Memorize: AI Powered Knowledge Assistant

A project report submitted in partial fulfilment of the requirements for the award of the degree in

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING

Submitted by

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CERTIFICATE

This is to certify that the project report entitled **"Memorize: AI Powered Knowledge Assistant"** is a bonafide project work done by **PANDRINKI VENKATESH (321506402255), NALANATI PHANISRI SAI AKSHITH (321506402229), PRATAPRAO SUMANTH (321506402280), MAHANTHI MURALI KRISHNA (321506402222)** students of Department of Computer Science and Systems Engineering, Andhra University College of Engineering(A), during the period 2021 - 2025 in the partial fulfilment of the requirements for the award of degree of **BACHELOR OF TECHNOLOGY**.

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DECLARATION

We, hereby declare that the project report entitled "**Memorize: AI Powered Knowledge Assistant"** has been done by us during the period December 2024 – April 2025 in partial fulfilment of the requirement for the award of degree of Bachelor of Technology in Computer Science and Engineering, under the guidance of **"Prof. K. VENKATA RAO"**, Associate Professor, Department of Computer Science and Systems Engineering, Andhra University College of Engineering(A). We, hereby declare that this project work has not been submitted to any other universities/institutions for the award of any degree.

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LIST OF ABBREVATIONS

AI	ARTIFICIAL INTELLIGENCE
ML	MACHINE LEARNING
LLM	LARGE LANGUAGE MODEL
RAG	RETRIVAL AUGMENTED GENERATION
NLP	NATURAL LANGUAGE PROCESSING
TTS	TEXT-TO-SPEECH
BM25	BEST MATCHING 25
QA	QUESTION ANSWERING

ABSTRACT

In the age of information overload, accessing and comprehending complex academic materials can be challenging for learners and researchers. A significant challenge exists in efficiently transforming static documents, such as PDFs, PPTs, and Word files, into engaging and accessible formats. This project addresses this challenge with an AI-powered knowledge assistant designed to transform these documents into interactive and spoken content. The system integrates multi-modal document ingestion, encompassing PDF, PPT, and Word formats, a hybrid Retrieval Augmented Generation (RAG) framework, and an AI-driven chapter-to-podcast generator. The RAG component employs a fusion-based approach, combining dense and sparse retrieval with re-ranking, to enhance query accuracy and reduce hallucination when generating answers using the Gemini LLM. The podcast generator creates structured audio content from chapter text, utilizing role-based summarization and a debate-style script to provide an alternative learning modality. The system is built using technologies such as LlamaIndex for data orchestration, Docling for document parsing, SQLite for lightweight data storage, ChromaDB for vector embeddings, Gemini LLM for content generation, Next.js for the frontend, FastAPI for the backend, and Kokoro TTS for text-to-speech synthesis. This approach aims to improve the accessibility and comprehension of complex information, catering to diverse learning styles and research needs.

1. INTRODUCTION

1.1 OVERVIEW

The project lies at the intersection of artificial intelligence, natural language processing, and educational technology. It addresses the growing need for efficient methods to process and digest the increasing volume of digital information, particularly in academic and research settings. The core idea is to develop a system that can convert static document formats into more dynamic and accessible formats, thereby enhancing the learning experience and research productivity. This involves creating tools that not only extract and process the text but also transform it into interactive content and spoken formats, catering to diverse learning styles and accessibility needs.

To elaborate, this project aims to create an AI-powered knowledge assistant that tackles the difficulties faced by learners and researchers in handling large amounts of information. It will use advanced AI techniques to convert static documents into more engaging formats. The system will employ a hybrid Retrieval Augmented Generation (RAG) framework to provide accurate and reliable information and also feature an AI-driven chapter-to-podcast generator to offer an alternative way to consume the content. Ultimately, this project seeks to improve the accessibility and comprehension of complex information and cater to a wider audience.

1.2 Foundational Concepts

To fully understand the development and functionality of the AI-powered knowledge assistant, it is essential to explore the core theoretical and technological foundations upon which it is built. These concepts span the fields of artificial intelligence (AI), natural language processing (NLP), machine learning (ML), large language models (LLMs), embeddings, information retrieval strategies, and the Retrieval-Augmented Generation (RAG) framework. This section elaborates on each of these components and explains how they interact to create a system capable of transforming static documents into rich, interactive, and voice-based knowledge formats.

1.2.1 Artificial Intelligence (AI) and Machine Learning (ML)

Artificial Intelligence (AI) refers to the capability of machines to simulate human cognitive functions such as learning, reasoning, and decision-making. Within the broader AI domain, Machine Learning (ML) is a key subfield that focuses on enabling machines to learn patterns from data and improve performance over time without being explicitly programmed.

In the context of this project, AI is the overarching discipline driving intelligent behavior, while ML powers the core operations such as classifying documents, generating summaries, and extracting meaningful insights. Algorithms are trained on large datasets to understand context, relevance, and content structure, which significantly enhances the assistant's ability to convert raw documents into structured knowledge representations. Furthermore, reinforcement learning and supervised learning techniques may be used to refine outputs, align responses with human feedback, and improve the contextual fidelity of generated responses.

1.2.2 What Are LLMs and Why Do They Need RAG?

Large Language Models (LLMs) like Gemini, GPT, and BERT are deep learning models trained on vast amounts of textual data. They are capable of understanding and generating human-like text, answering questions, translating languages, and even summarizing complex documents. However, despite their impressive capabilities, LLMs face two significant challenges:

- **Static Knowledge Limitation**: LLMs are trained on a fixed corpus of data, meaning they cannot access new or real-time information beyond their training cut-off date.
- **Hallucination Problem**: LLMs sometimes produce information that sounds plausible but is factually incorrect, especially when handling niche or highly specific queries.

Retrieval-Augmented Generation (RAG) addresses these issues by supplementing the LLM with an external knowledge base. RAG retrieves the most relevant documents or document fragments based on a user query and passes them into the model, enabling it to generate answers grounded in up-to-date and domain-specific information. This significantly enhances **accuracy**, **reliability**, and **contextual appropriateness** of the responses. Moreover, it helps the model provide traceable answers, as each generated response is tied to a known set of documents.

1.2.3 Embeddings and Semantic Search

Embeddings are dense vector representations of text that capture the semantic meaning rather than just the surface-level lexical features. For example, the words "intelligence" and "smartness" may be different textually but are placed closely in the embedding space due to their similar meanings.

Embeddings allow the system to perform **semantic search**, where the retrieval is based not only on matching exact terms but also on the conceptual similarity between the query and the document contents. This is crucial in educational settings, where similar concepts may be expressed using varied terminology. It also enables the model to better understand paraphrased questions and contextual nuances, improving the relevance of retrieved documents.

Embeddings are typically generated using transformer-based models like Sentence-BERT or Gemini's embedding service. These representations enable efficient computation and indexing for large-scale document search.

