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Original Article

An AI-Enhanced System for Context-Aware Information Retrieval and Summarization in AI-Assisted Learning

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Abstract - *In AI-assisted learning environments, the capacity to effectively extract and summarize educational content is critical for increasing student comprehension and engagement. This work describes an AI-enhanced approach for context-aware information retrieval and summarization that is specifically designed to extract pertinent text and associated tables and graphics from academic PDFs. The system comprises two phases. The first step employs a hierarchical retrieval technique that uses topic-, heading-, and text-level similarity checks to extract contextually relevant content. In terms of retrieval speed, the framework outperforms existing solutions such as ChatGPT, DeepSeek, and Grok.ai, and it is the only one that supports the extraction of multimodal content, which is vital for technical subjects. In the second phase, the collected content is run through a fine-tuned T5-small language model that is designed for abstractive summarization. The fine-tuned model produces more accurate and cohesive summaries than the base model, while also retaining important visual and structural elements like figures and tables. Comparative evaluations show that the system outperforms in both retrieval performance and summarization quality. The suggested system bridges the gap between text-only and multimodal understanding, providing a scalable and domain-adaptive solution for intelligent content delivery in digital education platforms.*

Keywords - *AI-Assisted Learning, Multimodal Summarization, Context-Aware Information Retrieval, Large Language Models, Fine-Tuned Language Models.*

1. Introduction

With rapid digitalization, Artificial Intelligence (AI) has emerged as a transformative force in education, revolutionizing the way learners access, process, and consume learning material [1]. The widespread availability of digital resources such as textbooks, research papers, and academic PDFs has created unprecedented opportunities for knowledge acquisition. However, this abundance also introduces a significant challenge: learners and educators are often overwhelmed by large volumes of unstructured content, making it difficult to efficiently locate contextually relevant information [19]. Traditional keyword-driven search systems struggle with semantic understanding, frequently returning irrelevant or superficial results that fail to meet the needs of learners [2].

Existing Research on information retrieval and summarization has primarily focused on text extraction, with limited consideration of domain-specific accuracy or the preservation of associated visual elements such as figures and tables. This creates a research gap where retrieved information often lacks completeness, and summaries lose essential pedagogical components. Furthermore, most summarization models operate in a generic setting without fine-tuning for educational contexts, resulting in summaries that may be incomplete, verbose, or imprecise.

To address these challenges, in this paper, we introduce a novel AI-enhanced framework for context-aware information retrieval and summarization in AI-assisted learning. The proposed system integrates a deep learning-based architecture [20] for text-side processing of multimodal learning material, allowing effective extraction of the text and related figures and tables from scholarly PDFs and eBooks. Information extraction and summarization are well-established applications of Natural Language Processing (NLP) [21]. The system works in two general phases: the first involves smart retrieval of contextually relevant content to a user query [3, 4], and the second involves summarization using a fine-tuned T5-small model [23] that condenses retrieved content into concise, pedagogically relevant summaries without loss of core context [5].

One of the key strengths of this framework lies in its ability to handle complex queries using semantic similarity techniques and domain-specific fine-tuned Large Language

Models (LLMs) [22]. Unlike general summarization tools, the system leverages domain-based fine-tuning of the T5-small LLM [23], significantly improving summaries' accuracy, coherence, and precision. A further novelty of the system is its ability to retain essential visual information, such as tables and figures, during both retrieval and summarization phases, thereby ensuring that learners receive complete and contextually rich information.

This Research thus contributes to the growing body of work on integrating AI into learning by providing an end-to-end solution bridging a critical research gap: the inability of existing retrieval and summarization systems to preserve multimodal elements (tables and images) while maintaining semantic summarisation accuracy. By combining advanced retrieval strategies with domain-specific summarization, the proposed system enhances the efficiency of accessing information and supports a deeper conceptual understanding of complex topics in AI-assisted learning environments.

2. Literature Review

A. Pandey et al. [6] analyze text-based Question Answering (QA) in the context of deep learning and Information Retrieval (IR) interaction by employing hybrid models like bi-encoder and tri-encoder architectures. Although many models and datasets are evaluated, the study lacks depth in the discussion of non-text data, like images or tables.

H. N. Van et al. [7] use XLM-RoBERTa for legal document retrieval and QA in ALQAC 2022. The model is effective with minimal labeled data, especially for low-resource languages. However, image or table processing is not stated.

