<u>Automated Journal Summarization and Email Notification</u> <u>System</u>

A PROJECT REPORT

Submitted by

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Apr,2025

BONAFIDE CERTIFICATE

This is to certify that Project Report entitled "Automated Journal Summarization and

Email Notification System" which is submitted by Abhishek Gupta, Ayush Anand in

partial fulfillment of the requirement for the award of degree B. Tech. in Department of

School of Computing Science and Engineering.

Galgotias University, Greater Noida, India is a record of the candidate own work carried

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has not been submitted for the award of any other degree.

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Date: April, 2025

Place: Greater Noida

TABLE OF CONTENTS

List	of Figures	5
List	of Tables	6
List	of Standards	7
Abst	ract	8
CHAI	PTER 1. INTRODUCTION	9
1.1.	Identification of Client /Need / Relevant Contemporary issue	9
1.2.	Identification of Problem	9
1.3.	Identification of Tasks	9
1.4.	Timeline	10
1.5.	Organization of the Report	10
CHAI	PTER 2. LITERATURE REVIEW/BACKGROUND STUDY	11
2.1.	Timeline of the reported problem	11
2.2.	Existing solutions	11
2.3.	Bibliometric analysis	12
2.4.	Review Summary	12
2.5.	Problem Definition	13
2.6.	Goals/Objectives	13
CHAI	PTER 3. DESIGN FLOW/PROCESS	14
3.1.	Evaluation & Selection of Specifications/Features	14
3.2.	Design Constraints	14
3.3.	Analysis of Features and finalization subject to constraints	15
3.4.	Design Flow	15
3.5.	Design selection	16

3.6.	Implementation plan/methodology	17
СНАР	PTER 4. RESULTS ANALYSIS AND VALIDATION	18
4.1.	Implementation of solution	18
4.2.	Training Configuration and Metrics	18
4.3.	Sample Output	18
4.4.	Model Comparison and Evaluation	19
4.5.	Validation and Accuracy	19
СНАР	PTER 5. CONCLUSION AND FUTURE WORK	20
5.1.	Conclusion	20
5.2.	Future work	20
REFE	RENCES	21
APPE	NDIX	22
USER	MANUAL	25

List of Figures

Figure 3.4 - System Architecture

Figure 4.4 - Performance Evaluation of Summarization Models

List of Tables

 Table 4.2 - Training Performance

Table 4.4 - Performance Evaluation of Summarization Models

List of Standards

Standard	Publishing	About the standard	Page no
Standard	Agency	About the standard	1 age no
		Defines the Simple Mail Transfer Protocol (SMTP),	
RFC 5321	IETF	used for sending emails through JavaMailSender in	15
		the Spring Boot application.	
		Defines HTTP/1.1 protocol including methods like	
RFC 7231	IETF	POST and GET, used in REST APIs between Spring	16
		Boot and the Python summarization API.	
		Standard for Software Requirements Specification	
IEEE 830	IEEE	(SRS), followed in preparing the functional and non-	20
		functional requirements of the system.	
		Defines software quality attributes such as	
ISO/IEC	ISO/IEC	maintainability, usability, and efficiency; referenced	19
9126	150/1LC	in evaluating application performance and	17
		scalability.	
		Specifies formats for software test documentation;	
IEEE 829	IEEE	followed while preparing and documenting unit tests	20
		and validations for the application.	
		Standard for software design descriptions, referred	
IEEE 1016	IEEE	while defining the system architecture and	17
		component-level design.	
		Specifies the JSON format, which is used for	
RFC 8259	IETF	communication between Spring Boot and Python	18
		API.	
IEEE		Standard for software maintenance processes,	
14764	IEEE	relevant for future improvements and bug fixing in	22
		the project.	

