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Mind Map AI: Intelligent Visual Knowledge Representation Platform Using Deep Learning

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ABSTRACT: The growing amount of digital text and information has made it difficult for users to effectively identify and comprehend the key ideas in unstructured documents. Traditional methods of summarizing text usually create straight-forward summaries that don't always show how different ideas are connected. To address this limitation, this paper introduces MindMap AI, an intelligent platform designed to transform unstructured text into interactive visual mind maps using advanced Natural Language Processing (NLP) techniques and Transformer-based models. The system first identifies key concepts from the input text and generates semantic embeddings through Sentence Transformer models. These embeddings are compared using cosine similarity to find connections between ideas and build a structured concept graph. In cases where meaningful relationships cannot be established, the system generates an abstractive AI-based summary as an alternative output. By arranging information in a visual way and showing how ideas are linked, the system helps users understand better and remember more. This makes it a good method for automatically creating visual representations of knowledge in schools and work environments.

KEYWORDS: Mind Map Generation, Semantic Concept Extraction, Sentence Transformers, Cosine Similarity, Knowledge Graph Visualization, Natural Language Processing, Abstractive Summarization.

I. INTRODUCTION

The rapid growth of digital information has led to a massive increase in the amount of unstructured textual data available to students, researchers, and professionals. Academic articles, technical reports, study materials, and various online resources often contain complex information that requires significant time and effort to read, analyze, and understand. Traditional reading and summarization methods usually present information in a linear format. While such approaches may highlight the key points of a document, they often fail to represent the relationships between different concepts. As a result, users may find it difficult to understand how ideas are interconnected, which can reduce knowledge retention and increase cognitive load.

Visual learning techniques, particularly mind maps, have been shown to improve comprehension by organizing information in a hierarchical structure and visually illustrating the connections between ideas. However, most existing mind mapping tools require manual effort, where users must read the content, interpret the important ideas, and structure them into a visual format themselves. This manual process can be time-consuming, subjective, and inefficient, especially when working with long or technically complex documents.

To overcome these challenges, this paper introduces **MindMap AI**, an intelligent system designed to automatically convert unstructured text into interactive visual mind maps using advanced Natural Language Processing (NLP) techniques and Transformer-based deep learning models. The system extracts key concepts from the input text, generates semantic embeddings, and identifies contextual relationships through cosine similarity.

These relationships are then used to build a graph-based visual representation of the information. In situations where meaningful conceptual connections cannot be identified, the system produces an AI-based abstractive summary to ensure that useful information is still provided to the user.

II. LITERATURE SURVEY

The rapid increase in digital textual data has led to growing research interest in areas such as **Natural Language Processing (NLP)**, automated knowledge extraction, and intelligent text analysis. Earlier techniques for handling large volumes of text mainly relied on statistical methods and graph-based algorithms to determine important words and sentences. One well-known approach is **TextRank**, introduced by Mihalcea and Tarau [1]. This method is inspired by the PageRank algorithm and represents textual units such as sentences or words as nodes within a graph, while the relationships between them are modeled as edges. By examining the strength of these connections, the algorithm identifies significant textual elements and extracts important sentences or keywords. Although TextRank has been widely applied in extractive summarization and keyword extraction tasks, it primarily depends on word co-occurrence patterns and therefore has limited capability in capturing deeper semantic relationships between concepts.

The development of **Transformer-based deep learning models** brought major improvements in how machines understand language context and meaning. Among these models, **BERT (Bidirectional Encoder Representations from Transformers)**, proposed by Devlin et al. [3], has become particularly influential. BERT employs a bidirectional learning strategy that allows the model to interpret text by considering both preceding and following context simultaneously. As a result, it produces more accurate contextual representations of words within sentences. This advancement significantly improved performance in several NLP tasks, including text classification, question answering, and semantic analysis, and established a strong foundation for later developments in contextual language modeling.

Extending the capabilities of BERT, **Sentence-BERT (SBERT)** was introduced by Reimers and Gurevych [2]. SBERT adapts the original BERT framework by using a Siamese network architecture to generate vector representations at the sentence level. These embeddings enable efficient measurement of semantic similarity between sentences through distance metrics such as cosine similarity. Because of this property, SBERT is widely used in applications that require comparing multiple pieces of text, including semantic search, clustering, and knowledge graph construction.