S. Zhao et al. [8] seek to enhance recommendation systems, the retrieval layer specifically, using deep learning for improved filtering of candidate items. The study points out system optimization, but no multimodal input.

Matsiuk et al. [9] present a thesaurus-supported domain-specific information retrieval system that supports search relevance and precision. The mechanism helps reduce information overload but is restricted to use in textual domains.

J. C. Scholtes [10] applies unsupervised neural network-based models for improved retrieval accuracy and automatic learning of features. The article focuses on scalability and flexibility but lacks details on implementation.

Benedetto et al. [11] address content overflow in learning systems by adopting summarization techniques to present short, relevant content. This approach improves learner engagement but does not cater to multimedia data.

Aksonov et al. [12] explore QA systems in environments that include large data volumes, which include challenges like scalability, heterogeneity of data, and overload. Their adaptive algorithmic approach maximizes system performance but is not multimodal integrated.

C. Xu [13] explored the use of the TextRank graph-based algorithm to enhance traditional IR systems by overcoming semantic vagueness and context variability. The approach is limited to text analysis.

K. Kanhaiya et al. [14] discuss the nature of legal judgments by proposing AI-IRE, a fine-grained NLP-based engine with tagged data sets and ML for efficient legal IR. The paper focuses on domain concerns but does not process multimedia.

H. L. Nguyen et al. [15] propose a very scalable, fault-tolerant IR model for Big Data, which addresses issues like heterogeneity and data inconsistencies through error correction and validation mechanisms. Their work is technically sophisticated but is only applicable to structured/unstructured text.

M. H. Joseph and S. D. Ravana [16] enhance IR evaluation with document similarity and pooling techniques for better relevance judgments. They transcend conventional evaluation limitations but handle textual data alone.

Y. Srivarsha and V. M. Manikandan [17] improve Content-Based Image Retrieval (CBIR) by incorporating textual metadata so as to enhance search precision and context-awareness. Their method highlights the complementarity of textual and visual information.

Nivid R. Limbasiya and Darshana V. Vekariya [18] recommend an LSTM-based QA system with Deep Factorization Machines and T-max pooling for ranking the responses. The system is accurate (>80%), lacks architectural details, and does not incorporate multimedia data processing.

Despite significant advancements in information retrieval and summarization systems, there remains an inherent deficiency in the context of multimodal data extraction, i.e., the retrieval and upkeep of tables and images within PDF documents.

State-of-the-art language models and retrieval models, such as ChatGPT, Gemini, and Copilot, are largely text data-optimized and seldom recognize, extract, or utilize non-textual data, including figures, graphs, and tabular data. This is a huge deficiency, especially in learning environments where comprehending concepts frequently relies on graphical illustrations and formatted data. In addition, during the summarization process, abstractive and extractive traditional models ignore or eliminate attached images and tables, losing significant amounts of context and pedagogical value.

Summarized outputs typically provide a text-reduced copy of the material, neglecting visual and structural components that often hold crucial explanatory or quantitative information.

This results in incomplete or contextually inaccurate summaries, incapacitating the learner from grasping complicated matters adequately. Although some existing work attempts to bridge the gap by employing metadata annotation or partial layout preservation, no general deep learning system is available to offer end-to-end text retrieval and summarization and associated figures/tables from technical or academic PDFs. Bridging this gap is crucial for constructing AI-assisted learning systems to facilitate comprehensive content understanding via multimodal information presentation.