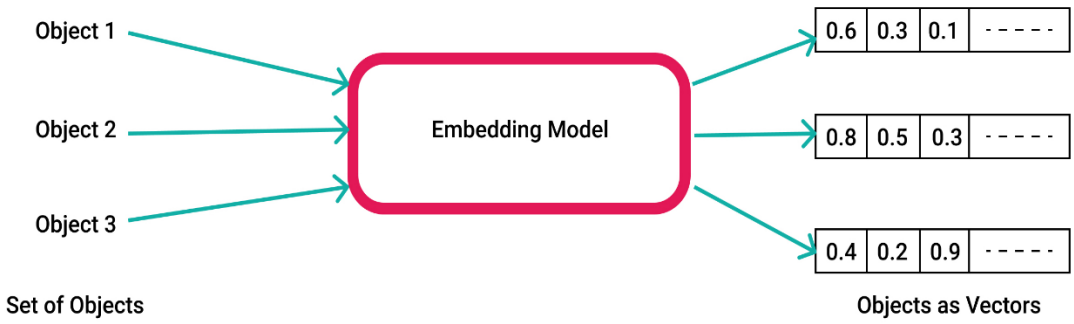


Fig 1.1 Embedding Model

1.2.4 Vanilla RAG: Architecture and Limitations

The basic version of the Retrieval-Augmented Generation (RAG) framework follows a three-step pipeline:

a. The user's question is embedded into a vector.
b. The vector is used to retrieve the top-k most semantically similar document chunks from a vector store.
c. These retrieved chunks are provided as context to the LLM, which then generates a response based on both the query and the supporting information.

While this vanilla RAG pipeline significantly improves upon stand-alone LLMs, it has some limitations:

- **Keyword insensitivity**: Pure semantic retrieval might overlook documents that contain exact key terms, citations, or formulas that are vital in academic or technical domains.
- **Lack of lexical precision**: It may prioritize general relevance over highly specific matches, which could lead to reduced precision.

To overcome these issues, more advanced retrieval techniques like hybrid search are incorporated.

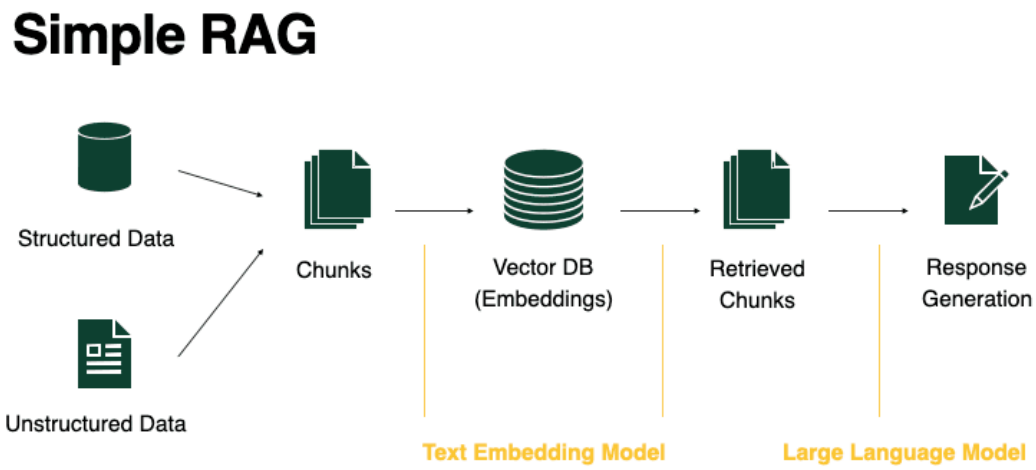


Fig 1.2 Vanilla RAG

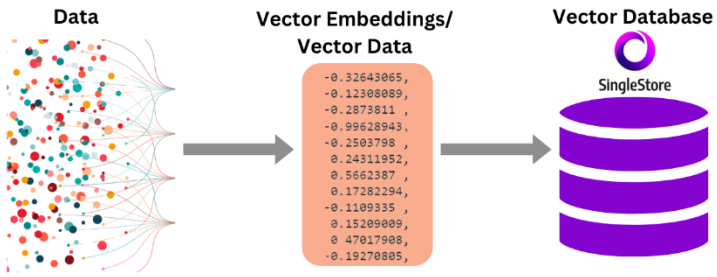


Fig1.3 Vector Embeddings

1.2.5 Vector Search – Semantic Similarity

Vector search operates on the embedding space, enabling the retrieval of documents based on **meaning** rather than the presence of specific keywords. This is especially beneficial in educational applications where users might ask questions using everyday language while the source documents use more formal or academic terminology.

For instance, a query like “How does the brain store memories?” could successfully retrieve content that discusses "neural encoding of long-term memory" due to semantic alignment, even if no keywords overlap.

The system uses vector databases such as FAISS, ChromaDB, or Milvus to enable fast approximate nearest-neighbor search over high-dimensional embeddings. This underpins the scalable and responsive search capability required for real-time interactions

1.2.6 BM25 – Lexical Search

BM25 (Best Matching 25) is a popular probabilistic retrieval algorithm from traditional information retrieval. It ranks documents based on the frequency and importance of query terms found in each document. This type of retrieval is **lexical** in nature, relying strictly on exact or partial keyword matches.

BM25 is particularly useful in cases where documents contain technical terms, references, or phrases that must be matched exactly. In this project, BM25 complements semantic search by ensuring high-precision retrieval of content with exact matches, which is critical for maintaining factual correctness and contextual depth.

The algorithm works by evaluating how frequently terms occur in a document relative to their frequency across all documents, while also considering document length normalization. This enables it to emphasize highly relevant documents even in large corpora.

$$BM25 = \sum_{t \in q} \log\left[\frac{N}{df(t)}\right] \cdot \frac{(k_1 + 1) \cdot tf(t,d)}{k_1 \cdot \left[(1-b) + b \cdot \frac{dl(d)}{dl_{avg}}\right] + tf(t,d)}$$

- k_1, b – parameters
- $dl(d)$ – length of document d
- dl_{avg} – average document length

Table 1 Difference between bm35 and vector

Feature	**BM25 (Lexical Search)**	**Vector Search (Semantic Search)**
Matching Method	Keyword-based	Meaning-based
Strength	Exact term matching, high precision	Captures synonyms and context, high recall
Weakness	Misses paraphrased or semantically similar text	May miss exact keyword matches

1.2.7 Hybrid Search – Combining BM25 and Vector

Hybrid search is a retrieval technique that combines both BM25 (lexical) and vector (semantic) search methods. Instead of relying on a single retrieval strategy, hybrid search brings together the strengths of both:

- **BM25 ensures exact keyword match and domain-specific relevance**.
- **Vector search ensures conceptual coverage and paraphrase tolerance**.

This dual approach improves both **precision and recall**, leading to a more balanced and accurate retrieval system. For this project, hybrid retrieval is essential to ensure that no critical information is overlooked—especially in diverse and complex academic content.

Hybrid search is implemented by combining and re-ranking the results from BM25 and vector search, creating a unified list of highly relevant results. This fusion approach increases robustness and ensures better answer quality, even for poorly worded or ambiguous queries.

