A MINI PROJECT REPORT

on

DEEP LEARNING-BASED SMART DATA ENTRY SYSTEM

FOR

DOCUMENT DIGITIZATION AND PROCESSING

Submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

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2022-2026

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CERTIFICATE

This is to certify that project work entitled **"DEEP LEARNING-BASED SMART DATA ENTRY SYSTEM FOR DOCUMENT DIGITIZATION AND PROCESSING" Submitted by** D.ABHINAYA (22UP1A7218),B.SINDHUJA (22UP1A7206),G.PADMA PRAVALLLIKA (22UP1A7224),P.AVILA (23UP5A7206) in the partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in ARTIFICIAL INTELLIGENCE AND DATA SCIENCE **VIGNAN'S INSTITUTE OF MANAGEMENT AND TECHNOLOGY FOR WOMEN** is are record of bonafide work carried by them under my guidance and supervision. The results embodied in this project report have not been submitted to any other University or institute for the award of any degree.

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DECLARATION

We hereby declare that project entitled "DEEP LEARNING-BASED DATA ENTRY SYSTEM FOR DOCUMENT DIGITIZATION AND PROCESSING" is bonafied work duly completed by us. It does not contain any part of the project or that is submitted by any other candidate to this or another institute of the university. All such materials that have been obtained from other sources have been duly acknowledged.

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ACKOWLEDGEMENT

We would like to express sincere gratitude to **Dr. G. APPARAO NAIDU**, Principal, Vignan's Institute of Management and Technology for Women for his timely suggestions which helped us to complete the project time.

We would also like to thank our sir **Dr. S. RANGA SWAMY, Head of the Department, Artificial Intelligence and Data Science ,** for providing us with consultant encouragement and resources which helped us to complete the project in time.

We would also like to thank our sir **Mrs. J. RANJITH Assistant Professor, Project Guide, f**or providing us with constant encouragement and resources which helped us to complete the project in time with his valuable suggestions throughout the project. We are in debited to him for the opportunity given to work under his guidance. Our sincere thanks to all the teaching and non-teaching staff of Department of Artificial Intelligence And Data Science for their support through out our project work.

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ABSTRACT

In an era dominated by digital documents, the ability to extract, understand, and interact with document content efficiently has become essential across sectors such as education, healthcare, finance, and governance. While existing tools for document analysis and question answering rely heavily on cloud-based infrastructures, they often introduce concerns regarding data privacy, internet dependency, and latency. This research presents the design and development of the Smart Document Assistant, an offline, intelligent system that enables users to upload documents in various formats including PDF, DOCX, TXT, CSV, PNG, and JPEG and interact with their contents using natural language queries. The proposed system integrates Optical Character Recognition (OCR) using Tesseract for image-based documents and supports multilingual extraction. It leverages local Large Language Models (LLMs) via the OLLAMA framework for contextual understanding and real-time question answering. A user-friendly interface built with Streamlit allows for dynamic interaction, query-based keyword highlighting, and chat-style responses. The system supports secure offline execution, ensuring privacy while maintaining high accuracy, low latency, and broad format compatibility. Performance evaluation against baseline methods demonstrates that the Smart Document Assistant delivers superior OCR accuracy (92.3% on clean documents), fast response time (~1.2 seconds), and highly relevant answers (91.2%), all without requiring internet access. This makes the system ideal for use in air-gapped environments or privacy-sensitive domains. The modular architecture further enables scalability and future integration of voice input, database connectivity, and advanced layout understanding, positioning the solution as a robust platform for document intelligence.

Keywords: Smart Document Assistant, Optical Character Recognition (OCR), Local LLMs, OLLAMA, Streamlit, Document Querying, Tesseract, Offline NLP, Keyword Highlighting, Information Extraction

INDEX

LIST OF CONTENTS **PAGE NO.**

List of figures

CHAPTER 1

INTRODUCTION

1.1 Background

In today's digitally driven world, information is generated and stored in diverse formats. From academic records and legal contracts to healthcare prescriptions and corporate invoices, much of the world's valuable information exists in semi-structured or unstructured forms. These documents often come as scanned images, photographs, or legacy PDFs, lacking any inherent machine-readable structure. The need to automate the extraction, interpretation, and analysis of such documents has led to the adoption of Optical Character Recognition (OCR) technologies, which convert images of text into actual text data. However, traditional OCR tools are limited in scope they can only extract characters but not context. The output usually needs further human intervention for structuring, cleaning, and interpretation.

