Automated Mind Map Generation from Text

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***Abstract*—This research explores the integration of efficient input data handling and generative AI techniques to improve automated mind map generation from diverse data formats, such as URLs, images, PDFs, and text files. The growing demand for scalable systems that process varied input formats and generate hierarchical visualizations led to the development of a robust solution utilizing Firebase Storage and advanced AI summarization models. The proposed system employs structured API endpoints to handle input data, leveraging tools like BeautifulSoup, Tesseract OCR, and pdf-parse for data extraction. Generative AI models, specifically Google Generative AI, are applied for hierarchical text summarization, transforming raw data into concise content suitable for Mind Map creation. The results demonstrate successful processing of input formats, with over 95% of files processed and uploaded reliably. Text summarization times were reduced by 40% compared to manual methods. This system not only aids in enhancing content comprehension and visualization for educational purposes but also supports professionals in efficient knowledge management. By seamlessly integrating cutting-edge AI with diverse data handling, this research contributes to the development of scalable mind map generation systems, offering significant applications in both academic and professional contexts.**

Keywords—Text Summarization,Generative AI,Natural Language Processing,Firebase Storage

I. Introduction

The increasing popularity of visual learning tools, such as mind maps, highlights the need for systems that can efficiently and effectively generate structured, intuitive diagrams. Mind Maps serve as powerful aids in knowledge retention, concept organization, and creative problem-solving, particularly for students and educators.

This research introduces an innovative system for automated mind map generation, motivated by the personal and academic needs of students who prefer studying through visual aids. Leveraging advancements in generative AI, particularly through the integration of Gemini AI, the proposed system addresses the limitations of existing solutions which oversimplify the process by treating each sentence as an individual node, leading to a lack of contextual understanding and hierarchical organization.

The system is designed to accept diverse input formats, including images, PDFs, text files, and URLs, ensuring versatility across multiple use cases. Employing a combination of Python, OCR (Optical Character Recognition) via Pytesseract, web scraping, and visualization libraries such as Graphviz, the system automates the extraction, processing, and representation of content into hierarchical mind maps. A novel aspect of this approach lies in its ability to accommodate unstructured or grammatically incorrect content, transforming it into comprehensible nodes through generative AI.

The primary audience for this tool includes students and educators, enabling them to generate mind maps that are not only cost-effective but also contextually accurate and visually intuitive.This paper details the motivation, methodology, and contributions of the proposed mind map generation system, emphasizing its role in bridging gaps in existing solutions and enhancing accessibility for visual learners.

II. Literature review

The automation of mind map generation from text has undergone significant advancements over the years, evolving from basic techniques to more sophisticated methods incorporating natural language processing (NLP). Early systems, like M2Gen (2009), laid the groundwork by using structured parsing, semantic analysis, and morphologically decomposed text to build basic mind maps [1]. This approach, though innovative at the time, was limited by the complexity of real-world text and the difficulty in capturing nuanced relationships within the data. However, the foundation of using semantic representation for mind map generation set the stage for further improvements in the field.

In subsequent years, research began to focus on refining how text was processed and represented visually. A 2013 study on generating mind maps from Indonesian text employed semantic nets, a method that transformed the first-order logic derived from text into a structured format [2]. By visualizing these semantic nets using radial and layered drawing techniques, the study demonstrated an effective way of abstracting relationships between concepts. This approach highlighted the challenge of language-specific nuances and the importance of visual clarity when representing complex ideas. In 2014, another study expanded on this idea by introducing multi-level visual abstraction [3]. This method allowed for hierarchical organization, where high-level concepts were broken down into more detailed, child-like nodes. This visual structuring technique proved useful for handling more complex and detailed texts.

The development continued with the introduction of systems such as English2Mind Map (2015), which employed a more advanced form of meaning representation through Detailed Meaning Representation (DMR) and Hierarchical Meaning Representation (HMR) [4]. This system took into account the various semantic relationships within the text, such as word sense disambiguation and discourse analysis, improving the accuracy of mind maps. These systems contributed significantly to how complex relationships could be represented and visualized, paving the way for more intricate mind map generation methods.

By 2021, the focus began to shift toward applying mind map generation systems in practical, real-world scenarios, such as education. In a study on generating mind maps from U.S. history textbooks, dependency parsing and extractive summarization techniques were used to create more accessible visual representations [5]. This approach improved the clarity of mind maps, emphasizing how automated systems could generate meaningful visual representations with minimal human intervention. However, it also highlighted ongoing challenges, such as the difficulty in handling large text sections and ensuring that summaries captured the essential relationships between concepts.