3. Proposed Framework

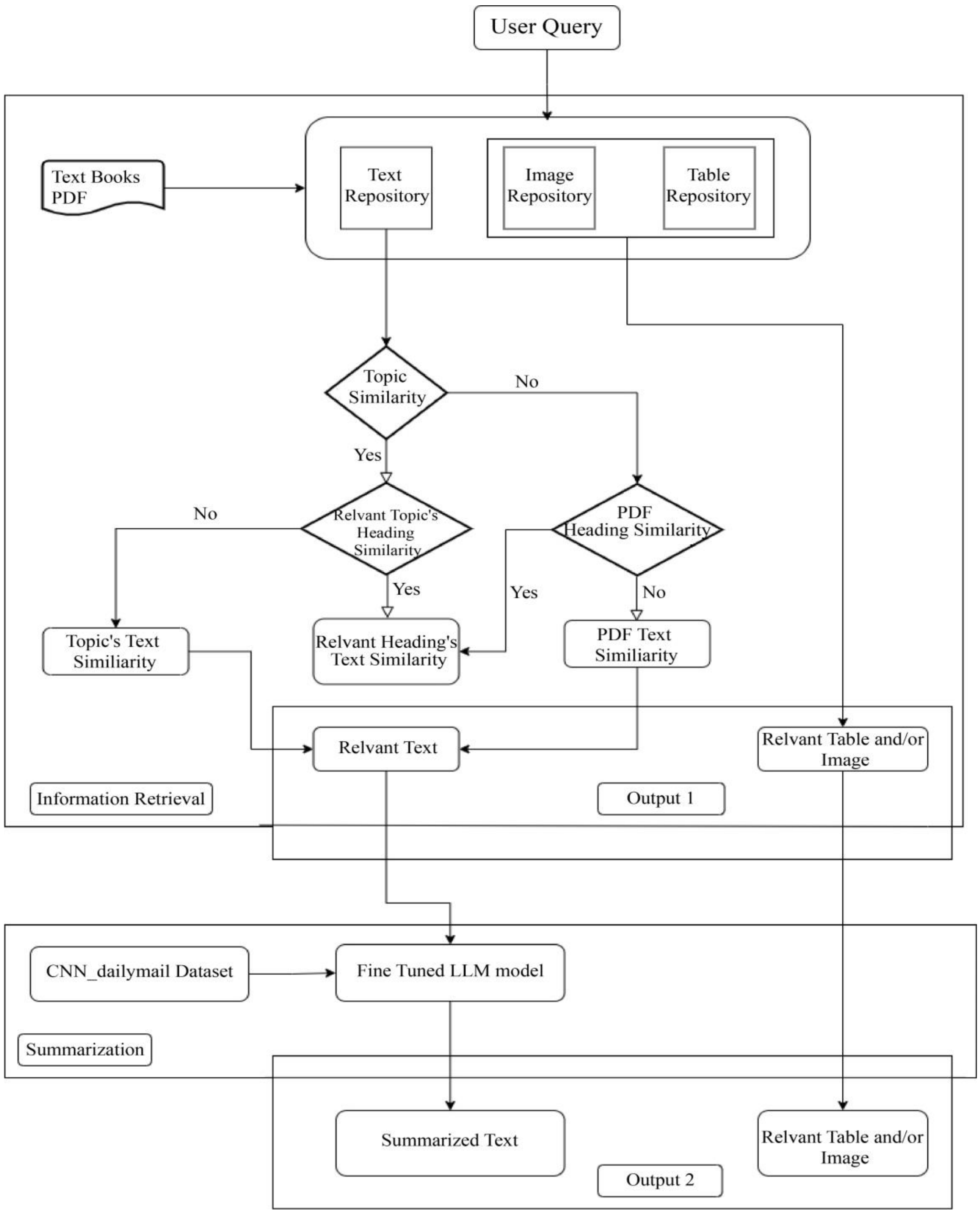

Fig. 1 Proposed deep learning framework for context-aware information retrieval and summarization in AI-assisted learning

Figure 1 represents the Deep Learning Framework for Context-Aware Information Retrieval and Summarization in AI-Assisted Learning. This system intelligently extracts relevant text, images, and tables from digital content such as textbooks and PDFs. This system works in two phases: Information Retrieval and Summarization.

3.1. Phase 1: Information Retrieval

The prime responsibility of this phase is to extract appropriate text and its tables and figures, if available.

Step 1: PDF Parsing

In the first step, the system scans the PDF supplied by the users and forms three repositories: text, image and table. These repositories are kept in Python's provided data type 'dictionary'. The Text Repository keeps content derived from textbooks and PDFs. At the same time, images and tables found in these sources are kept in independent repositories, such as Image Repository and Table Repository, so that multimodal information (textual and visual) can be retrieved as required.

Step 2: Processing of User Query

When a user performs a query on a particular topic, the query is provided to the repositories built by parsing the original text. The objective is to retrieve the most appropriate text, image and tables from existing repositories through analyzing the query and comparing it with the document content. The process of retrieving text adheres to a systematic procedure through various checks for similarity.

Step 3.1: Topic Similarity Check

When the user query is input, the system initially conducts a Topic Similarity Check to see whether any topic in the PDF or textbook is related to the input query.