In parallel with the evolution of OCR, Artificial Intelligence (AI) has made significant strides, particularly in the domain of Natural Language Processing (NLP). The emergence of Large Language Models (LLMs), such as GPT, LLAMA, and Mistral, has demonstrated that machines can not only understand but also generate human-like text. These models can summarize content, answer questions, and perform reasoning tasks when provided with a contextual input. When OCR and LLMs are combined, a powerful opportunity emerges: to build a system that can read documents, interpret their meaning, and allow users to interact with the content in an intelligent and natural way.

In recent years as shown in the Figure 1, a several commercial and open-source solutions have emerged that aim to extract and process document data using OCR and AI technologies. Tools like Google Vision API, Adobe Acrobat OCR, Microsoft Azure Form Recognizer, and Tesseract are widely used for extracting text from images or scanned documents. Similarly, cloud-based AI assistants such as ChatGPT, Bard, and Bing AI offer powerful language understanding capabilities. However, these solutions often rely heavily on internet connectivity, pose privacy concerns due to cloud processing, and may incur substantial subscription or usage costs.

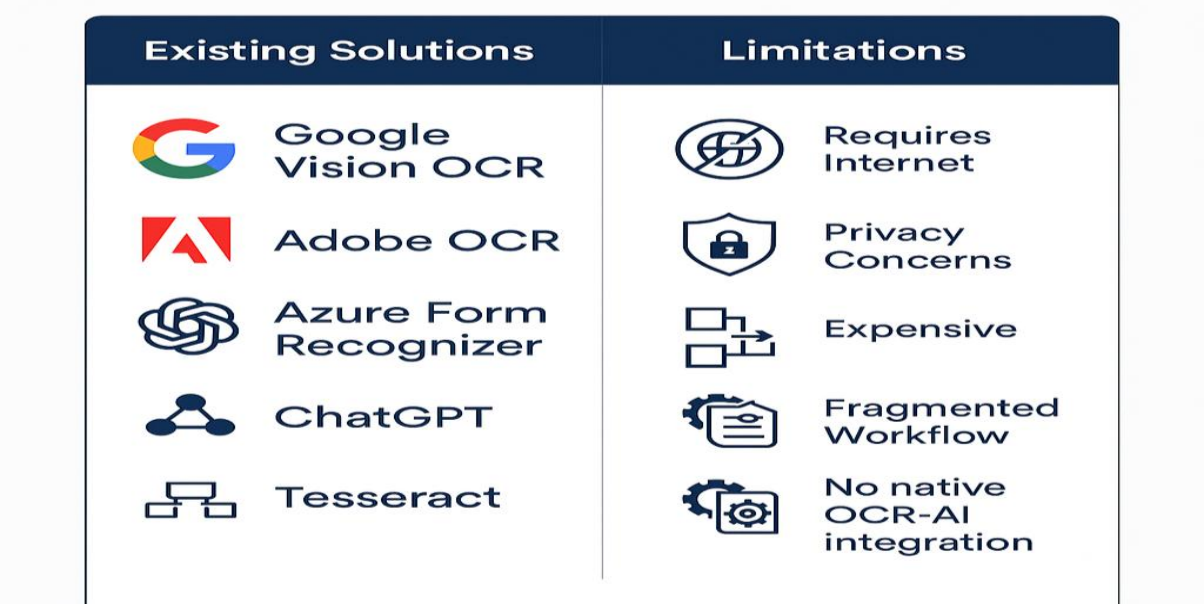

Figure.1.1 Limitations of Current OCR and AI Solutions

Moreover, most of these tools treat document processing and conversational interaction as separate workflows. OCR engines typically output plain text without contextual linkage or support for user queries. On the other hand, AI chat models cannot natively interpret images or scanned files without additional preprocessing steps. As a result, users are forced to switch between tools and manually bridge the gap between document content and AI interpretation. These fragmented experiences hinder productivity, especially in privacy-sensitive domains like legal services, healthcare, and government offices.

