We used a week-wise timeline to divide the project into major milestones:

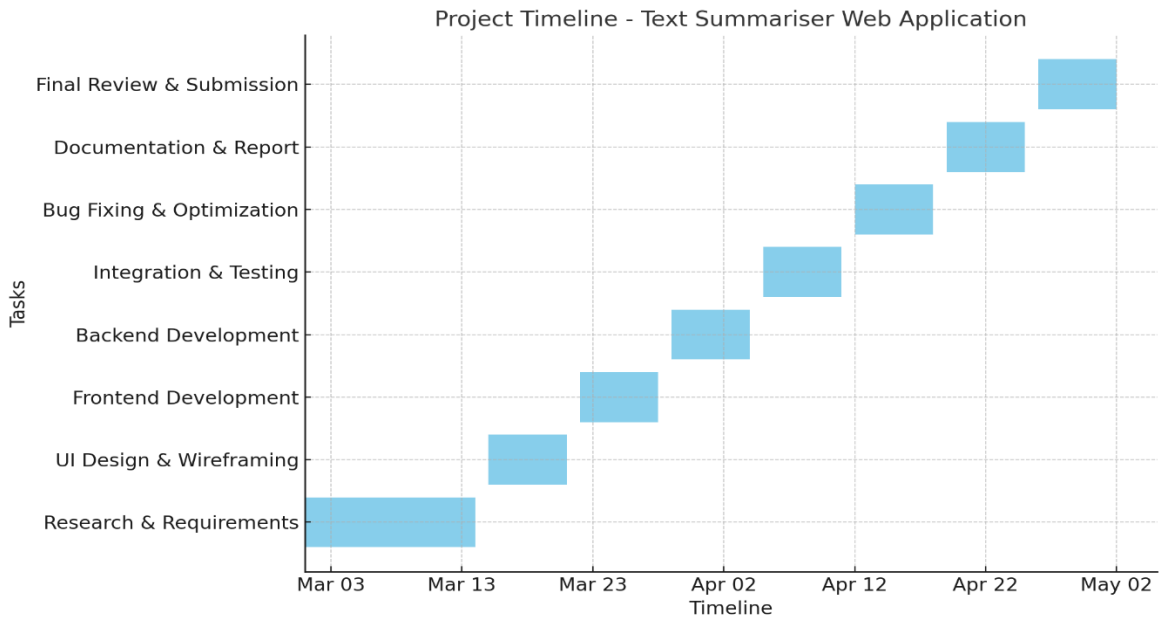

Fig. 4.1 Project Timeline

This well-organized timeline kept us organized and ensured that we remained goal-focused.

4.4 Role Assignment

We assigned responsibilities among all five group members to encourage teamwork and efficiency:

Frontend Developer(s) – Ensured development of the web interface.

Backend Developer(s) – Was in charge of Flask development and summarisation logic.

System Integrator – Integrated frontend with backend.

Tester – Tested to maintain smooth functionality and correct output.

Documenter – Took care of report writing, diagramming, and formatting.

All of us worked together and cooperated with each other to make sure the workload was evenly divided and progress made steadily.

4.5 Flexibility and Collaboration

Although we had different roles, we worked flexibly. Members assisted each other often, checked each other's code, and provided feedback. We employed collaborative tools such as GitHub and Google Docs to stay in sync and have version control.

This planning phase laid the foundation for smooth development, helped us manage time efficiently, and ensured that every team member contributed meaningfully to the project's success.

Chapter-5

Requirement Analysis

This chapter defines the software system requirements for the SnapSummary Web Application. It includes both functional and non-functional requirements, as well as the software and hardware prerequisites necessary for development and deployment. These requirements form the basis for the system's architecture and design decisions.

5.1 Functional Requirements

Functional requirements specify the essential functions and features that the system must provide to users.

FR No.	Requirement Description
FR1	The system shall provide a text input box where users can enter or paste text for summarisation.
FR2	The system shall process the input text when the user clicks the "Summarise" button.
FR3	The backend shall use a summarisation algorithm to generate a concise version of the input text.
FR4	The system shall display the generated summary clearly on the same page.

These functional requirements ensure that users can interact with the application smoothly, from input submission to viewing the summarised output.