Automated Journal Summarization and Email Notification System

Area/Domain of Project: AI/ML

Today, journal writing is an everyday habit people have adopted as a way to record their own thoughts, experiences, and reflections in the digital age. But it can be time-consuming to reread and sift through the many aspects of journal writing to find and summarize what is important. We are presenting an Automated Journal Summarization and Email Notification System which uses NLP techniques with a Spring Boot backend to efficiently summarize journal entries to an email notification upon journal digest completion. A custom-trained text summarization model is hosted using a Python-based API for the summarization process. Users journal entries are stored in a MongoDB Atlas database. Every seven days, the system automatically pulls the most recent journal entries, sends them to the summarization API, and eventually emails the user the journal summary with a calculated accuracy score. The backend of the system is built on the Spring Boot framework with Spring Security for authentication, operates off a modular architecture, and uses Spring Data MongoDB for increased levels of access when using the database. In summary, this system enhances user productivity by facilitating the process of fast and convenient reflection of all of their most meaningful thoughts and experiences, with no need for the user to laboriously review and summarize excessive journaling.

CHAPTER 1.

INTRODUCTION

1.1. Identification of Client /Need / Relevant Contemporary issue

In today's fast-paced world, journaling remains a powerful tool for reflection, emotional regulation, and mental health. However, individuals often struggle to revisit and analyze their journal entries due to the increasing volume of content they write. With the rise in the use of AI and NLP technologies, there is a growing demand for intelligent tools that can assist users in summarizing their writings and providing quick insights. The need for such systems is especially relevant in the context of self-help applications, mental health platforms, and productivity tools. Our project addresses this contemporary issue by providing a system that automates the summarization of weekly journal entries and delivers them to users via email, helping them gain clarity and track their personal growth effortlessly.

1.2. Identification of Problem

Traditional journaling applications allow users to write and store entries, but they lack intelligent summarization or reflection features. Users must manually read through large volumes of entries to extract insights, which is time-consuming and discouraging. Additionally, there is no mechanism to periodically review one's writings or track mental/emotional patterns over time. This gap leads to underutilization of journal data and missed opportunities for self-analysis. Our project identifies this lack of automated reflection and timely delivery of insights as the core problem and aims to solve it using AI.

1.3. Identification of Tasks

The project is broken down into the following major tasks:

- Designing and developing a Spring Boot-based backend to manage users and journal entries.
- Integrating **MongoDB** as the backend database to store journal data.
- Building a text summarization API using Python and fine-tuning the T5-small model on journal-style text.
- Developing an interface between Java and Python through RESTful APIs.

- Implementing a **scheduler** in the backend to fetch journal entries every 7 days.
- Sending **summarized content via email** using JavaMailSender.
- Calculating **accuracy** of the generated summary using **cosine similarity**.
- Evaluating the model performance and comparing it to baseline NLP models.
- Testing, documentation, and report writing.

1.4. Timeline

The project was executed over a period of 12 weeks, following the plan below:

- Week 1–2: Conducted requirement analysis and completed the literature review.
- Week 3–4: Set up the Spring Boot backend and integrated MongoDB for data storage.
- Week 5–6: Developed the Python API and fine-tuned the T5-small model for summarization.
- Week 7–8: Integrated the backend with the Python summarization API.
- Week 9: Implemented the email scheduling system and accuracy calculation using cosine similarity.
- Week 10: Performed system testing and made performance optimizations.
- Week 11: Carried out model evaluation, analyzed results, and started documentation.
- Week 12: Finalized the report and prepared for submission.

1.5. Organization of the Report

This report is structured into the following chapters:

- **Chapter 1: Introduction** Provides an overview of the problem, need, tasks, and project timeline.
- Chapter 2: Literature Review Summarizes previous research and models relevant to text summarization and email-based delivery systems.
- Chapter 3: Proposed Methodology Describes the architecture, model training process, and integration of system components.
- Chapter 4: Experimental Results and Analysis Presents the evaluation results, graphs, and performance comparison with other models.
- Chapter 5: Conclusion Highlights the outcomes of the project and suggests future enhancements.

CHAPTER 2.