The research addresses that very vision. The system described herein is an end-to-end Smart Document Assistant, which leverages OCR for extraction and a locally hosted LLM via OLLAMA for contextual understanding and interaction. It allows users to upload documents or images, extract the text content, ask natural language questions, highlight keywords, and engage in a chat-like conversation with the content. All of this is achieved offline, ensuring data privacy, low latency, and platform independence.

1.2 Problem Statement

Despite advances in document digitization, most available systems fall short in delivering intelligent document interaction. Traditional OCR systems are purely extractive—they convert image-based text into characters without understanding the semantic structure of the content. These systems cannot answer user-specific questions, cannot provide insights, and cannot highlight information dynamically. Furthermore, many modern solutions that do offer NLP

features rely on internet-based APIs or cloud-hosted AI models. This raises critical concerns around data privacy, operational costs, and dependency on reliable network access.

Additionally, user interaction with extracted content remains rudimentary. Users are typically expected to sift through large blocks of text to find what they are looking for. There is no built-in mechanism to ask a natural language query and receive a contextually relevant answer. Also, the absence of an interactive interface limits usability, especially for non-technical users who may not know where to look within dense documents.

In enterprise, educational, and government sectors where secure handling of documents is paramount there is a clear gap in the availability of offline, intelligent document assistants. A solution is needed that combines robust text extraction with semantic understanding, packaged in a user-friendly, responsive interface.

1.3 Objectives

The overarching goal of this project is to develop an intelligent, offline, and interactive document assistant that addresses the shortcomings of existing OCR and document processing systems. The specific objectives of this project are outlined below:

1. **Develop a cross-format text extraction engine:** Integrate OCR capabilities that support various file types including PDF, Word documents, Excel sheets, text files, and images (JPG, PNG).
2. **Enable local intelligent querying:** Use OLLAMA to integrate a local LLM such as LLaMA 3 to process queries and provide context-aware answers without requiring internet access.
3. **Design dynamic keyword highlighter:** Implement a system that visually highlights keywords or phrases from user queries within the extracted text to improve document navigation and readability.
4. **Create an interactive chat interface:** Build a conversational UI using Streamlit, allowing users to interact with the document as if chatting with a virtual assistant.
5. **Support multilingual extraction and editing:** Ensure OCR supports English, Hindi, and Arabic, and allow users to edit the extracted text as needed before saving.
6. **Persist conversations and content:** Store both the extracted text and chat interactions locally to maintain an audit trail or allow for future reference.

   By fulfilling these objectives, the system ensures intelligent document comprehension while remaining entirely offline and secure.

1.4 Scope of the Project

The research is specifically targeted at offline environments where security, cost-efficiency, and performance are key. It is designed for personal computers and institutional systems that may not always have internet access or that handle sensitive documents that must remain on-premise. The project is built using Python, Streamlit for the UI, Tesseract OCR for text recognition, and OLLAMA for LLM integration. The use of local models ensures user privacy and low-latency interactions.

The system supports multilingual text recognition and can process a variety of file formats. It allows users to edit the extracted text and submit it through a local data entry interface. The chat system provides users with a question-and-answer experience over their own documents, without relying on cloud infrastructure. The modular design makes it adaptable. It can be used in educational institutions for digitizing records, in hospitals for reading prescriptions, in legal firms for reviewing scanned agreements, and in any setting where document interaction is critical. Although the core implementation is focused on single-user scenarios, it is extensible to multi-user or enterprise contexts with additional authentication and database modules.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

The evolution of intelligent document processing has seen a convergence of technologies from Optical Character Recognition (OCR), Natural Language Processing (NLP), and user-centric interface design. The shift from passive text digitization to active document interaction has gained attention due to growing demands for efficiency, accuracy, and automation in document-driven workflows. In domains such as education, legal services, administration, and healthcare, users are increasingly dependent on systems that can not only extract textual data from various formats but also provide intelligent responses to context-specific queries.