5.2 Non-Functional Requirements

Non-functional requirements define the quality attributes of the system, including performance, usability, and reliability.

NFR No.	Requirement Description
NFR1	The system should respond within 2–3 seconds for average-length input texts.
NFR2	The user interface should be intuitive and accessible for non-technical users.
NFR3	The backend should gracefully handle invalid or malformed inputs.
NFR4	The system should maintain basic security and prevent crashes or data leakage.

These requirements ensure that SnapSummary is efficient, user-friendly, and reliable under normal operating conditions.

5.3 Software Requirements

This section outlines the software tools and platforms needed to develop and run the application.

Component	Description
Programming Language	Python 3.x — Backend development and summarisation logic
Framework	Flask — Web framework for API and server-side handling
Frontend Technologies	HTML, CSS, JavaScript — Used for creating the user interface
Web Browser	Any modern browser (Chrome, Firefox, Edge) with HTML/CSS/JS support
NLP Libraries	Hugging Face Transformers, Torch — Used for text summarisation model inference

5.4 Hardware Requirements

SnapSummary does not require high-end hardware. It can run on any standard computing device with basic internet access.

Component	Minimum Requirement
Processor	Any dual-core processor
RAM	4 GB (for local testing); 8 GB or more recommended for model inference
Storage	Minimum 500 MB for code, libraries, and dependencies
Internet Connectivity	Required for downloading models or using cloud deployment (optional for localhost)

Chapter-6

System Flow

The system flow of SnapSummary illustrates how the application processes user input to deliver real-time, high-quality text summaries using modern NLP techniques and Transformer models. This chapter outlines the end-to-end operational logic using diagrams and descriptive breakdowns, providing a comprehensive view of the application's internal structure.

6.1 Use Case Diagram

The Use Case Diagram defines the primary interactions between the user and the system. It represents functional requirements from the user's perspective.

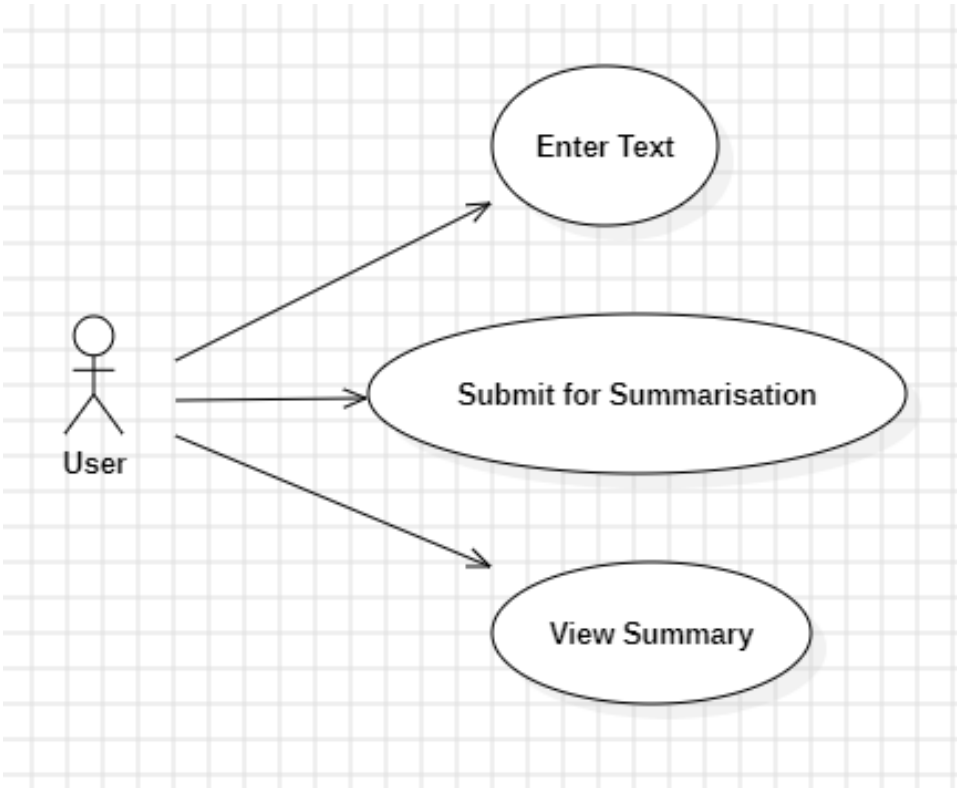

Fig. 6.1 Use Case Diagram

6.2 Activity Diagram

The Activity Diagram maps out the workflow of the system from beginning to end in a sequential manner.