Another important research area focuses on **automatic keyphrase extraction**, which aims to identify the most significant concepts within a document. Sahrawat et al. [5] proposed a deep learning approach that models keyphrase extraction as a sequence labeling problem using contextual embeddings. Their method uses neural architectures to detect important phrases in scholarly documents more effectively than traditional rule-based or statistical techniques.

Similarly, Nikzad-Khasmakhi et al. [4] introduced **Phraseformer**, a model that integrates Transformer-based contextual embeddings with graph-based representations. By combining these two perspectives, the approach improves the identification of meaningful keyphrases by capturing both contextual semantics and the relationships between terms.

Beyond extracting concepts, researchers have also investigated techniques for visually representing the relationships among those concepts. Graph-based visualization approaches enable complex networks of information to be displayed in a structured and interactive format. Such techniques help users better understand the connections between ideas and reduce cognitive load when analyzing large volumes of text.

Inspired by these developments in NLP, semantic embeddings, and knowledge visualization, the proposed **MindMap AI** system integrates multiple techniques within a single framework. The system employs Sentence Transformers to extract contextual concepts from text, applies cosine similarity to detect semantic relationships among them, and uses graph-based visualization methods to generate interactive mind maps.

III. METHODOLOGY

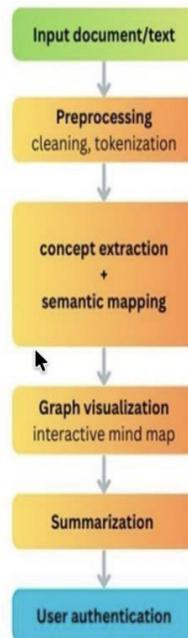


Fig. 1. MindMap AI System Methodology

The proposed **MindMap AI** system applies Transformer-based deep learning methods to convert unstructured textual information into interactive Mind Maps or structured summaries. The overall methodology follows a sequential processing pipeline that transforms raw text input into a semantic graph representation, as illustrated in Fig. 1.

The process begins at the **User Interface**, where users can either type text directly or upload documents for analysis. Once the input is received, it is handled by the **Text Preprocessing Module**, which prepares the data through several steps such as text cleaning, tokenization, removal of stop words, lemmatization, and **Named Entity Recognition (NER)**. These operations help identify and organize meaningful linguistic elements from the original text.

After preprocessing, the refined text is passed to the **Semantic Concept Extraction Module**. In this stage, Sentence Transformer models generate contextual embeddings for the identified concepts. These embeddings represent the semantic meaning of concepts within the context of the text, rather than relying only on simple keyword frequency. The system then measures **cosine similarity** between the embedding vectors to determine how closely the concepts are related.

Using predefined similarity thresholds, the system links related concepts to construct a **concept graph**, where nodes correspond to key ideas and edges represent their semantic relationships. This graph is visualized using a **force-directed layout algorithm** implemented with **D3.js**, creating an interactive Mind Map that allows users to navigate, zoom, and explore the relationships between concepts.

When the system does not detect sufficient semantic connections to form a meaningful graph, it activates an **abstractive summarization module** based on Transformer models. This module generates a concise summary of the input text, ensuring that useful output is still provided. Through this adaptive mechanism, the system supports effective visual knowledge representation and helps users better understand complex textual information.