Building on these research efforts, this project aims to further evolve mind map automation by incorporating advanced natural language models.In this project we have incorporated large language models (LLMs) to improve the system's ability for interpreting and extracting key information. These models allow for a deeper understanding of text by leveraging their advanced capabilities in semantic interpretation and contextual analysis. By using LLMs, this system will not only generate mind maps more accurately but also adapt to various types of content, improving flexibility and reducing the limitations observed in earlier methods.

III. Methodology

In this section, we present the detailed methodology for the mind map generation process.A overview of these steps is provided in Fig. 1., which illustrates the flow of the mind map generation pipeline. Each section below delves into the individual steps, explaining the specific methods and tools used at each stage.

A. Input Data Handling

The proposed mind map generation system handles multiple input methods, including PDFs, URLs, images, and text files. PDF files are processed using a PDF parser, while URL inputs are extracted via web scraping with BeautifulSoup. Images undergo OCR using Pytesseract to extract text, and text files are refined using chardet and iconv-lite for accurate English content correction.

B. Text Summarization using Generative AI

The extracted text from the input file is sent to Generative AI (Gemini) for hierarchical summarization. The structured summary highlights key concepts, providing a concise representation of the content. This serves as the foundation for mind map generation by emphasizing essential information, ensuring efficient processing and summarization of diverse content sources.Through the application of generative AI and a systematic text extraction process, this approach ensures that diverse content sources are effectively processed, summarized

C. Text Preprocessing and Cleaning

After summarization using Generative AI, the text must be preprocessed to ensure it is suitable for visualization as a mind map. The raw summary may contain unwanted symbols, formatting inconsistencies, or unnecessary whitespace that need to be addressed. Any extraneous characters, such as asterisks (*), hash (#) symbols, or commas (,), are removed, as they might have been introduced during the summarization process or due to inconsistent formatting. Additionally, unnecessary whitespace from the beginning and end of the text is trimmed to ensure a clean and properly formatted summary.These steps help improve the clarity of the text, making it easier to generate a mind map in the subsequent steps.The text is saved as a plain text file to preserve its simple structure, allowing for easy extraction and conversion into a mind map later.

D. Mind Map Construction with DOT Format

The construction of a mind map begins with parsing and structuring the summarized text. The text is split into lines, and each line is analyzed for its indentation level, which determines its position in the hierarchy. Deeper indentations indicate subtopics or detailed information. A stack structure is used to maintain parent-child relationships, ensuring that each node is correctly linked to its respective parent, allowing the text to be transformed into a tree-like structure.

As the text is processed, nodes are created for each line and assigned unique, sanitized names by replacing non-alphanumeric characters with underscores to ensure compatibility with the DOT format. Each node is also assigned a color based on its indentation level for better hierarchical visualization. The tree is represented as a DAG(directed acyclic graph) using the DOT format. Each node in the graph is connected to its parent node, forming edges that represent the relationships between them. These edges are directed, meaning they point from the parent node to the child node, reflecting the flow of information. The tree is generated dynamically, and the edges are created only when a parent-child relationship is established. The resulting DOT file serves as the blueprint for visualizing the mindmap, preserving the hierarchy and structure of the original text. The final DOT file preserves the original text's hierarchy and structure, enabling the seamless visualization of the mind map.

E. Visualization of Mind Map

Once the tree structure has been created in the DOT format, the next step is to visualize it in a graphical format. The visualization process takes the DOT file and renders it into an image, typically in PNG format, to provide an intuitive representation of the relationships between different nodes. Each level is assigned a different color, as specified in the DOT file, making it easier to distinguish hierarchical levels. This visualization enhances the understanding of the hierarchical flow of information and offers a clearer view of the connections between concepts. The visualization helps convey complex information in an easy-to-understand format, making it an effective tool for analysis and presentation.