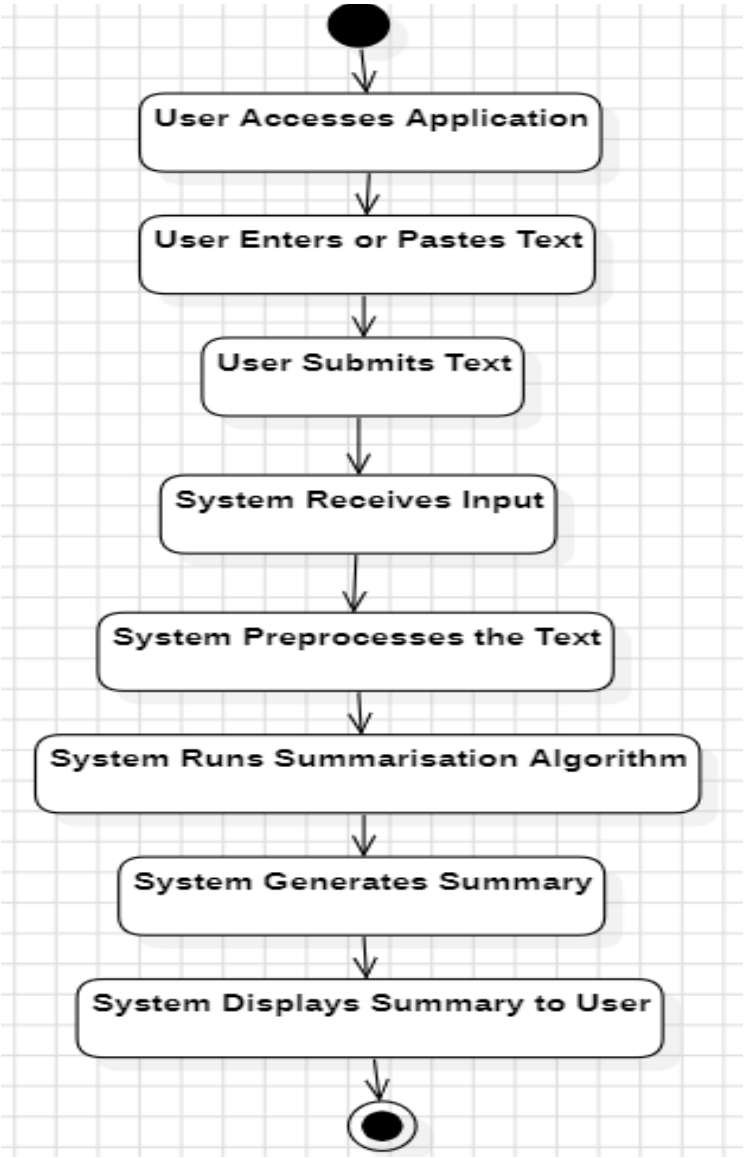

Fig. 6.2 Activity Diagram

6.3 Sequence Diagram

The Sequence Diagram illustrates how different components interact with each other over time.