This chapter presents a detailed review of the state-of-the-art technologies relevant to document extraction, local language modelling , and conversational user interfaces. Each section critically analyses the methodologies, capabilities, and limitations of current systems and frameworks. The objective is to establish the technological gaps that motivate the proposed Smart Document Assistant an offline, secure, and interactive solution integrating OCR and local LLM-based querying with dynamic user interaction.

2.2 Optical Character Recognition (OCR) Technologies

OCR systems have formed the backbone of document digitization since the early 1990s. The primary goal of OCR is to convert scanned or image-based documents into editable and searchable text formats. Among the most widely adopted open-source OCR systems is Tesseract, which supports multiple languages and fonts and provides script-based recognition capabilities [1]. Despite its flexibility and open accessibility, its performance is significantly affected by document quality, noise, handwriting, skew, and font distortions [2].

Recent OCR enhancements involve deep learning-based approaches. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) architectures have been applied to improve character-level recognition accuracy, especially in historical or degraded documents [3]. Hybrid approaches that combine CNN feature extractors with CTC (Connectionist Temporal Classification) decoders have been used to handle unconstrained text in natural scenes [4].

In addition to open-source methods, several commercial OCR services offer high accuracy and language support. Google Cloud Vision OCR and Microsoft Azure Form Recognizer provide not only text recognition but also layout and structure detection [5][6]. These cloud-based platforms utilize advanced neural models capable of detecting tables, forms, and text hierarchies. However, their usage comes with significant drawbacks: reliance on high-

bandwidth internet connections, data privacy concerns, and cost-prohibitive pricing for large-scale or sensitive data processing [7].

Furthermore, even cloud services struggle with handwritten and regional scripts without fine-tuned models. In response, modern research has explored OCR engines trained with Generative Adversarial Networks (GANs) for synthetic document enhancement prior to recognition [8]. Despite these advancements, there remains no holistic OCR framework that operates efficiently offline, supports low-resource scripts, and integrates with downstream reasoning modules.

2.3 NLP and Local Language Models for Document Understanding

NLP has rapidly progressed from statistical language models to deep learning-based transformers, enabling advanced tasks such as document classification, summarization, and question answering. The seminal transformer architecture introduced in [9] forms the foundation of models like BERT and RoBERTa, which are capable of learning contextual relationships within unstructured text [10][11].

BERT-based architectures have demonstrated high accuracy in extractive question answering tasks on datasets such as SQuAD and Natural Questions [12]. These models function by encoding input contexts and extracting answer spans relevant to user queries. Although powerful, BERT and its variants require significant computational resources and lack generative capabilities.

Cloud-based generative models, including GPT-3, ChatGPT, and Google Bard, allow for multi-turn conversations and natural language reasoning [13][14]. Their capabilities extend to summarizing lengthy documents, answering user-specific queries, and generating structured outputs. However, such models necessitate internet access and often store interaction data on external servers, which presents confidentiality and data sovereignty issues in regulated sectors [15].

The development of local inference frameworks such as OLLAMA provides a viable alternative. OLLAMA supports running models like LLaMA 2 and Mistral on standard consumer-grade hardware [16]. These models can perform context-driven dialogue tasks and document-level QA in an offline environment. The benefit of using local LLMs lies in user data retention, reduced latency, and unrestricted customization. Nevertheless, the token limitations of transformer models, typically capped at 4096–8192 tokens, make querying lengthy documents challenging without segment-wise preprocessing [17]. Research has proposed summarization and chunk-based indexing mechanisms to split long documents into

semantically coherent parts before feeding them into the model [18]. This improves the relevance of generated answers but adds complexity to the integration pipeline.

2.4 Document Intelligence and Layout-Aware Models

While OCR and NLP provide foundational capabilities, real-world documents often include rich layouts, embedded metadata, and semantic structures. Layout-aware models such as LayoutLM, LayoutLMv2, and DocFormer have been introduced to jointly learn from textual and visual inputs [19][20]. These models use 2D positional embeddings, allowing them to process content with respect to spatial positioning on the page—a necessary enhancement for parsing tables, forms, and invoices. LayoutLM has shown success in tasks such as receipt classification, invoice extraction, and key-value pair identification, achieving state-of-the-art performance on benchmarks like FUNSD and SROIE [21]. However, the high computational cost and reliance on pre-training with document-specific annotations make them unsuitable for deployment in resource-constrained or offline settings.