The System Architecture is as follows –

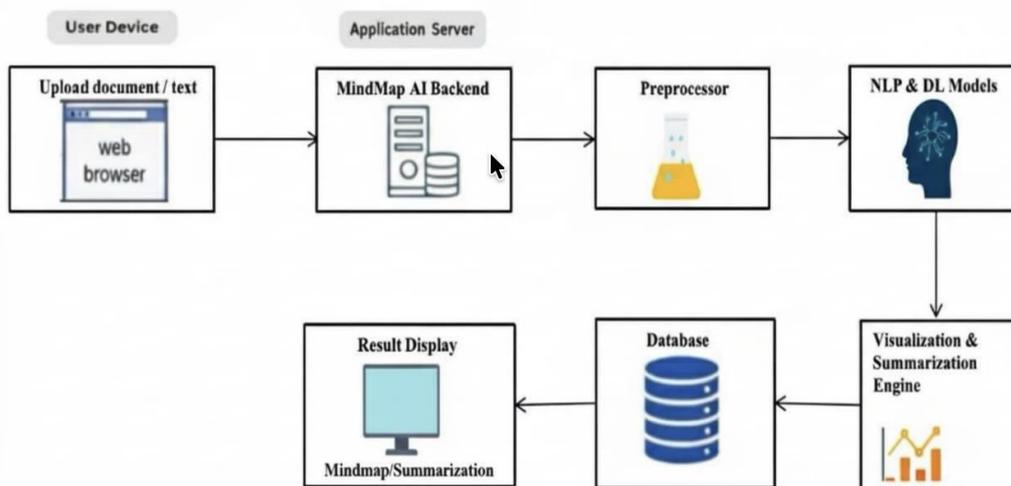


Fig. 2. System Architecture

The **MindMap AI** system is designed with a modular architecture that transforms unstructured textual data into either interactive Mind Maps or AI-generated summaries, as illustrated in Fig. 2. The workflow starts at the **User Interface**, where users can input text directly or upload documents through a web-based dashboard. This interface offers a straightforward and user-friendly way to submit textual content for analysis.

After the input is received, it is sent to the backend server and processed by the **Text Preprocessing Module**. At this stage, the raw text undergoes several preparation steps, including cleaning, tokenization, and the identification of important entities or concepts. These operations help convert the original unstructured content into a more organized format that can be effectively analyzed by the system.

The refined text is then passed to the **Semantic Processing Module**, where Sentence Transformer models generate contextual embeddings for the identified concepts. Using these embeddings, the system measures **cosine similarity** to determine the degree of semantic relationship between different concepts within the text.

Based on the calculated similarity values, the system constructs a **concept graph** that represents the connections among related ideas. This graph is displayed using a **force-directed visualization**, producing an interactive Mind Map that users can explore. If the system is unable to identify sufficient semantic relationships to form a meaningful graph, it instead activates a **Transformer-based summarization module**, which generates a concise summary of the input content.

Finally, the generated results are saved in the system database and presented through the visualization interface. This allows users to revisit and interact with the created Mind Maps or review the generated summaries. Overall, the architecture integrates text preprocessing, semantic analysis, visualization, and data storage to enable efficient and scalable knowledge representation.

IV. EXPERIMENTAL RESULTS

Figures 3–6 illustrate the output generated by the proposed **MindMap AI** system for different types of textual inputs. Fig. 3 shows the initial user interface where raw text is provided as input for analysis. The system processes the input through preprocessing, semantic embedding generation, and relationship inference modules.