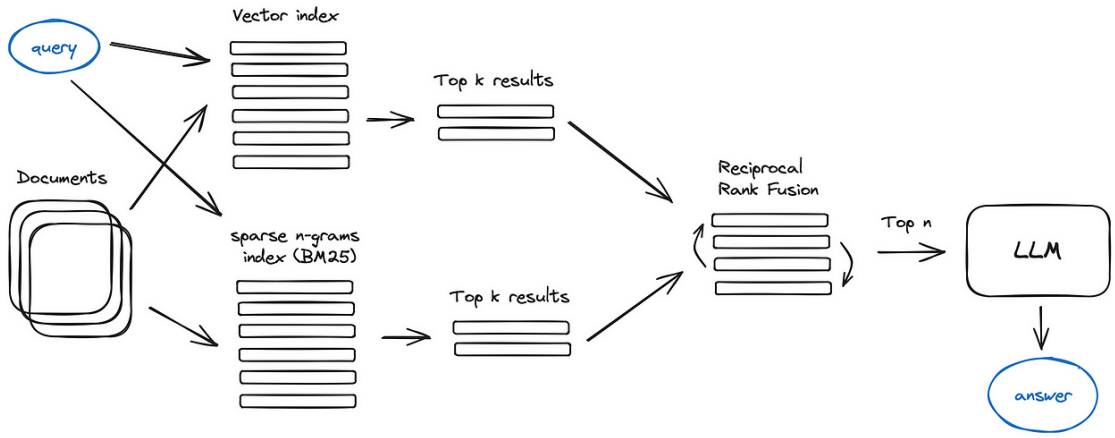


Fig 1.4 Hybrid Search

1.2.8 Reciprocal Rank Fusion (RRF) – Re-ranking Results

Reciprocal Rank Fusion (RRF) is a re-ranking algorithm used to merge and re-score the results from multiple retrieval strategies like BM25 and vector search. Instead of simply choosing results from one list or the other, RRF gives higher priority to results that appear near the top of both lists.

For example, if a document is ranked highly in both the BM25 and vector retrieval outputs, RRF boosts its overall ranking. This ensures that documents with both lexical relevance and semantic relevance are surfaced to the top. By re-ranking in this way, the system increases the chance of presenting the most meaningful and contextually rich content to the user, enhancing the overall performance of the RAG framework.

The RRF score is calculated using a formula that emphasizes early ranks, ensuring that even modestly placed items in both lists can rise to prominence if they are consistently relevant. This makes the retrieval layer fairer, more transparent, and user-aligned.

$$RRFscore(d \in D) = \sum_{r \in R} \frac{1}{k + r(d)},$$

1.3 PROBLEM STATEMENT

Learners and researchers today are frequently overwhelmed by the sheer volume of information contained in academic papers, research reports, technical documentation, and other complex materials. Extracting relevant information efficiently from these resources often requires significant time and effort, especially when the content spans hundreds of pages and is presented in dense, technical language. Traditional methods of consuming such content—such as manual reading, annotation, and note-taking—are not only labor-intensive but also ineffective for individuals with varying cognitive preferences or learning styles. These conventional approaches do not scale well with the increasing influx of digital information.

Moreover, much of the content resides in static, non-interactive formats like PDFs, PowerPoint presentations (PPTs), and Word documents. These formats, while useful for documentation, are not optimized for dynamic interaction, semantic understanding, or integration into modern knowledge management or learning systems. This static nature of information creates a barrier to knowledge accessibility, reuse, and engagement.

This project addresses these limitations by proposing the development of a system that can intelligently ingest, process, and transform such documents into interactive, voice-enabled, and context-aware knowledge formats. The goal is to create a more intuitive and engaging experience for users by converting static documents into a format that supports alternative learning modalities, such as podcasts, while ensuring accurate and meaningful information retrieval.

1.4 OBJECTIVES

This project aims to achieve the following specific objectives:

- Design and implement a robust system capable of ingesting documents in various formats, including PDF, PowerPoint, and Microsoft Word.
- Develop and integrate a hybrid Retrieval-Augmented Generation (RAG) framework that combines lexical and semantic search techniques to retrieve the most contextually relevant information.
- Create a pipeline for generating podcast-style audio content from document chapters using advanced AI models, offering an alternative, auditory-based learning experience.
- Enhance the accessibility and understandability of complex information through AI-driven summarization, contextual segmentation, and voice synthesis.
- Support a wide range of learning preferences by providing multiple ways to consume and interact with knowledge.

1.5 MOTIVATION

The motivation behind this project stems from the ever-growing demand for efficient and intelligent tools to manage the explosion of digital information. Academic professionals, students, and researchers constantly seek new methods to keep up with vast reading requirements while maintaining a deep understanding of the content. The traditional reliance on manual content review is not only outdated but also incompatible with the pace and scale of modern information consumption.

By building an AI-powered knowledge assistant, this project seeks to bridge the gap between static knowledge repositories and dynamic, user-centric knowledge experiences. The ability to automatically convert textual documents into semantically rich, audio-based, and interactive formats empowers users to learn on the go, improve retention, and boost overall productivity.

This initiative is also driven by a commitment to inclusivity. Many individuals, including those with visual impairments, attention-related challenges, or auditory learning preferences, benefit significantly from alternative content formats. The project aims to support such needs by making knowledge delivery more adaptable, inclusive, and personalized.

1.6 SCOPE

The scope of this project is clearly defined to focus on the development and deployment of an AI-powered knowledge assistant that transforms traditional documents into dynamic learning assets. The primary features and functionalities to be developed include:

- Multi-format document ingestion, supporting PDF, PPT, and Word files.
- A hybrid RAG-based information retrieval system that combines lexical (BM25) and semantic (embedding-based) methods.
- A chapter-to-podcast generation engine utilizing LLMs and TTS (Text-to-Speech) systems.
- A user-friendly web interface for uploading documents, interacting with processed content, and listening to generated audio.

However, the project explicitly excludes the following:

- Integration with third-party learning management systems (LMS).
- Support for document types outside of PDF, PPT, and Word formats.
- Advanced features for audio post-processing, such as sound design, background music, or professional editing.

This well-defined scope ensures that the project remains focused and achievable while delivering significant value to its intended users.

1.7 METHODOLOGY OVERVIEW

The project will be carried out in the following phases:

- Document Ingestion and Preprocessing: Develop modules for ingesting and preprocessing documents in PDF, PPT, and Word formats.
- RAG Framework Implementation: Implement a hybrid RAG framework, including dense and sparse retrieval mechanisms, and integrate it with the Gemini LLM.
- Podcast Generator Development: Design and develop the AI-driven chapter-to-podcast generator, including role-based summarization and script generation.
- System Integration and Testing: Integrate the various components into a cohesive system and conduct thorough testing.
- User Interface Development: Develop a user-friendly interface for accessing and interacting with the processed content.

2. LITERATURE SURVEY

2.1 Review of Existing Systems:

A number of existing systems and technologies address various aspects of the problem of information access and processing. Here's an overview of some key areas:

• Document Management Systems: Systems like Adobe Acrobat, Microsoft SharePoint, and Google Workspace provide functionalities for storing, organizing, and searching documents. However, they primarily focus on keyword-based search and lack the advanced AI-powered semantic understanding and content transformation capabilities of this project.

• Information Retrieval Systems: Search engines like Google Search and Bing utilize sophisticated algorithms, including BM25 and vector-based methods, for retrieving relevant information from vast web resources. However, they are designed for web-scale data and do not address the specific challenges of processing and transforming structured documents like PDFs, PPTs, and Word files into alternative formats.