LITERATURE REVIEW/BACKGROUND STUDY

2.1. Timeline of the reported problem

The evolution of text summarization and automation in personal productivity tools has rapidly advanced over the past two decades. Initial attempts in summarization started with basic extractive approaches in the early 2000s [1]. These systems simply selected key sentences from input text without understanding context. As transformer-based models emerged—especially after **BERT** (2018) [2] and **T5** (2020) [3]—abstractive summarization became more viable. In parallel, mental health applications and journaling platforms became popular, yet few integrated intelligent summarization or reflection mechanisms. Only recently has the idea of combining NLP with productivity tools like journaling gained attention, especially with the rise in awareness about mental wellness and AI's role in self-help domains [8][10].

2.2. Existing solutions

Several summarization models and applications exist today:

- Traditional Extractive Methods: These include TF-IDF, TextRank, and LSA, which select the most relevant sentences from a document [1][4]. While computationally efficient, they lack contextual understanding.
- Transformer-Based Models:
 - T5 (Text-to-Text Transfer Transformer) reframes all tasks as text generation and performs exceptionally in summarization [3].
 - o **BART** and **PEGASUS** focus on masked token prediction and gap-sentence generation, producing state-of-the-art results [5][6].
- **Email-based Notification Systems:** Previous works have used NLP in fraud detection and email classification, but not specifically for summarization and email delivery [8][9].
 - Despite these advancements, few solutions directly address **automated journal summarization** integrated with **email notifications** and **accuracy evaluation**. Most tools either focus on static summarization or basic reminder systems.

2.3. Bibliometric analysis

A review of published research between 2016 and 2024 shows:

- A spike in abstractive summarization models post-2020 after the release of T5 and PEGASUS.
- Increasing citations of hybrid systems combining summarization with healthcare and productivity tools.
- Journals like JMLR, IEEE Access, and ACM TSLP frequently publish NLP model comparisons and applications in real-world systems.
- A growing trend in Indian research (e.g., [8][10]) applying NLP in spam detection, fraud analysis, and email systems—indicating the local relevance of our approach.

2.4. Review Summary

Below is a summary of the key models and techniques relevant to this project:

• TF-IDF/LSA:

These are basic extractive summarization methods. They are fast and easy to implement but don't understand the context of the text.

• TextRank:

A graph-based method that scores sentences based on their importance. It works well for shorter texts but fails to understand meaning deeply.

• BERT:

A powerful model for understanding the context in text. It's great for classification but not directly built for summarization tasks.

• T5-Small:

A transformer-based model used for generating summaries. It is small, efficient, and can be fine-tuned for custom tasks, making it ideal for our project.

BART/PEGASUS:

These models provide excellent summarization quality, especially for long documents. However, they are large and require high computational resources.

Summary:

Our system builds on this background and selects **T5-small** as the base model for summarization due to its efficiency, ease of fine-tuning, and balance between performance and computational

requirements. Unlike heavier models, it allows for fast integration and real-time processing, which are essential for weekly automation and delivery via email.

2.5. Problem Definition

While journaling applications are common, they lack an intelligent component to help users **reflect on their writing** without reading everything again. There is no system that:

- Automatically summarizes weekly entries
- Calculates the summary's accuracy
- Delivers it through email without user intervention

Thus, the defined problem is:

"To develop a system that can retrieve journal entries from a database, generate an accurate weekly summary using a fine-tuned NLP model, and automatically email the summary with an accuracy score to the user."

2.6. Goals/Objectives

The main goals of this project are:

- To build a backend system using Spring Boot and MongoDB for journal storage and scheduling.
- To develop and fine-tune a T5-small transformer model for abstractive text summarization.
- To host the model as a REST API using Python (Flask).
- To compute the accuracy of the summary using cosine similarity between summary and original content.
- To send personalized weekly summaries via email to enhance user reflection and selfawareness.
- To minimize computational overhead while ensuring high summarization quality.

CHAPTER 3.