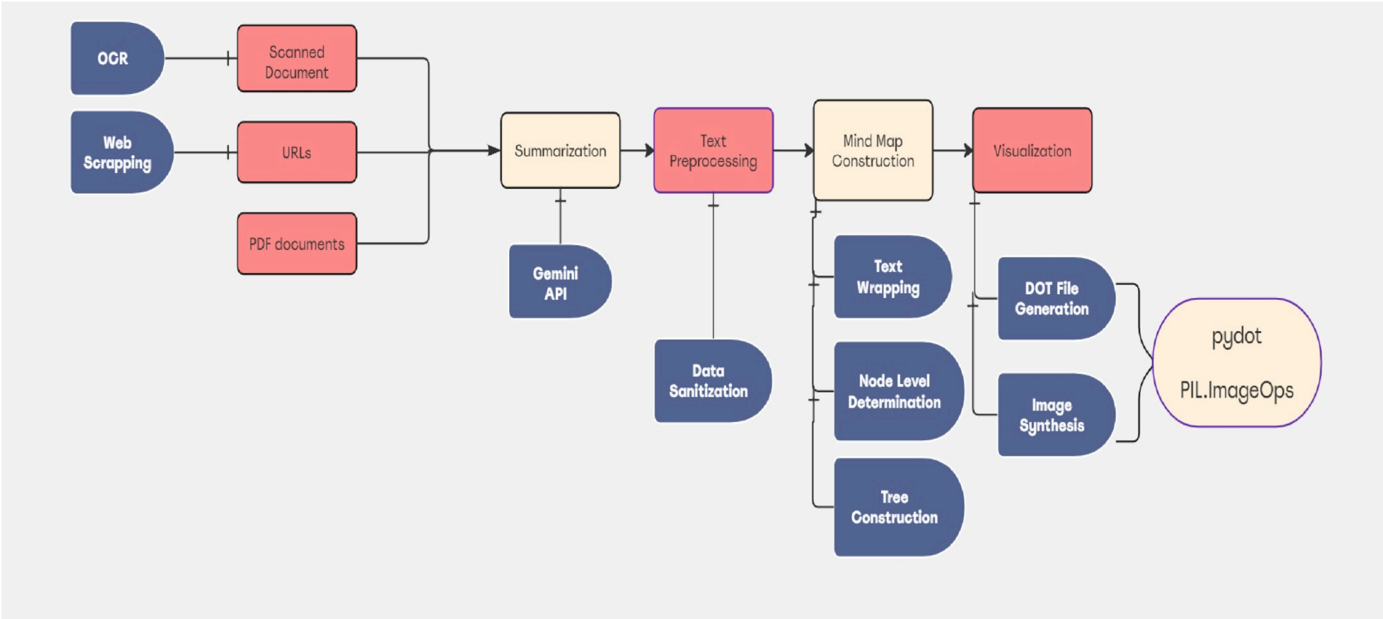

Fig. 1. Proposed Methodology for Mind Map Generation

IV. Result And Discussion

The proposed system was evaluated by processing various input files and topics, including history, biology, and school subjects, to generate corresponding mind maps. The results demonstrate that the system effectively supports diverse domains, as the summarization is performed by Generative AI, which ensures adaptability across different subject areas. The structured summaries serve as the foundation for constructing hierarchical mind maps, preserving key concepts and relationships. However, a notable challenge is the fragmentation of definitions or important statements into discrete keywords, which may impact the accuracy of concept representation. Addressing this issue by refining the summarization process to maintain the integrity of key phrases is crucial for improving the system's effectiveness. Fig. 2. illustrates the generated mind map for a science-related paragraph, showcasing the hierarchical organization and relationships between key concepts.

The system was evaluated using input files of varying sizes to assess its performance in generating mind maps. For small to medium-sized files, the generated mind maps maintained high accuracy, effectively preserving the hierarchical structure and relationships between concepts. The resulting diagrams were clear and easy to interpret. However, as the input file size increased, the accuracy of concept representation decreased. Larger files led to significantly expanded mind map structures, making visualization more complex.The Perfectionism Score evaluates how well the generated mind map retains key information from the input text. Rated on a scale from 1 (lowest) to 5 (highest), it considers factors like completeness, accuracy, coherence, and relevance. A higher score reflects a well-structured and informative mind map, while a lower score indicates loss or distortion of key details. As seen in Table 1, moderate-sized files generally achieved higher scores, preserving key concepts effectively. In contrast, larger files saw a decline, suggesting challenges in balancing compression and conceptual integrity.