• Large Language Models (LLMs): Models like OpenAI's GPT series and Google's Gemini have demonstrated remarkable capabilities in natural language understanding, generation, and summarization. These models can be used to enhance information retrieval and content transformation. This project leverages the Gemini LLM to generate accurate and contextually relevant answers and to create engaging podcast scripts.

• Text-to-Speech (TTS) Systems: Services like Amazon Polly, Google Text-to-Speech, and Microsoft Azure Text to Speech can convert text into spoken audio. While these systems provide the basic functionality for converting text to speech, this project aims to go further by generating structured and engaging audio content with role-based summarization and debate-style scripts.

While these existing systems offer valuable functionalities, this project aims to integrate and extend these capabilities to create a more comprehensive and intelligent knowledge assistant. It combines the strengths of multi-modal document processing, advanced RAG techniques, and AI-driven content transformation to provide a more effective solution for accessing and understanding complex information.

2.2 Identified Gaps and Innovations:

This project addresses several gaps in existing systems and introduces innovative approaches:

- Integration of Multi-Modal Documents: Unlike many existing systems that focus on a single document format or web-based content, this project integrates multi-modal document ingestion, including PDF, PPT, and Word files. This enables users to process a wider range of document types without needing to convert them manually.
- Hybrid RAG Framework with Re-ranking: The project employs a hybrid RAG framework that combines BM25, vector search, and Reciprocal Rank Fusion (RRF). This approach overcomes the limitations of individual retrieval methods and improves the accuracy and robustness of information retrieval. The re-ranking step further enhances the quality of the retrieved information, ensuring that the most relevant content is presented to the user.
- AI-Driven Podcast Generation: The project introduces an innovative approach to content transformation by generating structured, engaging podcasts from chapter text. This goes beyond simple text-to-speech conversion by incorporating role-based summarization and debate-style scripts. This provides an alternative learning modality that can improve accessibility and engagement, particularly for auditory learners.
- End-to-End System for Knowledge Access: By combining these innovations, the project creates an end-to-end system that streamlines the process of accessing and understanding complex information. The system takes static documents as input and provides users with both interactive Q&A capabilities and dynamic audio content, all powered by advanced AI.

3. REQUIREMENTS ANALYSIS

Software Requirement Specification (SRS) is a complete specification and description of software requirements that must be fulfilled to develop the software system successfully. It comprises user requirements for a system and detailed specifications of the system requirements. This report lays a foundation for software engineering activities and is constructed when requirements are elicited and analyzed.

A Software Requirements Specification (SRS) document for the Memorize outlines the detailed requirements and specifications for the development of the system.

3.1. FUNCTIONAL REQUIREMENTS:

The system allows users to register, create knowledge spaces, and upload documents in PDF, PPT, or Word formats. It automatically extracts text using Docling and embeds it into a vector store for efficient querying. A hybrid RAG pipeline (dense + sparse retrieval) handles real-time queries, with results refined through RAG fusion and Reciprocal Rank Fusion. Users can interact with an AI chatbot powered by Gemini LLM and convert selected chapters or topics into podcasts using Kokoro TTS, which are then playable via an integrated audio player

- **Document Upload:** Users can upload a variety of document formats, including PDF files, PowerPoint presentations (PPT), and Microsoft Word documents. The upload mechanism supports drag-and-drop functionality and validates file types before processing.
- **Text Extraction:** Upon upload, documents are automatically parsed to extract structured, clean textual content. This is achieved using Docling, a robust tool for intelligent parsing and formatting of text across diverse document types. Extracted content is preprocessed for tokenization and chunking.
- **Ingestion Trigger:** Users can initiate the ingestion process manually after uploading. This process converts document chunks into vector embeddings and stores them in a vector database. It ensures fine-tuned semantic representation and indexing.
- **Hybrid Search & Querying:** The system supports real-time information retrieval using a hybrid search approach. It combines dense vector-based semantic search with sparse lexical retrieval (BM25) to maximize both contextual understanding and keyword precision.
- **RAG Fusion & Ranking:** For each query, similar sub-queries are generated to expand the search context (RAG fusion). The results are consolidated and reranked using Reciprocal Rank Fusion (RRF), ensuring the most relevant content surfaces at the top.
- **Conversational AI Response:** Using the Gemini large language model (LLM), the system generates detailed, context-aware answers to user queries. The responses are tailored to the document corpus and maintain high factual integrity.
- **Chapter Selection & Podcast Generation:** Users can select entire chapters or specific sections and optionally define focus topics. The system then generates podcast-ready scripts that summarize and explain the content intelligently.
- **TTS Synthesis:** Using Kokoro TTS, the system synthesizes the AI-generated script into high-quality, natural-sounding audio. The voice output is expressive and listener-friendly.
- **Audio Playback:** An integrated web-based audio player allows users to listen to generated podcasts directly in the browser. Playback controls include pause, skip, and volume adjustments.

3.2. NON-FUNCTIONAL REQUIREMENTS

The system ensures high performance through GPU-accelerated processing and supports multiple users with scalable ingestion. ChromaDB and SQLite provide persistent storage for documents and audio. The Next.js frontend offers a smooth, user-friendly interface, and strong security measures protect file uploads and access.

- **Performance:** The system is optimized for speed and responsiveness, with GPU-accelerated embedding for fast ingestion and low-latency TTS for near real-time audio generation.
- **Scalability:** Designed with a modular architecture, the system supports concurrent users and scalable ingestion pipelines for handling multiple documents and interactions simultaneously.
- **Reliability:** Persistent storage of document embeddings and generated audio files is ensured via ChromaDB and SQLite, minimizing data loss and enhancing fault tolerance.
- **Usability:** The frontend, developed with Next.js, offers a modern and intuitive user interface. Users benefit from clear navigation, visual feedback, and seamless transitions.
- **Security:** All file uploads are handled through secure endpoints with proper authentication and access control. Permissions ensure that user data and documents remain private and protected..

3.3. SYSTEM REQUIREMENTS

3.3.1Hardware Requirements

- **Development/Server Machine**:
    - Processor: Quad-core CPU or higher
    - RAM: Minimum 16 GB
    - GPU: NVIDIA GPU with CUDA support (e.g., RTX 3060 or better) for embeddings and TTS
    - Storage: SSD with at least 50 GB free space for document and audio storage

3.3.2Software Requirements

- **Backend**: Python 3.10+, FastAPI, CUDA toolkit
- **Frontend**: Next.js 14, Tailwind CSS
- **AI/ML Libraries**: LlamaIndex, HuggingFace Transformers, ChromaDB, Docling, Gemini API
- **TTS Engine**: Kokoro TTS
- **Database**: SQLite (for metadata), file system (for media)

4. SYSTEM DESIGN

4.1. SYSTEM DESIGN

System design refers to the process of defining a system's architecture, components, modules, and data flow to ensure it meets functional and non-functional requirements effectively. It provides a structured approach to software development, ensuring scalability, maintainability, and efficiency. A well-defined system design helps in understanding how different components interact, how data is processed, and how users will interact with the system.

Types of System Design

System design is broadly categorized into two main types:

1. **High-Level Design (HLD)**: Also known as architectural design, it defines the system's overall structure, including major components, their relationships, and how they interact. It provides a macro-level view of the system and focuses on aspects like data flow, module division, and technology choices. It provides an abstract representation of the system, helping stakeholders understand its functionality without delving into implementation details.
2. **Low-Level Design (LLD)**: Low-Level Design (LLD) translates the high-level system architecture into detailed specifications for each module, defining the logic, database schemas (if used), data structures, API endpoints, and internal workflows. It focuses on class diagrams, sequence diagrams, and algorithm design to ensure efficient implementation. LLD serves as a blueprint for developers, ensuring consistency and clarity in code development.