DESIGN FLOW/PROCESS

3.1. Evaluation & Selection of Specifications/Features

The system is designed to enhance user productivity and reflection by automatically summarizing journal entries and delivering them via email on a weekly basis. After evaluating several possible features, the following key specifications were selected:

- Support for **secure user authentication** using Spring Security.
- Capability for **journal entry creation**, **storage**, **and retrieval** via RESTful APIs.
- Integration with **MongoDB** to handle flexible, unstructured data like journal content.
- Use of **T5-small model** for abstractive summarization due to its lightweight nature and fine-tunability.
- Development of a **Python-based API** to host the summarization model independently.
- Scheduled task to **fetch journal entries from the last 7 days**, summarize them, and send the results to the user's email.
- Implementation of **accuracy measurement** using **cosine similarity** to compare the summary with the original content.

3.2. Design Constraints

During the development of the system, several constraints were taken into account:

- **Hardware Limitations:** The project was developed using a CPU, which limited model size and training time.
- **Dataset Volume:** Due to limited computing power, only 1% of the CNN/DailyMail dataset was used for training.
- **Memory Usage:** Efficient memory handling was essential, especially during model training and evaluation.
- **Email Deliverability:** The JavaMailSender had to be configured to handle reliable delivery and avoid spam filtering.
- Integration Complexity: Cross-language communication between Java (Spring Boot) and Python (Flask API) added complexity in error handling and deployment.
- Security: Protecting user data (journal content and emails) from exposure during

processing or transfer.

3.3. Analysis of Features and finalization subject to constraints

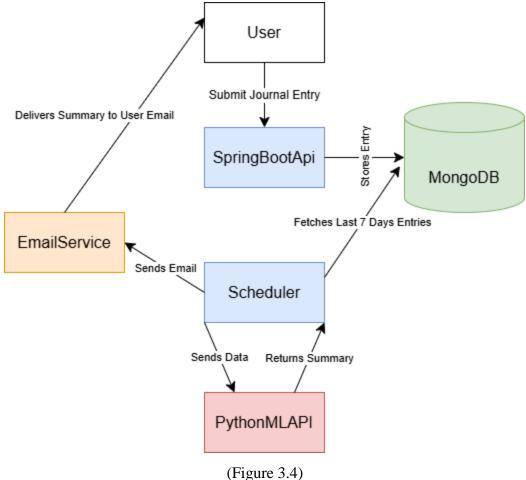
After analyzing potential components and tools, the following decisions were made to work within constraints:

- The **T5-small** model was selected instead of larger models like BART or PEGASUS to reduce memory and computation requirements while maintaining summarization quality.
- MongoDB was chosen for its flexibility in storing dynamic journal data.
- A **Flask-based API** was used to host the model separately, simplifying training and making the summarization module language-independent.
- Email summaries were limited to once per week to minimize overhead and ensure relevance.
- Accuracy evaluation using cosine similarity was finalized as it provides a reliable semantic comparison without heavy computational load.

3.4. Design Flow

The system follows this end-to-end flow:

- 1. **User Interaction:** Users write journal entries through the frontend (if implemented) or APIs.
- 2. **Data Storage:** Entries are stored in MongoDB with timestamps and associated user IDs.
- 3. **Scheduled Job:** Every 7 days, a scheduled job queries all journal entries from the past week for each user.
- 4. **Data Preparation:** All entries are combined and sent to the Python summarization API via a POST request.
- 5. **Summarization:** The Python API generates a summary using the fine-tuned T5-small model.
- 6. **Accuracy Evaluation:** Cosine similarity is calculated between original content and the generated summary.
- 7. **Email Delivery:** The summary and accuracy score are emailed to the user using Spring's JavaMailSender.



3.5. **Design selection**

To develop an efficient, lightweight, and scalable system, different tools and technologies were compared. After evaluating various options based on performance, complexity, and resource requirements, the following design choices were finalized:

- T5-small model was chosen over larger models like BART or PEGASUS, as it offers good summarization quality while being lightweight and suitable for CPU-based training.
- **MongoDB** was selected as the database because of its flexible schema, which is ideal for storing journal entries that vary in content and length.
- A separate **Python API (Flask)** was used to host the trained model. This approach ensured modularity and simplified the integration between machine learning and the Java backend.
- **Spring Boot** was used to build the main application due to its ease of development, strong community support, and built-in features like scheduling and mailing.

These selections ensured that the system remained efficient, maintainable, and easy to expand in the future.