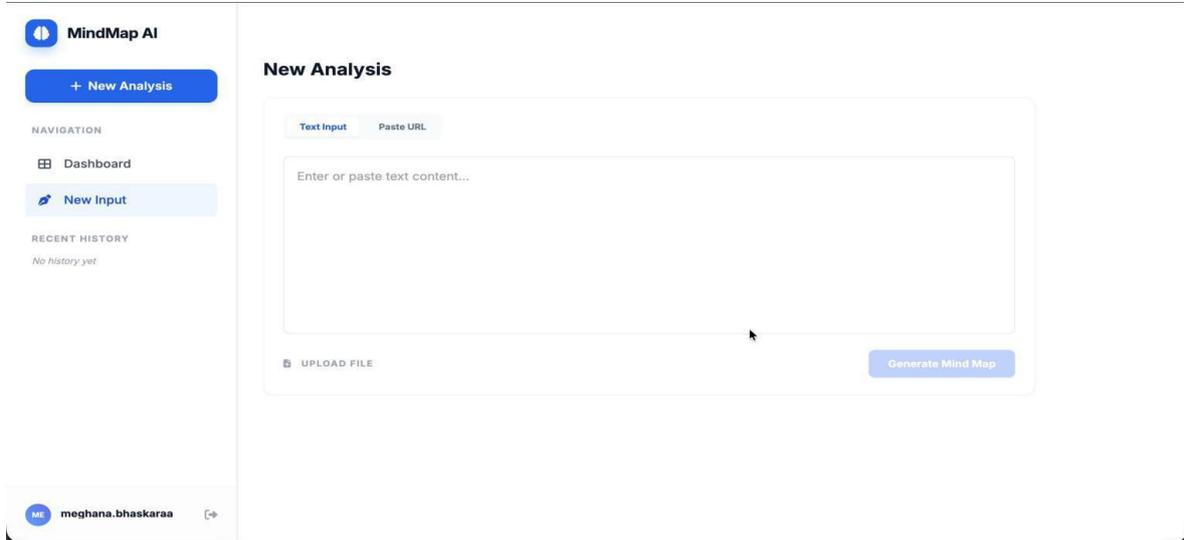


Fig. 3(a). User Interface

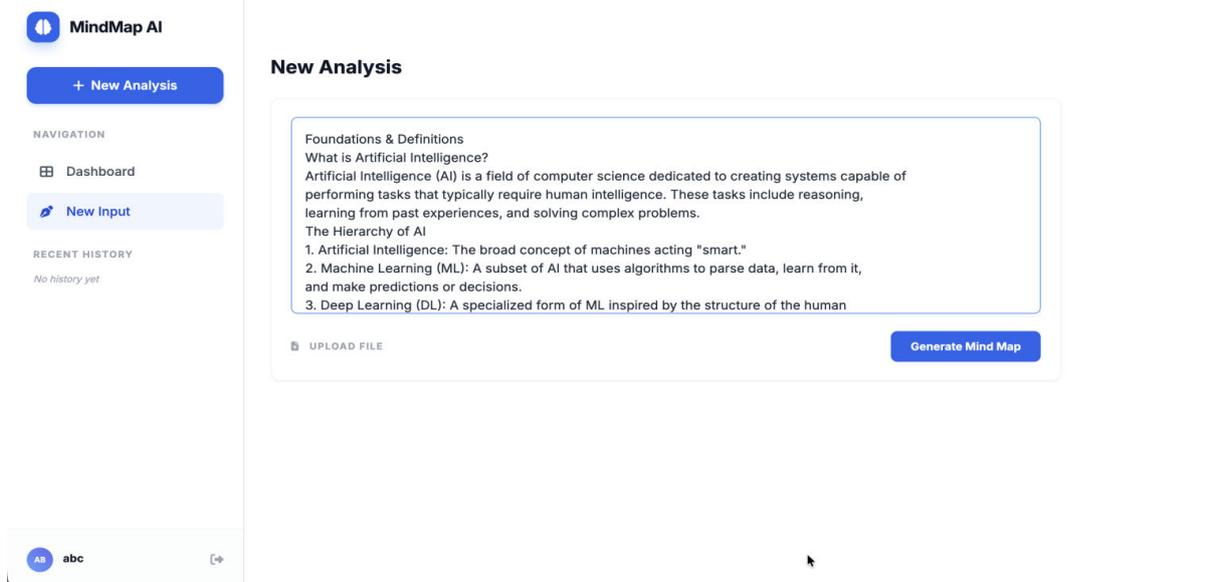


Fig. 3(b). Text Input

Fig. 4 shows the final interactive Mind Map rendered using a force-directed layout algorithm.