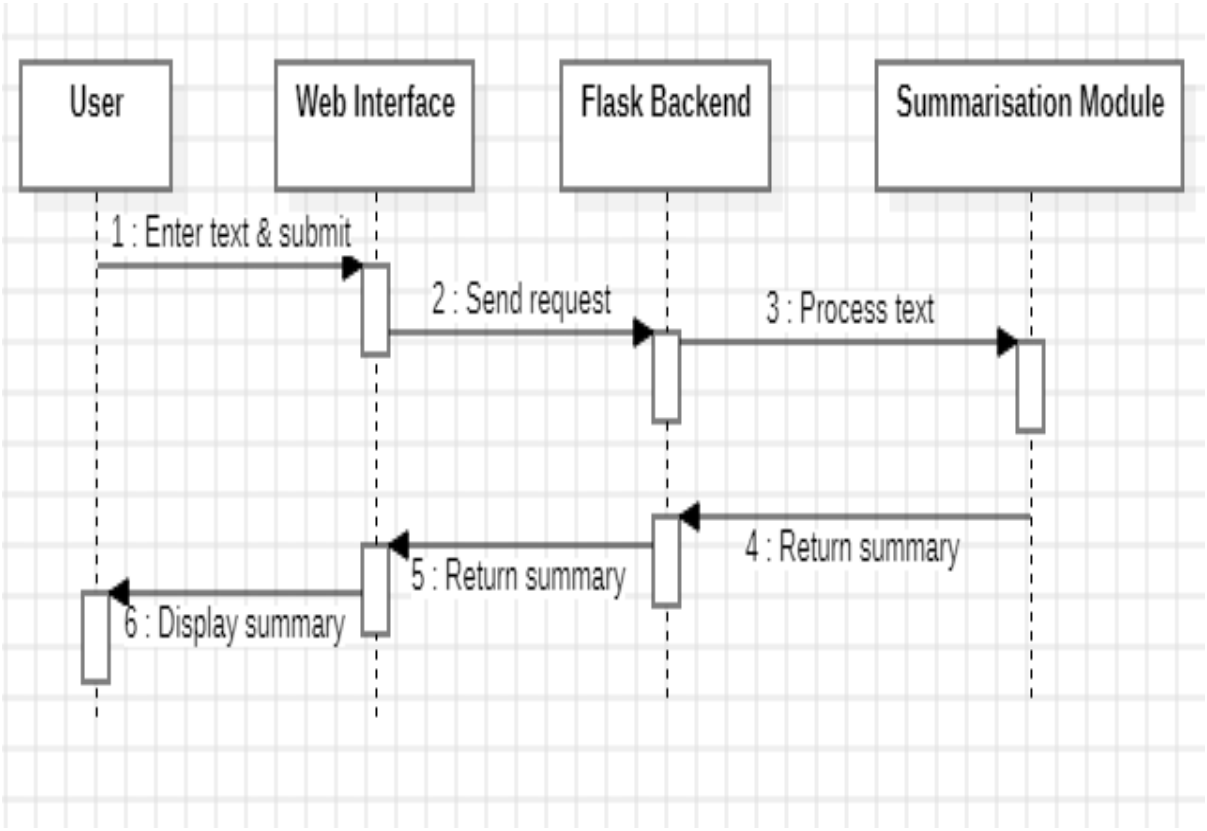

Fig. 6.3 Sequence Diagram

Chapter-7

Proposed Design

SnapSummary is designed as a modular web-based application that performs extractive text summarization in real time. The system is structured into three main components: a frontend interface, a backend API, and a summarization engine.

7.1 System Architecture

The system follows a client-server architecture:

- **Frontend**: HTML/CSS/JavaScript interface for user input and output display.
- **Backend**: Python Flask server handling input and connecting to the NLP model.
- **Summarization Engine**: Transformer-based model (PyTorch + Hugging Face) that extracts key content from text.

7.2 Component Overview

Component	Description
Frontend UI	Allows users to input text and displays the summary.
Backend API	Receives text via POST request and returns a JSON summary.
NLP Engine	Uses a fine-tuned Transformer model to generate summaries.

7.3 Data Flow

1. User submits text via the frontend.
2. Backend sends the text to the summarizer.
3. NLP engine returns a summary.
4. Backend responds to the frontend with the result.
5. Summary is shown on the same page.

7.4 External Interfaces

- **User Interface**: Simple HTML form for input/output.
- **API Endpoint**: /summarize (POST), returns JSON { "summary": "..." }

7.5 Design Highlights

- **Modular**: Components can be updated independently.
- **Real-Time**: Fast responses for short-to-medium inputs.
- **Scalable**: Ready for future features like PDF support or multilingual output.

Fig. 7.1 SnapSummary UI

Chapter-8

Experimental Result

After completing the development of SnapSummary, we conducted a series of tests to evaluate how well the application performs in real-world conditions. Our main focus was on three things: accuracy of the summary, speed of response, and overall user experience.