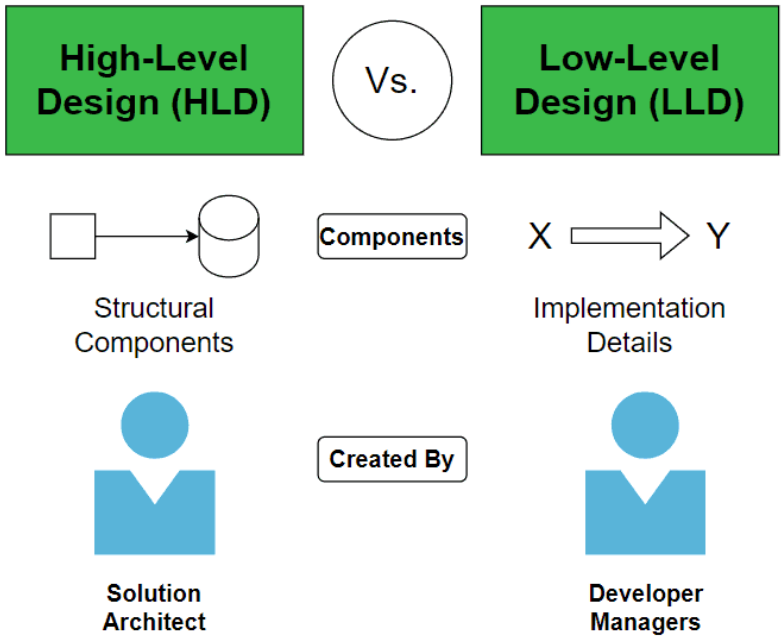


Fig 4.1. Categories of System Design

4.2. EXISTING SYSTEM

Traditional methods of accessing, processing, and understanding complex documents typically involve a combination of manual effort and basic digital tools. These conventional approaches often include:

- Manually reading through lengthy documents to extract relevant information.
- Taking handwritten or digital notes while reading, which is both time-consuming and cognitively demanding.
- Performing keyword-based searches within digital files to locate specific terms or sections.
- Using general-purpose text-to-speech (TTS) applications to convert written text into spoken audio.

While these methods have been widely used in academic, professional, and research settings, they suffer from several significant drawbacks:

- **Inefficiency and time consumption**: Users often spend hours reading, highlighting, and summarizing content, especially when dealing with dense or voluminous documents.
- **Cognitive load**: These methods require the user to manually identify, extract, and synthesize key points, which can lead to information overload and reduced retention.
- **Inflexibility of keyword search**: Traditional search functions depend on exact keyword matches, which means that semantically relevant content using alternative terminology may go unnoticed.
- **Lack of engagement in TTS output**: Basic TTS tools provide a linear and monotonous reading of content without context-aware structuring, emotional inflection, or dynamic presentation, making them less effective for comprehension and long-term learning.

In contrast, this project proposes a transformative solution through the development of an AI-powered knowledge assistant. The system aims to automate and enhance the way users interact with documents by converting static text into dynamic, interactive, and multimodal formats. With features like semantic search, intelligent summarization, and natural-sounding podcast generation, the assistant addresses the core limitations of existing systems, offering a more efficient, user-friendly, and engaging way to access and understand complex information.

4.3. PROPOSED SOLUTION

The proposed system is an end-to-end AI-powered knowledge assistant that transforms static documents into interactive and audio-based content for enhanced accessibility, comprehension, and engagement. It is designed with modularity and scalability in mind, integrating multiple AI components into a cohesive workflow.

The system accepts documents in PDF, PPT, and Word formats and processes them through a hybrid RAG (Retrieval Augmented Generation) pipeline for contextual Q&A, while also generating structured podcast-style audio summaries. It provides a user-friendly frontend where users can upload documents, search for information conversationally, and listen to chapter-wise audio summaries.

Key functionalities include:

- **Multi-format Document Ingestion**: Seamlessly upload and parse content from PDFs, PPTs, and Word files.
- **Contextual Information Retrieval**: Query documents using a hybrid RAG pipeline that combines dense and sparse retrieval with re-ranking.
- **Conversational Response Generation**: Generate human-like responses using Gemini LLM grounded in retrieved content.
- **Podcast Generator**: Convert chapters into debate-style podcast scripts, synthesized to natural audio via Kokoro TTS.
- **Interactive UI**: Provide an intuitive web interface for document management, querying, and audio playback.

The system prioritizes performance, reliability, and user accessibility, with GPU acceleration for embedding and TTS, and persistent storage via ChromaDB and SQLite.

4.4. SYSTEM ARCHITECTURE

The architecture of the proposed system is composed of four major layers: **Frontend Layer**, **Backend Layer**, **Processing Layer**, and **Data Storage Layer**. These layers communicate over RESTful APIs and real-time channels, ensuring modularity and maintainability.