If the topic is similar, the system then analyzes the headings within the identified topic.

If the topic is not similar, the system checks the similarity of the PDF heading to identify a match at a larger level.

Step 3.2: Image and Table Extraction

In tandem with the text retrieval, the user query is also sent to the Image and Table repositories so as to detect, extract, and present corresponding figures and tables.

Step 4A: Heading Similarity Check for Relevant Topic

When a relevant topic is detected, the system repeats the search by searching for heading similarity within the topic.

If a suitable heading is discovered, the system goes on to check the text similarity in the discovered heading.

If no suitable heading is discovered, the system goes on to check for text similarity directly in the discovered topic.

Step 4B: PDF Heading Similarity Check

If the system fails to identify a topic of relevance from the initial check, it conducts a PDF-wide heading similarity search. This is to ensure that even if the primary topic is not identified as such, there may still be relevant information under other headings in the document.

If a similar heading is identified, the system then checks for text similarity within that heading.

If no matching heading is available, the system conducts text similarity throughout the whole PDF document to find related information.

Step 5: Text Similarity Analysis

The system finds related text based on similarity checks conducted at varying levels in this step.

If the search was conducted on a topic, the system compares text similarity in that topic.

If the search was conducted on a heading, the system compares text similarity in that heading.

If a topic or heading match is not found, the system does a PDF-wide search for text similarity to make sure that matching content is not overlooked.

Step 6: Retrieval of Relevant Text

When the system finishes performing the similarity checks, it retrieves the most relevant text and outputs the final result. The text is most contextually related to the information from the textbook or PDF that best matches the user's query.

3.1.1. Output 1

The text retrieved via the above similarity checks is classified as "Relevant Text", which constitutes the central output of the Information Retrieval module. In addition to textual information, the system also scans the Image and Table Repositories for relevant images or tables related to the text retrieved (Step 3.2). The integration of relevant text and visual aids (images/tables) constitutes Output 1 of the system.

3.1.2. Key Features of Phase 1

Hierarchical Search Strategy: The application employs a multi-stage filtering technique that starts with a general topic-level similarity test. If a topic is detected, it then advances to heading-level and finally text-level similarity, making it a precise and refined retrieval.

Strong Information Retrieval: The model is made to capture no relevant information at all, even when topic-level similarity does not work. It utilizes both heading-level tests and document-wide scanning to find contextually similar content.

Context-Aware Similarity Matching: The system employs a multi-layered technique, incorporating topic similarity, heading similarity, and text similarity. This guarantees that the final extracted text is semantically connected and extremely relevant to the user's query in context.

Multimodal Content Extraction (Images and Tables): Concurrently with text, the system does simultaneous querying of Image and Table Repositories. It retrieves the corresponding figures and tables corresponding to the query of the user or the obtained textual material, offering a visual aid for easier comprehension and improved learning.

Scalable and Extensible Design: The architecture is extensible enough to accommodate large amounts of content from research papers, academic textbooks, or technical documentation. The system can be scaled for use in AI-driven learning environments or education resource portals.

Semantic Coherence in Multimodal Output: The architecture ensures that retrieved text, tables, and images are contextually connected via metadata or document structure, providing a coherent and meaningful learning experience to the end user.

3.2. Phase 2: Summarization

To make reading easier and facilitate quicker understanding, the system has a summarization module. The text obtained in Output 1 is sent through a Fine-tuned Large Language Model (LLM) that was trained on the CNN/DailyMail summarization dataset. This dataset is very popular for abstractive summarization and assists the LLM in creating short and meaningful summaries of longer text. To demonstrate the applicability of this process, a small LLM named the T5 Small has been employed in the current Research. The fine-tuned model extracts the semantic meaning of the input content and generates a simplified version appropriate for fast reading or browsing.

3.2.1. Output 2

The last Summarized Text, which is produced by the LLM, is merged with the earlier extracted relevant table or image (if present) to provide Output 2. This dual-response format offers the user two levels of response: one in the form of an elaborate result (Output 1) and a brief summary (Output 2), along with supportive visual content where necessary. This allows users to either delve into lengthy content or gain a quick overview according to their needs.

3.2.2. Key Features of Phase 2

Abstractive Summarization with Fine-Tuned LLM: The model applies a fine-tuned T5 Small model, which is trained on the CNN/DailyMail dataset, to create human-like abstractive summaries that are understandable and relevant.