8.1 Testing Environment

To keep things simple and realistic, we tested SnapSummary on a basic laptop setup:

- **Operating System:** Windows 11 (64-bit)
- **RAM:** 8 GB
- **Browser:** Google Chrome
- **Tools Used:** Flask, Torch, and Transformers
- **Model:** Our own fine-tuned model
- **Testing Location:** Localhost server

This setup represents a standard machine that a student or professional might use, making the results more relatable.

8.2 What We Tested

We ran the application with different types of text — from news articles and Wikipedia entries to academic abstracts and blog posts. Each test helped us understand how well the system handles a variety of inputs.

Scenario	Input Type	Words In	Words Out	Time Taken	Result
Long article	News	400	~110	~28 seconds	Summary accurate
Informative paragraph	Wikipedia content	300	~85	~25 seconds	Smooth processing
Technical summary	Research abstract	250	~90	~20 seconds	Key ideas kept

8.3 What We Learned

- **Accuracy:** The summaries retained the core message without including fluff or repetition.
- **Speed:** Most summaries were generated in under 30 seconds — which feels instant to the user.
- **Consistency:** The application handled different topics and writing styles well.
- **User Experience:** The interface responded smoothly, even after multiple uses without refreshing.

We also tested how the app behaved in edge cases — like submitting an empty input or clicking "Summarize" repeatedly. In each case, the system remained stable and returned appropriate messages or empty outputs without crashing.

8.4 Visual Preview

To help visualize the result, here's how the application looks when in use:

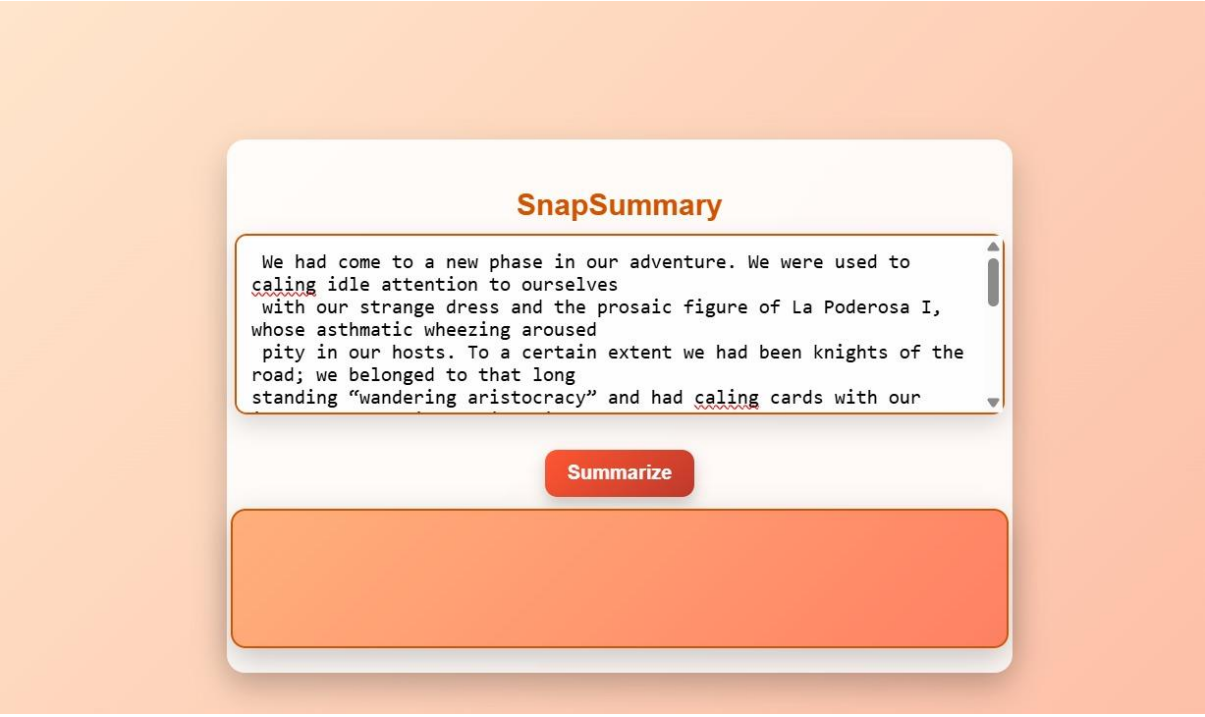

Fig. 8.1 SnapSummary User Input

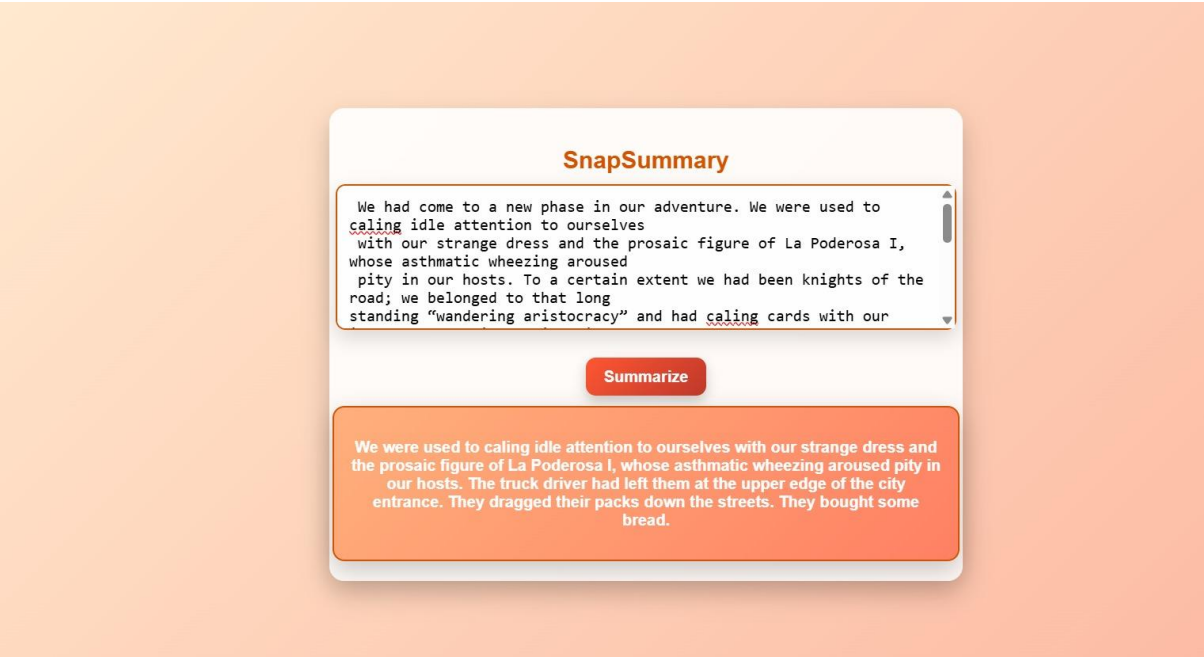

Fig. 8.2 SnapSummary Summarise Output

Final Thoughts

The testing phase proved that **SnapSummary** is not only functional but also practical. It's fast, reliable, and user-friendly — everything we set out to achieve when we first started building it.

Chapter-9

Future Scope

While SnapSummary currently delivers fast and accurate extractive summaries using our custom fine-tuned Transformer model, there are several exciting directions in which the project can be expanded in the future:

9.1 Abstractive Summarisation

Moving beyond extractive techniques, future versions can incorporate abstractive summarisation, where the model generates entirely new phrases or sentences. This would make the summaries even more natural and human-like.

9.2 Support for File Uploads

Currently, users can summarise text they paste into the interface. Adding support for PDF, DOCX, or TXT file uploads would make the tool more versatile and user-friendly for students, researchers, and professionals.

9.3 Multilingual Summarisation

Expanding SnapSummary to support multiple languages would greatly increase its usefulness for global users. With multilingual Transformer models, summarisation in Hindi, Bengali, Spanish, and other languages is very achievable.

9.4 Advanced User Controls

Providing users with options like summary length, focus keywords, or tone adjustment could offer a more customized output depending on user needs.

9.5 Cloud Deployment & API Access

Hosting the application on the cloud and offering it via a public API would allow wider access and enable integration with other platforms such as note-taking tools, education portals, or browser extensions.