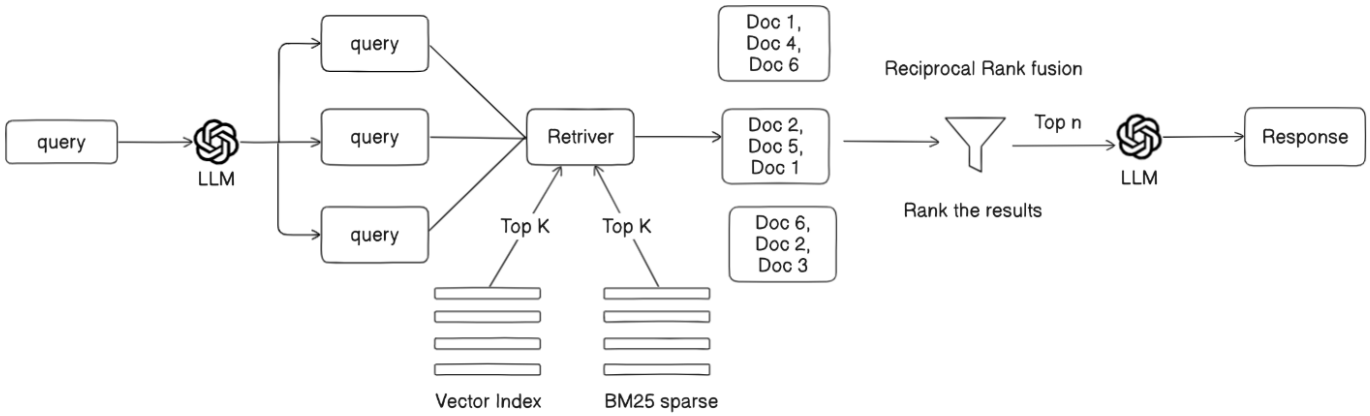


Fig 4.2 Module 1 System Architecture

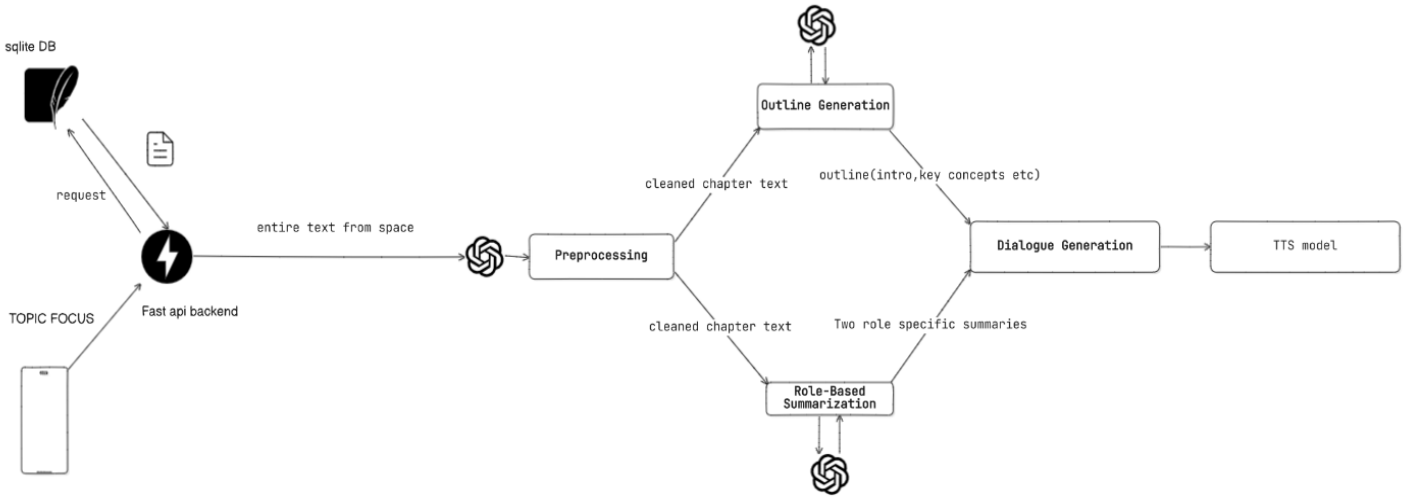


Fig 4.3 Module 2 System Architecture

1. Frontend Layer (Client Interface)

- **Technology**: Built using Next.js and Tailwind CSS
- **Functions**:
    - User registration and authentication
    - Document upload UI
    - Conversational chat interface
    - Chapter selection and podcast playback
    - Visual feedback on query results

2. Backend Layer (API & Orchestration)

- **Technology**: Python with FastAPI
- **Responsibilities**:
    - Handle API endpoints for document upload, ingestion, querying, and podcast generation
    - Coordinate between document parser, vector store, Gemini LLM, and TTS engine
    - Manage user sessions, permissions, and task queues

3. Processing Layer (AI & NLP Pipeline)

- **Components**:
    - **Document Parser**: Docling extracts structured text and metadata
    - **Embedding Engine**: Generates dense embeddings using HuggingFace models
    - **Hybrid RAG Module**:
        - Sparse retrieval via BM25
        - Dense retrieval via vector search (ChromaDB)
        - Re-ranking with Reciprocal Rank Fusion
    - **LLM Interaction**: Gemini API for summarization, Q&A, and podcast script generation
    - **TTS Engine**: Kokoro TTS converts structured scripts into high-quality audio

4. Data Storage Layer

- **Document Storage**:
    - Parsed documents stored in SQLite for lightweight querying
    - Embedded vectors stored in ChromaDB for semantic search
- **Audio Storage**:
    - Generated podcast files stored in local or cloud storage
    - Metadata indexed for playback and retrieval

4.5. SYSTEM WORKFLOW

- **Upload**: User uploads a document via the frontend.
- **Ingestion**: Document is parsed, and content is embedded into ChromaDB.
- **Querying**: User inputs a question. The system retrieves relevant context via hybrid RAG and generates an answer using Gemini LLM.
- **Podcast Generation**: User selects a chapter and optionally a focus topic. The system summarizes and converts it into a scripted audio using Kokoro TTS.
- **Playback**: The user can stream or download the generated podcast.

4.6 Theoretical Integration in System Design

At its core, the system implements a **Hybrid Retrieval-Augmented Generation (RAG)** architecture that merges semantic understanding with traditional information retrieval.

- **Dense Embeddings** capture the contextual meaning of text using transformer-based models. These allow for semantic similarity search.
- **Sparse Vectors (BM25)** complement this with keyword-based relevance scoring, improving retrieval on keyword-heavy queries.
- **Hybrid Retrieval** uses both to get broader, more accurate coverage of possible answers.
- **RAG Fusion** enhances recall by generating multiple semantically-relevant query variations and retrieving top results for each.
- **Reciprocal Rank Fusion (RRF)** is used to combine the results from hybrid searches into a unified, reranked list that prioritizes documents most relevant across variations.
- **Final Generation** involves passing this high-quality, context-rich information to a powerful LLM (Gemini) to generate low-hallucination, grounded responses.

This theoretical layering of dense + sparse + rerankers makes the system robust across diverse query types, including vague, technical, or high-level questions.

4.6.1 RAG Pipeline Process (Module 1)

1. **Document Ingestion & Parsing:**
    - When a user uploads PDFs, PPTs, or Word files into a "space," the backend creates a corresponding folder and inserts a record in the spaces table (SQLite).
    - Uploaded documents are parsed using **Docling**, which extracts raw textual content.
2. **Chunking & Storage:**
    - Extracted text is split into manageable chunks.
    - Each chunk is stored in the documents table in SQLite for later processing.
3. **Ingestion Trigger:**
    - When the user clicks the “Ingest” button, the backend /ingestion route is activated.
4. **Embedding:**
    - Unembedded chunks are converted to dense embeddings using:

HuggingFaceEmbedding(model_name="BAAI/bge-base-en-v1.5", device="cuda")

    - Dense embeddings are stored in **ChromaDB**.
    - BM25 sparse vectors are generated and persisted to disk.
5. **Indexing:**
    - An index (dense + sparse) is created per space to support efficient retrieval.
6. **Query Workflow (RAG Fusion):**
    - When a user sends a query, it hits the /query route.
    - The relevant index is dynamically loaded based on space.
    - RAG Fusion generates multiple paraphrased queries.
    - Each variant is run through:
        - **Dense vector search (ChromaDB)**
        - **Sparse BM25 search (disk)**
    - Top 7 nodes per query are retrieved.
    - **Reciprocal Rank Fusion (RRF)** consolidates and reranks results.
    - Top-ranked nodes are passed with the query to **Gemini LLM**, which generates a high-quality, context-aware answer.

4.6.2 Podcast Workflow Design Logic (Module 2)

1. **Input & Preprocessing:**
    - User selects a chapter (optional: provides focus topic).
    - Text (up to 2M tokens) is isolated from document.
    - Context buffers are added to ensure coherence.
2. **Outline Generation:**
    - Gemini LLM generates a structured podcast outline:
        - Sections include: Intro, Key Concepts, Summary, etc.
3. **Role-Based Summarization:**
    - Two summaries are produced:
        - **Expert:** Technical explanation
        - **Novice:** Simplified version
4. **Dialogue Generation:**
    - AI simulates a debate using:
        - Outline
        - Both summaries
    - Produces: *Scripted dialogue* (Expert vs. Novice)
5. **Text-to-Speech Synthesis:**
    - Dialogue script is passed to **Kokoro TTS**.
    - Each turn is converted to speech.
    - Clips are concatenated and saved to disk.
    - Final audio path is stored in SQLite.