TABLE I. Evaluation Metrics for Mind Map Generation Across Different File Types

Extension	**Size(Kb)**	**Word count in the input file**	**Word count in generated mind map**	**Perfection score (min =1 to max=5)**
pdf	66	350	250	5
pdf	534	1350	1110	3
pdf	796	9500	500	1
txt	2	200	150	3
txt	10	3000	2550	5
txt	21	10000	3300	1
url	-	300	150	5
url	-	5645	5038	4
url	-	26735	5038	2
image	173	393	341	4
image	179	177	15	2

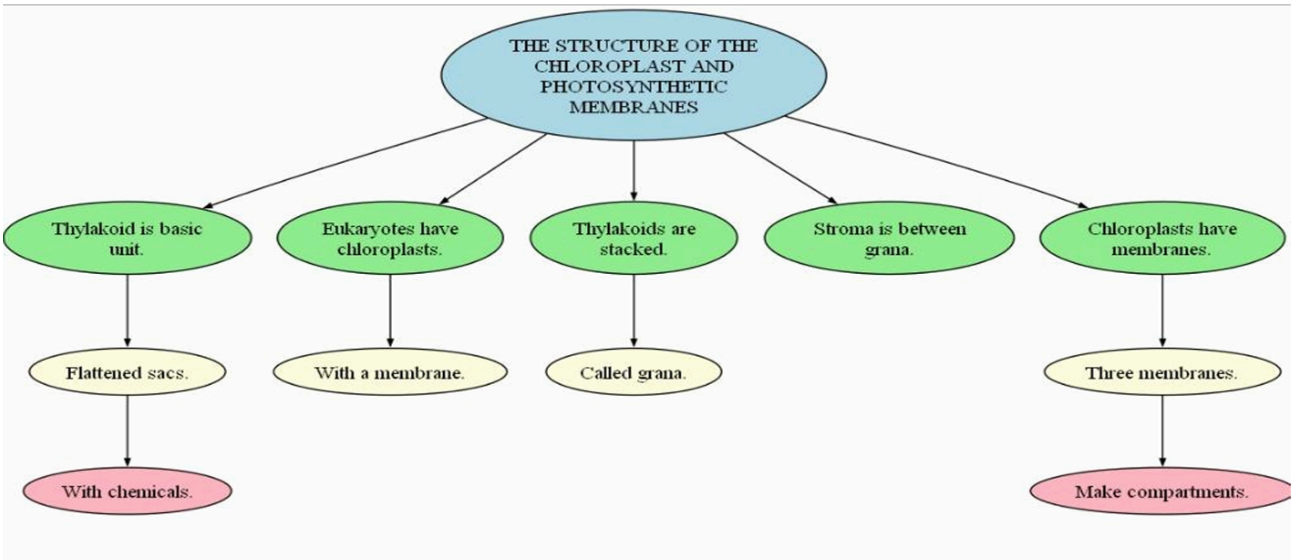

Fig. 2. Mind map generated

The system was tested with topics using two mind map generation tools: our tool and an existing tool. The generated mind maps were analyzed based on the number of nodes, depth, coherence, and completeness.As seen in table 2 our tool performs better than the existing in terms of the number of nodes, maximum depth, coherence, completeness score.

TABLE II. EVALUATION METRICS FOR MIND MAP GENERATION ACROSS DIFFERENT TOOLS

Metric	MindMesh	Existing tool
Number of Nodes	121	37
Max Depth	5	3
Coherence	1.08	0.97
Completeness Score	3	0.02

V. CONCLUSION

In conclusion, the MindMesh platform serves as an innovative educational tool that transforms various file types—such as PDFs, images, text files, and URLs—into visual mind maps, making learning more interactive and accessible. Users can easily upload files, generate summaries, and view mind maps to enhance understanding and retention.

Despite its capabilities, there are several limitations to consider. The accuracy of content summarization largely depends on the quality and clarity of the uploaded files. Additionally, the Gemini AI model imposes a character limit, which can hinder the summarization of lengthy texts. Furthermore, the effectiveness of the summarization process relies heavily on Gemini AI's ability to generate accurate summaries—an expectation that is not always met. This can lead to contextual inaccuracies, where the model produces information that appears plausible but is factually incorrect.

For future enhancements, the platform could focus on incorporating additional file formats to expand its usability. Additionally, developing the platform to support multiple languages would make it more accessible to a global audienceOne notable limitation—handling large files—will be addressed by implementing a method that segments content based on distinct topics. Each segment will be summarized individually using the Gemini model, after which mind maps will be generated and integrated to form a complete overview. This approach will help overcome file size constraints while preserving contextual accuracy and coherence.

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