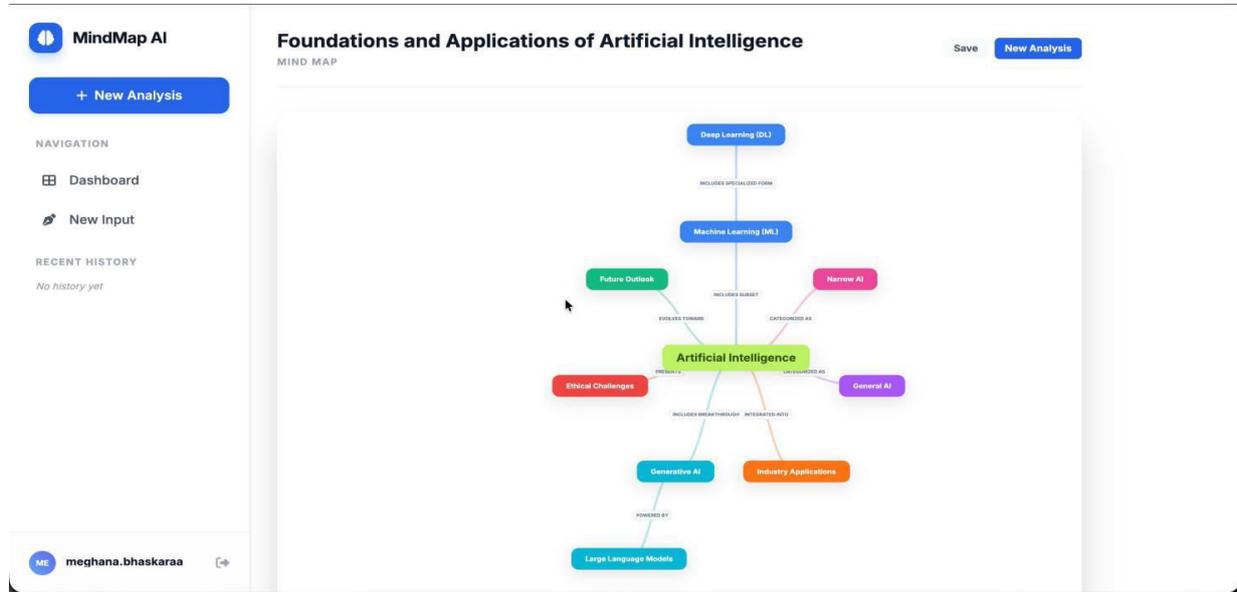


Fig. 4. Mind Map Generation

Fig. 5 shows the original abstract narrative input. It illustrates the topology notice indicating that mind map generation was skipped due to weak relational structure. It displays the AI-generated abstractive summary produced by the Transformer-based summarization model.

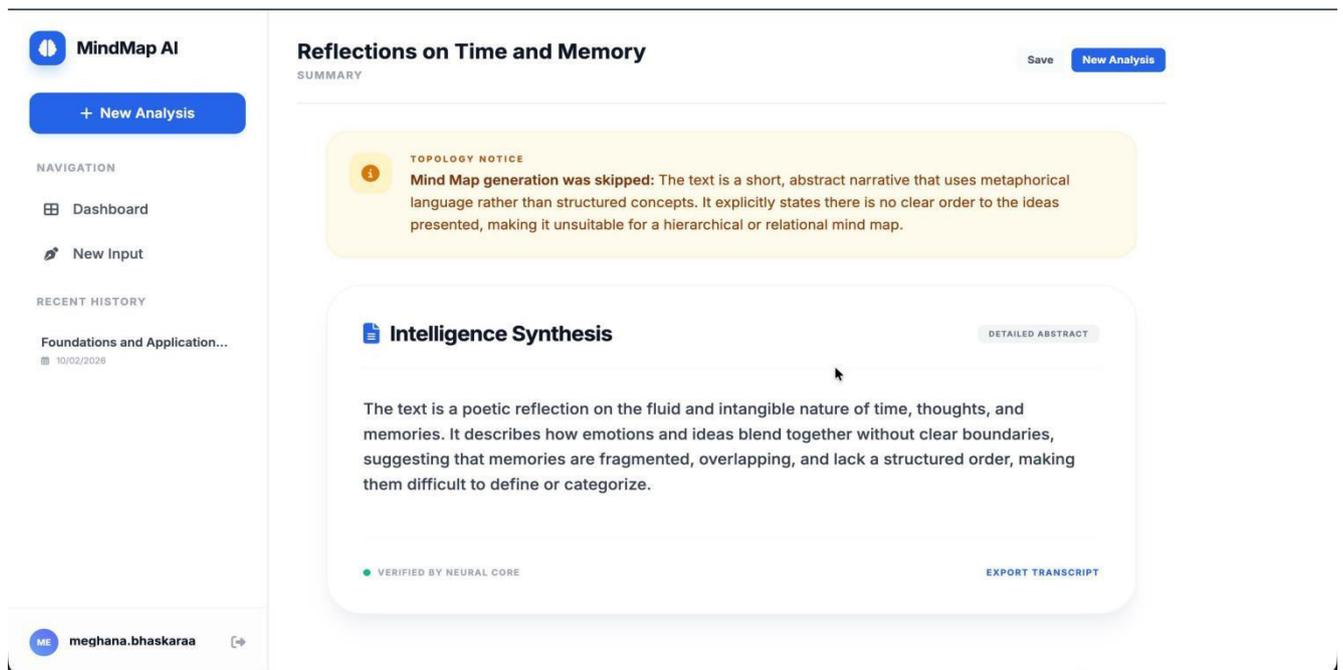


Fig. 5. Mind Map fall back

Fig. 6 presents the **Personal Dashboard** interface of the MindMap AI system. The dashboard lists previously generated Mind Maps along with relevant details such as their titles, short preview snippets, creation timestamps, and status indicators. Each generated analysis is stored in the system database, allowing users to revisit and review their results later through the “View Result” option.