Semantic Compression of Information: The model summarizes long academic or technical material into concise, readable, and semantically-rich summaries that enable users to quickly understand complex information.

Maintains Relevance with Original Content: The summarizer preserves essential concepts and technical precision from the recovered content such that the summary is well-matched to the user's original search request and information requirements.

Lightweight and Efficient Model: With the utilization of T5 Small, the system guarantees low-latency summarization, effective in real-time or restricted resource applications without loss of quality.

Integrated Visual Support: The abstracted text is accompanied by supporting tables and images (retrieved during Phase 1), presenting a brief but thorough response to the user question in multimodal form.

Dual-Level Output for Adaptive Learning: The system presents Output 1 (extended content) and Output 2 (abstract version). This enables users to opt for an in-depth investigation or a rapid glance, depending on their needs or time availability.

4. Results and Discussion

4.1. Phase 1: Information Retrieval Results

One of the significant contributions of the suggested Research is that it can directly extract and provide structured (tabular) information and contextual images or diagrams from academic PDFs. This is an important feature in AI-supported learning systems, especially for fields such as engineering and computer science, where comprehension relies on visual support and data tables contained within text.

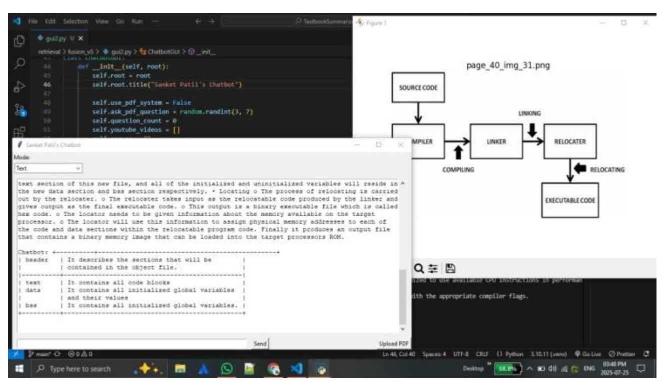

Fig. 2 IR with image and table

As evident from Figure 2, the system interface fetches an appropriate flowchart (symbolizing the compilation process) and a tabular depiction of object file sections (header, text, data, and bss) along with the context explanatory content. Figure 2 demonstrates how the system parses the source content and how it intelligently recognizes and displays both graphical and structured textual components. This feature solves an important research gap seen in most of the present retrieval and summarization systems, which often overlook such embedded visual or tabular content. The suggested system provides a more comprehensive, multimodal learning experience that transcends plain text retrieval and summarization by filling this gap.

4.2. Phase 1: Information Retrieval System Analysis

Table 1 shows that the proposed information retrieval system reflects better efficiency than ChatGPT, DeepSeek, and Grok.ai in processing speed. PDF parsing within the proposed system takes merely 0.51 to 0.7 seconds, much quicker than ChatGPT (3.21 sec) and close to DeepSeek (0.5 sec).

Table 1. Comparative Analysis of Retrieval Time

Process	Proposed Research (sec)	ChatGPT (sec)	DeepSeek (sec)	Grok.ai (Sec)
PDF Parsing	0.51 - 0.7	3.21	0.5	
Query 1: Characteristics of Embedded Systems	0.028	1.02	0.2	0.6
Query 2: Downloading the Embedded Code	0.011	0.97	0.2	0.85
Query 3: Scheduling Points	0.041	1.15	0.2	0.5

For query execution, the proposed system outperforms all alternatives. Query 1 (Characteristics of Embedded Systems) is processed in 0.028 sec, much faster than ChatGPT (1.02 sec) and Grok.ai (0.6 sec), and slightly better than DeepSeek (0.2 sec). Query 2 (Downloading the Embedded Code) takes just 0.011 sec, far surpassing ChatGPT (0.97 sec), DeepSeek (0.2 sec), and Grok.ai (0.85 sec). Query 3 (Scheduling Points) is fetched in 0.041 sec, yet again faster than ChatGPT (1.15 sec) and Grok.ai (0.5 sec), though close to DeepSeek (0.2 sec).

The overall system considerably decreases retrieval time, showcasing enormous efficiency in PDF parsing as well as query response time, thus making it a great system for fast and effective AI-powered learning solutions.