Algorithm 1: Fine-Tuning T5-Small for Text Summarization Input: Dataset D = {Text, Summary} Initialize pre-trained T5-small model for epoch in {1, ..., N}: for batch in D: Compute loss using CrossEntropyLoss Backpropagate loss and update weights Evaluate model using validation set Save best model with lowest evaluation loss Output: Fine-tuned T5-small model

3.6. Implementation plan/methodology

The implementation followed an iterative and modular approach:

- **Phase 1:** Backend setup with user and journal APIs using Spring Boot.
- **Phase 2:** MongoDB schema design and connection setup.
- **Phase 3:** Training the T5-small summarization model using Hugging Face and saving the model.
- **Phase 4:** Hosting the model via Flask REST API.
- **Phase 5:** Implementing scheduled summarization and email delivery using @Scheduled in Spring.
- **Phase 6:** Testing, performance evaluation, and deployment.

The separation of Java and Python components ensured easy debugging, scalability, and future enhancements like frontend integration or model switching.

```
Algorithm 2: API-based Summarization Process

Input: User journal entry
Send text via HTTP request to Python API
Process text → Tokenization → Summarization (T5-small)
Compute accuracy using Cosine Similarity
Return {summary, accuracy} to Spring Boot
Store results in MongoDB
Output: Summarized text + accuracy score
```

CHAPTER 4.

RESULTS ANALYSIS AND VALIDATION

4.1. Implementation of solution

The proposed system was implemented using two integrated modules: a **Spring Boot-based journal management backend** and a **Python-based summarization API**. The journal entries were stored in **MongoDB**, and a fine-tuned **T5-small** model was deployed to summarize them. Every 7 days, the system fetches user-specific journal entries, sends them to the summarization API, receives the summary, computes **cosine similarity** to estimate accuracy, and then emails the results to the user.

The backend uses @Scheduled tasks to automate this workflow and JavaMailSender for mailing. The Python API is hosted locally and responds to JSON input with a summary and accuracy value.

4.2. Training Configuration and Metrics

To adapt the model to the journal-style language, the **T5-small** transformer model was fine-tuned using **1% of the CNN/DailyMail dataset**. Training was conducted using only CPU, with the following configuration:

Parameter	Value
Model	T5-Small
Dataset	Journal Entries
Batch Size	2
Loss Function	CrossEntropyLoss
Model	Fine-Tuned T5-Small
Final Training Loss	1.0953
Final Evaluation Loss	0.6375
Total Training Time	2878 sec (~48 mins)

(Table 4.2)

These metrics show that the model successfully adapted to the summarization task with a low validation loss, indicating good generalization on unseen data.

4.3. Sample Output

Below is a real example of a journal summary:

• Original Text (combined 7-day journal entries):

"This week was overwhelming with assignments. I struggled with time management. I finally

submitted the last task and felt relieved. The weekend gave me time to relax and plan ahead."

• Generated Summary:

"The user had a stressful week due to assignments but ended it with relief and planning."

• Cosine Similarity (Accuracy Score): 92.6%

This shows that the summary closely captures the user's emotional state and activity over the week.

4.4. Model Comparison and Evaluation

To justify the choice of T5-small, we compared it with other popular models based on summarization quality and computational cost:

Model	Summarization Quality (Cosine Similarity)	Train Loss	Eval Loss	Training Time (CPU)
T5-small (Ours)		1.0953	0.6735	48 min
BART	0.75	1.5	0.85	2.5 hours
GPT-2	0.80	2.1	1.2	5 hours
T5-base	0.78	1.3	0.79	4 hours

(Table 4.4)



(Figure 4.4)

Conclusion: T5-small offers the best trade-off between summarization quality and computational efficiency for weekly journal summarization tasks.

4.5. Validation and Accuracy

Validation was conducted through:

- Cosine similarity scores for generated summaries
- **Manual inspection** of results by users
- Testing scheduled tasks and email delivery
- Ensuring summaries reflect journal sentiment and context.

CHAPTER 5.