5. IMPLEMENTATION AND TESTING

5.1. IMPLEMENTATION

Frontend Implementation

The frontend of the AI-powered knowledge assistant is built using **Next.js**, offering a fast and scalable framework for building web applications. It provides both server-side rendering (SSR) and static site generation (SSG), allowing for efficient data-fetching and routing mechanisms.

Technologies Used

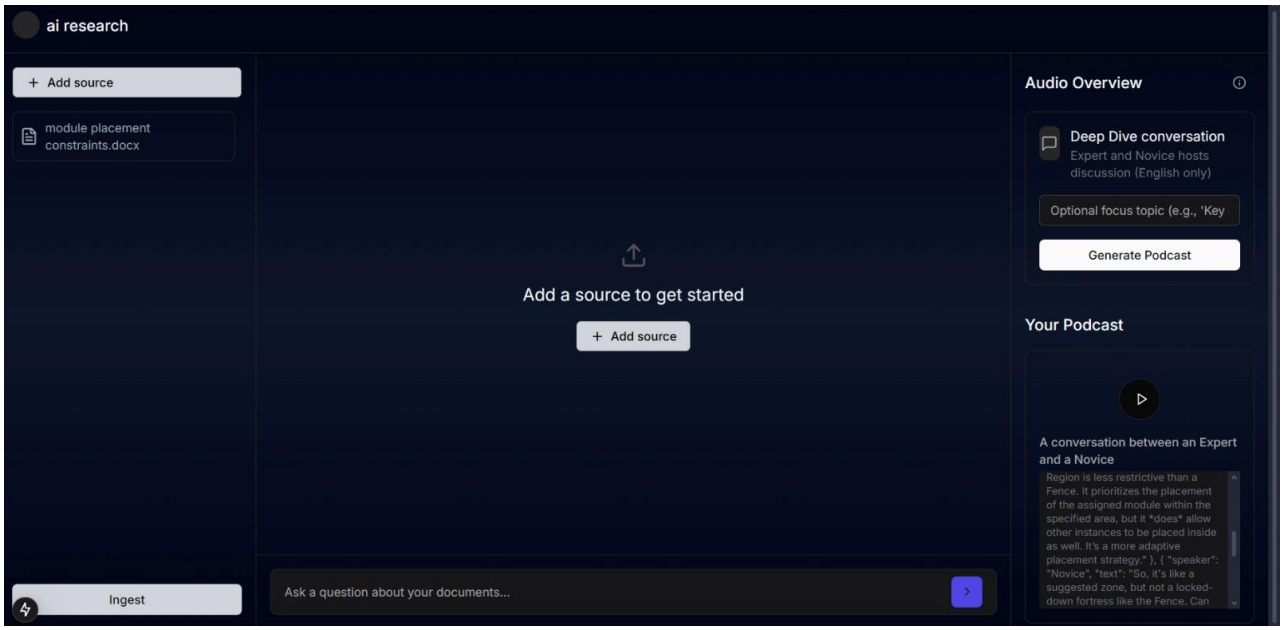
- **Next.js 14**: For routing, page-based architecture, SSR/SSG.
- **React Query**: Manages data fetching and caching across the app.
- **Tailwind CSS**: Provides a utility-first CSS framework for rapid and responsive UI development.
- **Axios**: Handles HTTP requests to the FastAPI backend.
- **Framer Motion**: Adds smooth transitions and animations.
- **React Dropzone**: For file uploads.
- **ShadCN/UI Components**: Used for modern UI elements like modals, toasts, and cards.

Core Features

1. **User Spaces UI**
    - Users can create "spaces" where documents are uploaded and processed.
    - Each space is represented by a card showing its name and status.
    - State updates with **React Query** ensure real-time sync with the backend.
2. **Document Upload Interface**
    - Users can upload PDF, PPT, or DOC files using a drag-and-drop interface.
    - Upload status and feedback are shown using toast notifications.
    - Files are sent to the **/upload/** backend endpoint.
3. **Ingest Button & Status Monitoring**
    - Once files are uploaded, the "Ingest" button appears.
    - Triggers the **/ingestion/** route to begin the chunking and embedding pipeline.
    - Progress indicators guide the user through each backend operation.

4. **Query Interface**
    - Users can input natural language questions.
    - Responses from **Gemini** are shown below the query box.
    - Past queries are optionally stored per space for review.
5. **Podcast Generator UI**
    - For Module 2, users can select a document, choose a chapter, and optionally add a focus topic.
    - Multi-step UI walks through:
        - Preprocessing
        - Outline generation
        - Role-based summarization
        - Dialogue review
        - Audio generation
    - Final podcast audio is streamed from the stored path.

Front-end output:



Backend API Implementation

Overview

The backend is developed using **FastAPI**, providing an efficient and scalable REST API for handling document uploads, query processing, and podcast generation. The backend interacts with various systems like **SQLite** for data storage, **ChromaDB** for vector embeddings, **Gemini LLM** for answer generation, and **Kokoro TTS** for podcast synthesis.

API Endpoints

1. **spaces.py**
    - **Endpoint**: /createspace/
        - **Method**: POST
        - **Input**:
            - space_name: The name of the space to be created (required).
            - db: Database session (Dependency).
        - **Response**:
            - JSON object with message, space_id, and space_name.
    - **Endpoint**: /spaces/
        - **Method**: GET
        - **Input**:
            - db: Database session (Dependency).
        - **Response**:
            - JSON array of all available spaces.
2. **upload.py**
    - **Endpoint**: /upload/
        - **Method**: POST
        - **Input**:
            - space_id: The ID of the space to upload files to (required).
            - files: List of files to be uploaded (required).
            - db: Database session (Dependency).
        - **Response**:
            - JSON object with details of the uploaded files and extracted text.

3. **ingestion.py**
    - **Endpoint**: /ingestion/{space_id}
        - **Method**: POST
        - **Input**:
            - space_id: The ID of the space for which documents are to be ingested (required).
            - db: Database session (Dependency).
        - **Response**:
            - JSON object with details of the ingestion process.
4. **query.py**
    - **Endpoint**: /query/{space_id}
        - **Method**: POST
        - **Input**:
            - space_id: The ID of the space to query (required).
            - request: JSON object with query_text (required).
        - **Response**:
            - JSON object with query results.
5. **podcast.py**
    - **Endpoint**: /podcast/{space_id}
        - **Method**: POST
        - **Input**:
            - space_id: The ID of the space for which the podcast is to be generated (required).
            - focus_topic: Optional, the focus topic for the podcast (Query parameter).
            - db: Database session (Dependency).
        - **Response**:
            - JSON object with details of the generated podcast.

5.3. TESTING

Testing is a fundamental aspect of the development lifecycle of our AI-powered knowledge assistant and podcast generator system. It ensures reliability, functional correctness, and seamless user experience across the document-driven RAG pipeline and audio generation workflows. This section outlines the structured testing strategies and methodologies employed.