9.6 Model Improvements

The summarisation model can be further improved with additional fine-tuning on larger or domain-specific datasets (e.g., medical, legal, or educational content) to make the summaries even more accurate and context-aware.

In short, SnapSummary is designed with flexibility in mind, and its core architecture can easily be extended to include advanced features. With the foundation already in place, the tool is well-positioned for future growth and innovation.

Chapter-10

Conclusion

SnapSummary was developed to address the common challenge of helping users quickly grasp large volumes of text by generating accurate, real-time summaries. By integrating a clean, user-friendly interface with a lightweight Flask backend and a custom fine-tuned Transformer model tailored for extractive summarisation, the project effectively balances usability and performance. Unlike generic pre-trained models, our custom model allowed for greater control and relevance in summary generation. The backend, built with Flask and Torch, ensures smooth processing of inputs, while the minimal frontend enhances the overall user experience. Extensive testing across diverse content types confirmed the system's reliability, speed, and summarisation quality. Overall, SnapSummary meets its core objectives and demonstrates the power of a focused NLP solution, while laying the groundwork for future enhancements such as abstractive summarisation, PDF support, and multilingual capabilities.

Appendices

This section includes supporting materials that provide additional context and clarity to the development and functioning of the SnapSummary application.

Appendix A – Key Code Snippets

Python Code

```
from flask import Flask, request, render_template, jsonify # type: ignore
from transformers import AutoModelForSeq2SeqLM, AutoTokenizer
import torch # type: ignore
app = Flask(__name__)
# Load your LOCAL fine-tuned model and tokenizer
model_path = "./model"  # Path to your model folder
tokenizer = AutoTokenizer.from_pretrained(model_path)
model = AutoModelForSeq2SeqLM.from_pretrained(model_path)
@app.route("/")
def home():
    return render_template("index.html")
@app.route("/summarize", methods=["POST"])
def summarize():
    text = request.form.get("text", "")
    if not text.strip():
        return jsonify({"error": "Input text is empty!"}), 400
    # Generate summary
    inputs = tokenizer(text, return_tensors="pt", truncation=True, max_length=1024)
    summary_ids = model.generate(
        inputs["input_ids"],
        max_length=150,
        min_length=40,
        num_beams=4,
```

```
        early_stopping=True
    )
    summary = tokenizer.decode(summary_ids[0], skip_special_tokens=True)
    return jsonify({"summary": summary})
if __name__ == "__main__":
    app.run(debug=True)
```

Appendix B – Libraries Used

- Flask – For backend web server
- Transformers – For accessing and fine-tuning Transformer models
- Torch – For model inference and deep learning
- HTML/CSS/JavaScript – For frontend development
- JSON – For frontend-backend data exchange