Table 2. Comparative analysis of table and image retrieval

System	Table Retrieval	Image Retrieval
Proposed Research	Yes	Yes
ChatGPT	No	No
Gemini	No	No
DeepSeek	Yes	No
Copilot	No	No

Table 2 illustrates a comparison of the ability of different AI systems to pull out and process tables and images from input material, particularly PDF-based learning resources. The emphasis here is whether these systems could identify, pull out, and display structured tabular information and embedded images, which are sometimes imperative for conceptual understanding in learning materials.

The table clearly shows that the Proposed Research System is unique in providing both table retrieval and image retrieval functionality. This double capability makes it particularly worthwhile for educational and technical students, where diagrams, charts, and structured data tables are often used to make things easier to understand.

ChatGPT, Gemini, and Copilot do not support both table and image retrieval.

Though they work efficiently in natural language generation and understanding, their inability to interpret or extract structured or visual information from documents hinders their application in multimodal learning environments.

DeepSeek, one of the listed substitutes, partly addresses the needs by offering table retrieval, but not image retrieval. Although this grants some benefit over the others, the absence of image support continues to limit its efficacy when handling graphically-intensive material like circuit diagrams, block illustrations, or workflow graphics commonly present within engineering and scientific content.

4.3. Phase 2: Summarization System Results

One of the major improvements in the envisioned AI-based learning system is the fact that it can maintain and display related tables and images even after executing text summarization. Most summarizing systems will condense input material into textual highlights at the expense of the crucial diagrams and structured data important to thorough understanding, particularly in technical fields.

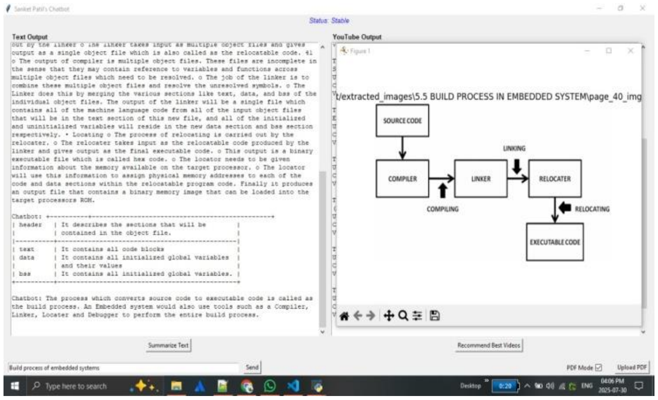

Fig. 3 Summarization results

As shown in Figure 3, the interface not only extracts pertinent information from the PDF (such as an elaborate flowchart of the build process and a table describing object file sections) but also keeps these components available in the summary output window. This multimodal coherence allows learners not to miss out on important visual data at the time of compression of intricate subjects.

For instance, the system has maintained a tabular description of header, text, data, and BSS sections of an object file and a flowchart picture illustrating the process from source code to executable code through compiler, linker, and relocater.

In order to implement effective and context-sensitive summarization of academic content, the system combines a fine-tuned T5-small model, which has been optimized specifically for domain-specific academic content. The T5 (Text-to-Text Transfer Transformer) structure approaches all NLP tasks, such as summarization, as a text-to-text problem, and hence it is a very versatile model.

4.4. Phase 2: Summarization System Analysis

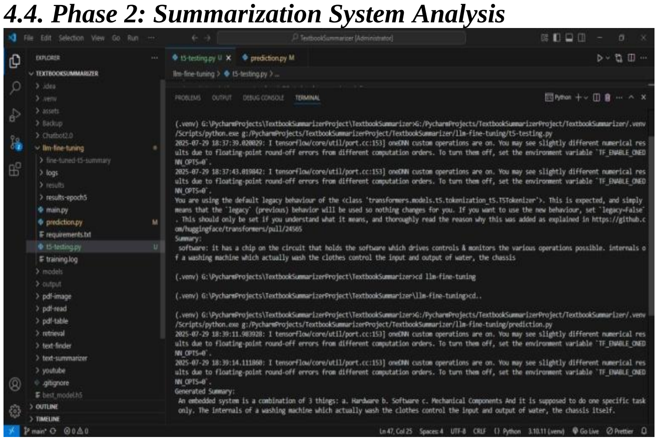

Fig. 4 Summarization analysis

Figure 4 demonstrates how effectively the T5-small model can be fine-tuned for domain-specific summarization tasks.