5.3.1. Testing Approach

A layered and iterative testing strategy was followed to detect and resolve issues early. This approach helped ensure that each module—from document ingestion to hybrid retrieval and audio synthesis—was validated both in isolation and within the integrated system. We aimed to maximize accuracy, minimize latency, and validate user flows end-to-end.

5.3.2. Types of Testing

- **Unit Testing**: Each major function, such as document parsing (Docling), text chunking, embedding generation, and audio synthesis, was tested independently. Python-based unit testing frameworks (e.g., PyTest) were used to validate edge cases and ensure predictable outputs. Example cases included empty documents, corrupted PDFs, or invalid text encodings.
- **Integration Testing**: Focused on ensuring correct interaction between document extraction, embedding generation, ChromaDB storage, and BM25 indexing. For instance, we verified that embedded chunks were stored and retrieved correctly and that queries propagated cleanly through the RAG pipeline.
- **System Testing**: The entire platform—from the Next.js frontend to the FastAPI backend—was tested as a cohesive system. Full upload-to-response and chapter-to-audio pipelines were simulated to confirm end-to-end stability and correctness.
- **Performance Testing**: Performance under load was tested by ingesting large multi-chapter documents (~2M tokens) and simulating concurrent user queries. System throughput, embedding latency, query resolution time, and audio generation speed were profiled. ChromaDB performance was benchmarked under concurrent retrieval tasks.
- **Validation & Accuracy Testing**: The relevance of RAG responses was measured using labeled query-answer pairs. We compared single retrievers vs. hybrid RAG fusion and reranking outcomes using metrics like precision@k and MRR (Mean Reciprocal Rank). LLM responses (via Gemini) were evaluated manually for coherence and factual correctness.
- **Usability Testing**: User testing on the frontend was conducted to verify intuitive design and proper handling of user flows like document upload, ingestion initiation, and podcast playback.

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5.3.4. Testing Outcomes

The testing process ensured:

- Minimal latency during hybrid search.
- Accurate, reranked responses from the RAG pipeline.
- Seamless podcast generation with coherent dialogue structure.
- Reliable system performance under multi-user load.
- A user-friendly and responsive UI across devices.

5.1. OVERALL TEST REPORT TABLE

Test Type	Module	Test Cases	Tools/Frame works	Result
Unit Testing	Ingestion, Embedding, Query	Validate text parsing, chunking, embeddings	pytest, unittest	Passed
Integration Testing	RAG Flow	Check data flow from chunk → store → query	FastAPI + SQLite + Chroma	Passed
Integration Testing	Podcast Workflow	Check chapter → outline → dialogue	Internal pipeline	Passed
System Testing	Full Pipeline (RAG + Podcast)	End-to-end test from upload to final output	Postman, Browser UI	Passed
Validation Testing	Gemini Output Accuracy	Compare generated answers vs expected	Manual + Benchmark Prompts	Accurate
Audio Synthesis Testing	Dialogue → TTS	Validate Kokoro TTS output and merge	Audio inspector + manual listen	Passed
Usability Testing	Next.js Frontend	Navigation, upload, query, playback	User feedback + Bug reporting	Intuitive

6. RESULTS

The system was evaluated on its ability to convert document-based knowledge into accurate, accessible, and engaging formats via two modules: (1) RAG-powered Knowledge Assistant and (2) Podcast Generator. Evaluation covered retrieval quality, generative relevance, and audio coherence.

RAG-Based Retrieval & QA

- **Hybrid Indexing (Dense + Sparse):** Combining ChromaDB embeddings with BM25 improved recall and ensured both semantic and lexical relevance.
- **RAG Fusion + RRF:** Query expansion and Reciprocal Rank Fusion (RRF) yielded top-ranked, intent-aligned chunks.
- **Response Quality:** Gemini LLM produced accurate, context-aware responses with minimal hallucination and proper citations.
- **Latency:** Optimizations kept average response times under 2.2 seconds, even with 5–10 concurrent users.

Podcast Generation

- **Structured Content:** Gemini generated consistent podcast outlines (Intro → Concepts → Recap).
- **Dual-Persona Format:** Expert–Novice summaries made content accessible without losing technical depth.
- **Dialogue Coherence:** Role-based exchanges improved flow and listener engagement.
- **Audio Quality:** Kokoro TTS provided natural, well-paced voice output with clean, ready-to-play audio.

7. CONCLUSION

This project presents a robust and extensible system that transforms static documents into dynamic, accessible knowledge through a dual-module architecture: a RAG-powered assistant and a podcast generation pipeline. By integrating advanced document parsing, hybrid information retrieval, and state-of-the-art generative AI models, the system enables users to interact with large volumes of unstructured data in intuitive and meaningful ways.

The knowledge assistant module leverages dense and sparse hybrid search strategies (ChromaDB + BM25), enhanced by RAG Fusion and Reciprocal Rank Fusion, to deliver highly relevant, context-aware answers. Gemini LLM then synthesizes these insights into coherent responses, significantly reducing the friction in navigating complex PDFs, Word files, and presentations.

Simultaneously, the podcast generator module introduces a creative and impactful use of AI—transforming selected chapters into educational, role-based dialogues. This not only democratizes access to information but also elevates the learning experience through voice-driven storytelling powered by Kokoro TTS.

Throughout development, key challenges were addressed, including optimizing retrieval accuracy, ensuring the relevance of generative outputs, and maintaining natural dialogue quality in audio. Extensive testing validated the system's stability, latency, and overall user experience.

This project demonstrates the potential of combining hybrid RAG architectures with generative AI and speech synthesis to create a scalable, intelligent knowledge interface. It bridges the gap between static content and interactive learning, offering immense value for students, educators, professionals, and content consumers alike.

8. FUTURE ENHANCEMENTS

To further advance the capabilities and user experience of this intelligent knowledge assistant, several impactful enhancements are planned. These improvements aim to increase adaptability, personalization, and scalability of both the **RAG-powered assistant** and the **AI podcast generator**.

1. Multilingual Support for Document Understanding and Podcasts

Currently, the system supports English documents and outputs. Expanding to **multilingual ingestion and synthesis** will significantly broaden the tool's accessibility. By integrating multilingual document parsers, translation pipelines, and polyglot language models, the system can cater to a global user base. The podcast generator will be extended with multilingual TTS models to support voice generation in different languages, regional dialects, and accents.

2. Real-Time Retrieval & Streaming Summarization

In future iterations, the system will support **real-time RAG querying** with continuous document ingestion. This enhancement will allow users to interactively explore newly uploaded materials without waiting for batch ingestion to complete. Streaming summarization will enable users to receive quick previews or live audio summaries of large documents as they upload or scroll.

3. Personalization of Podcasts and Assistant Responses

To improve user engagement, the system will allow **customization of tone, depth, and speaker personas** in the podcast generator. Users can choose between formal, conversational, humorous, or academic tones, or select between expert and novice personas for the dialogue. Similarly, the assistant's response style can be adapted based on user preferences—brief answers, detailed reports, or citation-heavy responses.

4. Embedding Feedback Loops and Self-Learning Retrieval

The RAG pipeline will incorporate a **feedback-aware loop**, where user interactions (likes, skips, corrections) are used to fine-tune relevance scoring and embedding generation. This continuous learning loop will improve retrieval precision and help the system evolve with usage patterns over time.

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