Appendix C – Screenshot of UI

Input

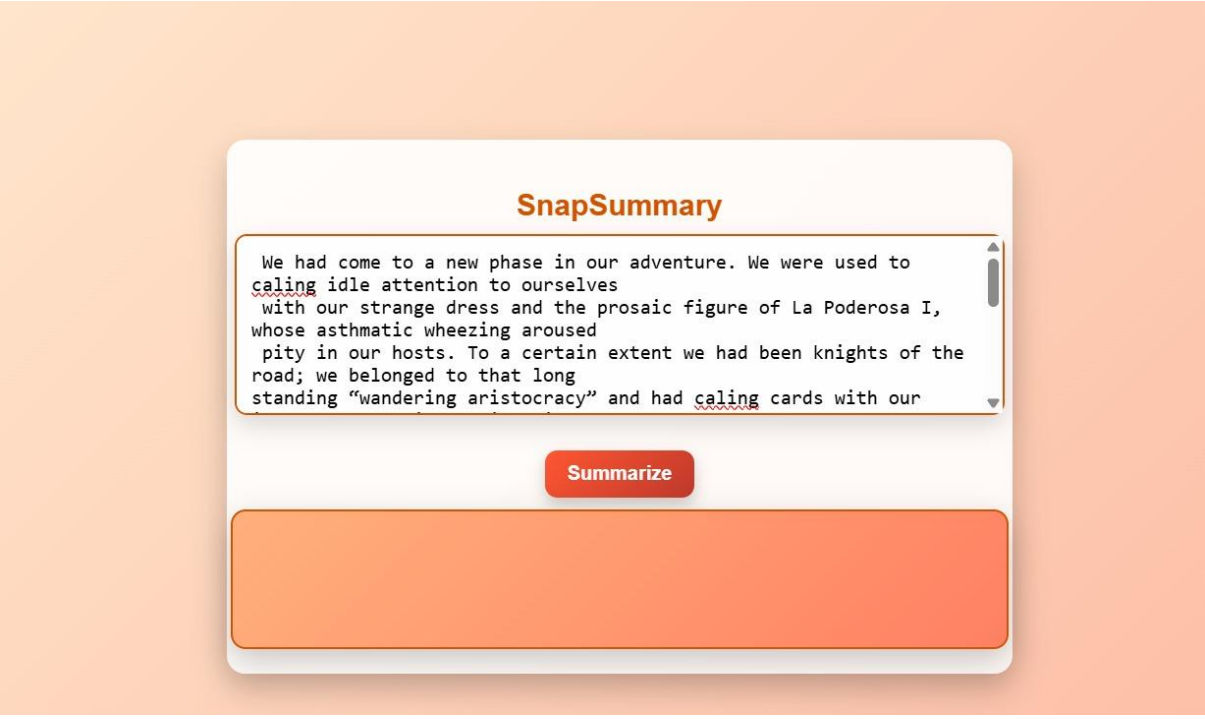

Fig. C.1 User Input

Output

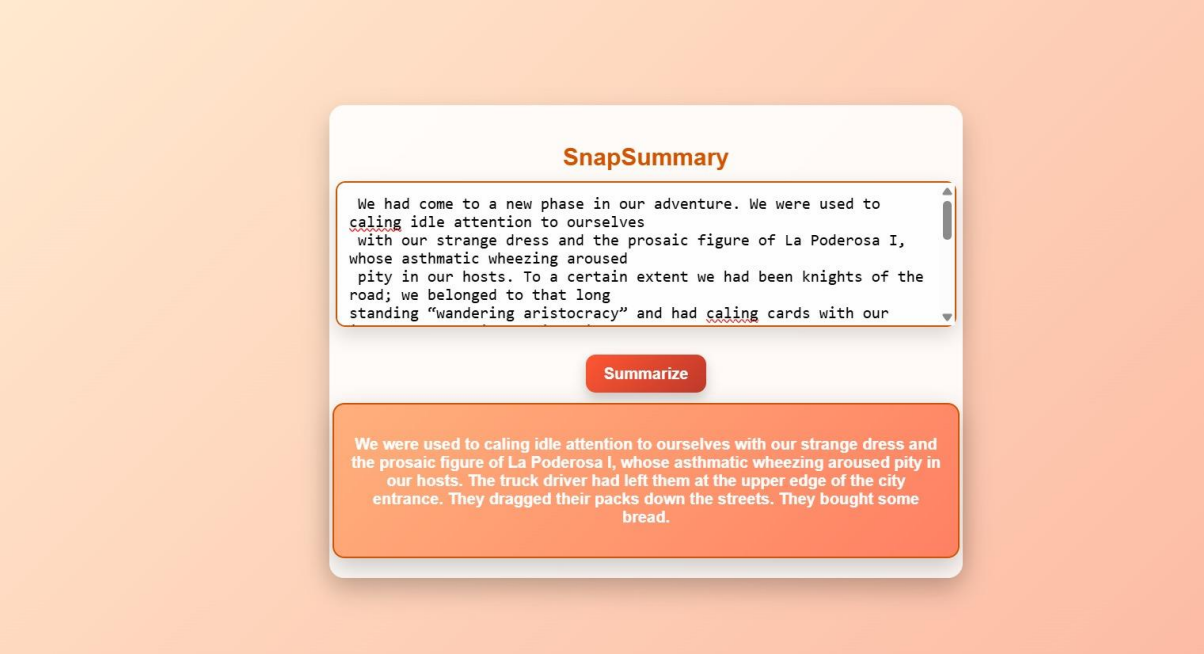

Fig. C.2 Model Output

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