The outcome of the T5-small model is software: it possesses a chip on the circuit that contains the software which powers, controls, and regulates the different operations possible. The internals of a washing machine that washes clothes control the input and output of water and the chassis. The outcome of the Fine-Tuned T5 result is that an embedded system is a mix of 3 things: a. hardware, b. Software c. Mechanical Parts, and do one solitary task.

The inside of a washing machine that really washes the clothes manages the in and out of water, the frame itself. A comparison between the basic T5-small model and the fine-tuned T5-small model indicates noticeable gains in terms of the clarity and completeness of the summaries generated after fine-tuning.

The basic T5 model generated a semi-coherent summary with focus on some of the elements (e.g., software and the inside of a washing machine), but it was unstructured and omitted some of the important contextual items. Its output was staccato, grammatically incoherent, and did not give the overall idea of the concept.

Contrarily, the fine-tuned T5-small model produced a much more organized and semantically rich summary. It appropriately pointed out the definition of an embedded system and its three fundamental parts: hardware, software, and mechanical components. In addition, it sustained the contextual continuity by describing the example of a washing machine, while sustaining the technical purity of the explanation.

This qualitative enhancement highlights the efficacy of domain-specific fine-tuning to generate accurate, relevant, and pedagogically useful summaries. By fine-tuning the model to educational text, particularly from engineering and technical areas, the system guarantees that students learn precise and concentrated information, thus improving conceptual understanding and lessening cognitive load.

These results justify the inclusion of a refined language model as part of the summarization process of the proposed framework, particularly when it comes to complicated academic content that needs both factual accuracy and conceptual coherence.

5. Key Contributions

The major contributions of this Research can be summarized as follows:

5.1. Context-Aware Retrieval Framework

In response to user inquiries, we provide an AI-enhanced information retrieval framework that can extract contextually relevant content from academic PDFs and eBooks. In contrast to traditional systems, our framework preserves important instructional information by retrieving text, related tables and graphics.

5.2. Comparative Analysis with State-of-the-Art Systems

The suggested framework's higher retrieval time efficiency and special capacity to handle multimodal material are demonstrated by a methodical assessment against other models, including ChatGPT, Gemini, DeepSeek, and Copilot.

5.3. Using the Fine-Tuned T5 Model for Summarization

Abstractive summarization is done using a refined version of the T5-small model. The findings demonstrate that, compared to the baseline T5-small model, the refined model generates domain-adapted summaries, semantically richer and more organized, while keeping pertinent tables and graphics.

5.4. End-to-End Pipeline for AI-Assisted Learning

By integrating retrieval and summarization into a unified workflow, this work presents one of the first end-to-end solutions for AI-assisted learning that supports multimodal educational content. This ensures learners and educators receive comprehensive, accurate, and context-preserving summaries.

6. Conclusion

This study introduces a new deep learning architecture for context-sensitive information retrieval and summarization, designed particularly for AI-enabled learning environments. The system aims to overcome key shortcomings of current retrieval and summarization systems by combining multimodal features-i.e., extracting and retaining textual, tabular, and visual information from scholarly sources like PDFs and eBooks. For Phase 1, the system proposed for information retrieval showed better performance in both speed and level of content extraction. Comparative studies indicated that our system far outperforms popular tools such as ChatGPT, DeepSeek, and Grok.ai in terms of retrieval time for various academic queries. Further, a unique feature of the proposed system is that it can also retrieve tables and images, an area not met by any other systems. This is particularly important in technical and engineering fields where visual and tabular information form part of complex concepts comprehension.

In Phase 2, the summarization module over the T5-small architecture further improves the efficiency of learning. Domain-specific fine-tuning of the T5-small model resulted in significantly better summarization quality. In comparison with the generic T5-small model, the fine-tuned model produced summaries that were more accurate, well-organized, and semantically informative and closely matched the original context of the content. More significantly, our system's summarization process preserves extracted tables and images to ensure that important non-textual information is maintained and included with the textual summary-something that traditional summarizers do not.

In combination, the two phases create a well-integrated multimodal framework that can retrieve pertinent textual, tabular, and visual content and produce contextually sound, learner-focused summaries. This creates a more well-rounded and natural learning experience. The presented framework thereby represents an important milestone in AI-aided learning tools with the potential to extend influence into a wide variety of educational and technical fields in which precise and complete content presentation is essential.

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