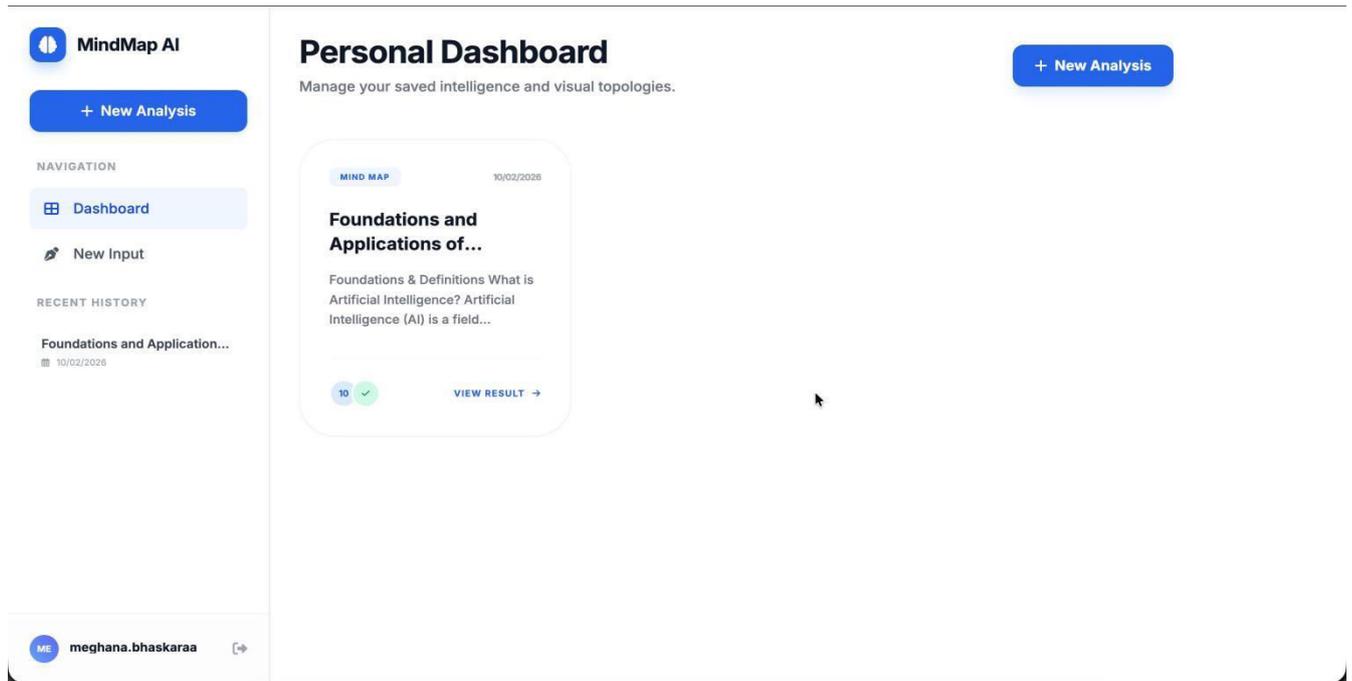


Fig. 6. Personal Dashboard

The experimental results indicate that the proposed system is capable of effectively generating structured and interactive Mind Maps when the input text contains clearly identifiable concepts. In cases where the input consists of more abstract or loosely structured narratives, the system instead produces clear and coherent summaries. The presence of an adaptive switching mechanism further improves the system’s reliability, allowing it to select the most appropriate output format and maintain meaningful results across a wide range of textual inputs.

V. CONCLUSION

The development of **MindMap AI** represents an important step toward enhancing AI-based knowledge visualization and automated organization of information. The system integrates several modern techniques, including Transformer-based semantic analysis, Sentence Transformer embeddings, cosine similarity for identifying relationships among concepts, and interactive graph visualization. Through the combination of these components, the platform demonstrates how deep learning can transform unstructured textual data into structured visual representations that are easier to interpret.

In addition, the system incorporates an adaptive summarization mechanism that produces meaningful textual output when strong semantic links between concepts cannot be identified. Another key focus of the project is usability. The system provides features such as document upload, interactive exploration of generated mind maps, dashboard-based storage of results, and export options for saving outputs. These functionalities allow users to conveniently manage and revisit previously generated analyses. Evaluation of the system across several parameters—including functionality, integration, performance, and usability—indicates that the platform performs reliably while maintaining responsiveness and the ability to handle larger workloads.

In summary, the proposed system offers an efficient method for automatically generating Mind Maps and organizing knowledge from textual information. Its modular structure makes the framework flexible and suitable for future enhancements. The system also shows promising applications in areas such as education, academic research, knowledge management, and digital learning platforms. As a result, this work contributes toward the continued development of AI-driven visual knowledge representation and intelligent learning support tools.

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