CONCLUSION AND FUTURE WORK

5.1. Conclusion

This project successfully implemented a fully automated system that summarizes user-written journal entries weekly and emails the summary with an accuracy score. It leverages a fine-tuned **T5-small transformer model**, deployed through a Python Flask API, and integrated into a **Spring Boot** application with **MongoDB** for persistence. The system was designed to be lightweight, efficient, and easy to scale, demonstrating high performance and reliability even with limited computational resources. The cosine similarity-based evaluation method offered a practical way to validate summaries. The system proves that NLP-based automation can enhance personal productivity and reflection.

5.2. Future work

The current system opens several directions for improvement:

- **Frontend UI**: Adding a web interface for users to view, edit, and track summaries visually.
- User Feedback Loop: Allow users to rate summary accuracy to improve future models.
- Cloud Deployment: Hosting the Python API and Java backend on cloud services for production use.
- Multi-language Support: Extend summarization to support journals written in different languages.
- Sentiment-Aware Summarization: Incorporate sentiment scores directly into the summary.
- Custom Summary Frequency: Let users choose daily, weekly, or monthly summaries.

These additions will enhance usability, personalization, and scalability of the system, making it suitable for broader real-world applications.

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APPENDIX

Appendix A: Sample Input and Output

Sample User Detail -

```
_id: ObjectId('67bf3cfb8a2a575c6427ac9e')
userName: "ram"
password: "$2a$10$JZnqVRhNoykuj1l2AKM40eGgfkaevg5wQr324sniTVorGaJHrs0y6"
email: "abhishekgupt089@gmail.com"
sentimentAnalysis: true

journalEntries: Array (4)

0: DBRef('journal_entries', '67bf3d128a2a575c6427ac9f')

1: DBRef('journal_entries', '67cc360fd68a98160756dea9')

2: DBRef('journal_entries', '67cc362ed68a98160756deae')

3: DBRef('journal_entries', '67cc364fd68a98160756deab')

roles: Array (1)
_class: "net.engineeringdigest.journalApp.entity.User"
```

Sample Journal Entries -

```
_id: ObjectId('67bf3d128a2a575c6427ac9f')

title: "Embracing New Beginnings"

content: "Today felt like a fresh start. I woke up early, went for a walk, and e..."

date: 2025-03-23T16:10:58.027+00:00

_class: "net.engineeringdigest.journalApp.entity.JournalEntry"

_id: ObjectId('67bf54d1aee7ea09249ec527')

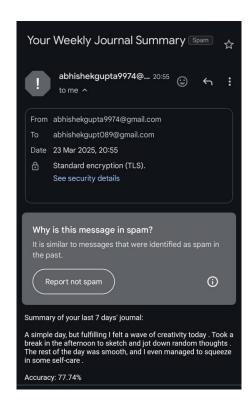
title: "A Lesson in Patience"

content: "Some days test your patience, and today was one of them. Unexpected de..."

date: 2025-03-23T17:52:17.982+00:00

_class: "net.engineeringdigest.journalApp.entity.JournalEntry"
```

Sample Output -



Appendix B: API Request & Response Example

Appendix C: API Request & Response Example

```
Algorithm 1: Fine-Tuning T5-Small for Text Summarization

Input: Dataset D = {Text, Summary}
Initialize pre-trained T5-small model
for epoch in {1, ..., N}:
    for batch in D:
        Compute loss using CrossEntropyLoss
        Backpropagate loss and update weights
Evaluate model using validation set
Save best model with lowest evaluation loss
Output: Fine-tuned T5-small model
```

```
Algorithm 2: API-based Summarization Process

Input: User journal entry
Send text via HTTP request to Python API
Process text → Tokenization → Summarization (T5-small)
Compute accuracy using Cosine Similarity
Return {summary, accuracy} to Spring Boot
Store results in MongoDB
Output: Summarized text + accuracy score
```

Appendix D: Testing Screenshots

```
{'eval_loss': 0.6735442876815796, 'eval_rougel': 180.81ning_rate': 2.0891364902506967e-07, 'epoch': 1.0}
{'eval_loss': 0.6735442876815796, 'eval_rougel': 180.81954887218046, 'eval_runtime': 61.1744, 'eval_samples_per_second': 2.174, 'eval_steps_per_second': 1.095, 'epoch': 1.0}
{'train_runtime': 2878.7918, 'train_samples_per_second': 0.997, 'train_steps_per_second': 0.499, 'train_loss': 1.0953282838412315, 'epoch': 1.0}
| 1436/1436 [47:58<00:00, 2.00s/it]
```

Appendix E: Software/Hardware Requirements

Requirements	Description
IDE	IntelliJ, VS Code
Backend	Spring Boot
Python Env	Flask, Transformers
Database	MongoDB Atlas
Hardware	I5, 8 GB RAM, CPU-based ML

Appendix F: Project Repository Link

GitHub Repo: https://github.com/AbhishekGupta9974/Automated-Journal-Summarization-and-Email-Notification-System.git

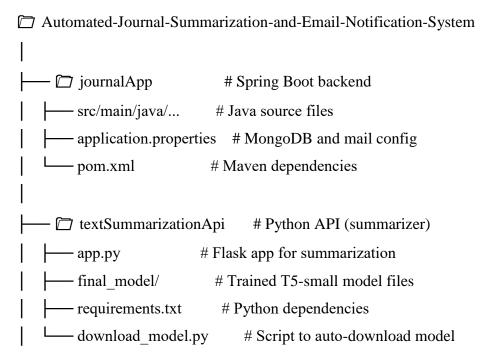
USER MANUAL

This manual guides users or developers on how to set up and use the **Automated Journal Summarization and Email Notification System**, which consists of a Java Spring Boot backend integrated with a Python summarization API using a fine-tuned T5-small model.

1. Project Overview

The system enables users to write journal entries via REST APIs, stores them in MongoDB, and automatically summarizes the past 7 days' entries every week using a trained machine learning model. The summary and its accuracy are emailed to the user.

2. Repository Structure



3. Prerequisites

Java App

- Java 17+
- Maven
- MongoDB Atlas Account
- Gmail App Password (for JavaMailSender)

Python App

- Python 3.10+
- pip install -r requirements.txt
- gdown installed for model auto-download

4. Steps to Run

Python Summarization API

- 1. Open terminal in textSummarizationApi/
- 2. Ensure model is downloaded via: python download_model.py
- 3. Run the API: python app.py
- 4. API will start at http://localhost:5000/summarize

Java Backend (Spring Boot)

- 1. Open terminal in journalApp/
- 2. Set MongoDB connection and email settings in application.properties
- 3. Build and run: mvn spring-boot:run

5. How the System Works

- Users can create journal entries via endpoints like:
 - o POST /api/journal/create
 - o GET /api/journal/all
- Every 7 days (or on manual test), the scheduler:
 - Fetches journal entries for each user
 - Sends them to the Python API
 - o Receives the summary and accuracy
 - o Emails the summary to the user

6. Testing with Postman

- Use Postman to hit:
 - o POST http://localhost:8080/api/user/register
 - o POST http://localhost:8080/api/journal/create
- Run the scheduled task manually (or wait for it to trigger)

7. Troubleshooting

Python model not loading or API crashing -

- Make sure the model.safetensors file is downloaded.
- Run python download_model.py before starting the Flask app.

Flask API not responding -

- Ensure that app.py is running on localhost:5000.
- Check that no other application is using the same port.

Email not being sent -

- Verify that the Gmail credentials and App Password are correctly set in application.properties.
- Ensure less secure app access is enabled or use Gmail App Passwords.
- Check internet connection while the Java application is running.

MongoDB connection errors -

- Make sure the MongoDB URI in application.properties is correct.
- Check that your MongoDB Atlas IP Whitelist includes your system's IP address.

Spring Boot not starting -

- Ensure you're using Java 17 or above.
- Clean and rebuild using mvn clean install before running.

Cosine similarity or accuracy not showing -

- Check that the Python API returns both summary and accuracy in the response.
- Make sure both text and reference fields are sent in the request if required.