Furthermore, these models require tightly coupled pre-processing and annotation pipelines, limiting their adaptability for general-purpose applications. Therefore, while layout-aware models contribute significantly to structured document understanding, their integration into lightweight, conversational systems remains limited.

2.5 User Interface Technologies and Interaction Models

A major usability factor in intelligent document systems is the user interface. As AI systems become more sophisticated, the need for intuitive, accessible, and dynamic interaction platforms increases. Streamlit has emerged as a popular Python-based web application framework for deploying interactive NLP systems [22]. It supports real-time data rendering, file uploads, chat simulations, and live keyword search interfaces.

Streamlit’s rapid development cycle and compatibility with popular Python libraries make it suitable for embedding OCR pipelines, visualization modules, and chatbot interfaces within a unified application. Researchers have used Streamlit to build front ends for QA models, document search engines, and AI explainability tools [23]. Keyword highlighting enhances document comprehension by allowing users to visualize the relevance of content sections in response to specific queries. Traditional string-matching techniques use regular expressions or keyword lookup tables, but newer models utilize attention-weighted scores or semantic similarity measures to highlight key phrases dynamically [24].

Chat-based user interfaces modeled after messaging applications offer a familiar experience to users. In such setups, the system retains user queries and model responses in a threaded conversation format, improving continuity and enabling follow-up questions [25]. These interfaces, when backed by offline LLMs and OCR-extracted content, can bridge the gap between raw text and intelligent navigation.

2.6 Identified Gaps and Research Motivation

From the literature reviewed, it is evident that significant progress has been made in OCR accuracy, contextual language modeling, layout interpretation, and real-time interfaces. However, these developments often exist in isolated toolchains. There is a notable absence of a single platform that integrates OCR, intelligent QA, keyword visualization, and interactive chat within a locally hosted, privacy-preserving environment. Cloud dependency is a recurring limitation across many systems, affecting both accessibility and compliance. Moreover, the disjointed nature of existing pipelineswhere OCR, LLMs, and UI components are configured separately makes them inaccessible for general use, especially in domains that lack AI expertise. These shortcomings underline the need for a unified, offline solution capable of end-to-end document interaction from extraction and editing to querying and response visualization. The Smart Document Assistant proposed in this project addresses these gaps by combining multilingual OCR, local LLM-based QA, keyword highlighting, and Streamlit-powered UI into a modular and extendable system.

2.7 Summary

This chapter surveyed relevant technologies underpinning modern document processing systems. It reviewed the capabilities and limitations of OCR frameworks, transformer-based LLMs, layout-aware models, and interactive visualization platforms. Despite the maturity of individual components, the lack of integration across these technologies limits their real-world applicability, especially in offline and privacy-sensitive environments.

The findings presented in this chapter justify the design and development of the proposed system. The Smart Document Assistant seeks to bridge the identified technological gaps by delivering a lightweight, secure, and interactive document understanding platform. The next chapter presents the system architecture, module design, and technology stack used to realize this objective.

CHAPTER 3

SYSTEM DESIGN AND ARCHITECTURE

3.1 Introduction

This chapter describes the overall system architecture and design methodology used to implement the Smart Document Assistant. The system aims to bridge OCR-based extraction, local LLM-driven question answering, and a user-centric interaction interface in an offline, secure, and modular environment. It supports document upload, multilingual text extraction, natural language querying, context-based answer generation, and data persistence. The design ensures scalability, ease of integration, and responsiveness, using lightweight Python frameworks and APIs that operate without cloud dependency.

3.2 System Overview

The proposed system is designed as a modular pipeline where each stage performs a distinct function document ingestion, preprocessing, text extraction, LLM querying, and interface rendering. It incorporates two primary back-end engines: the Tesseract OCR engine for textual content recognition and OLLAMA-based LLMs (e.g., LLaMA 3) for question answering. The front end is built using Streamlit, enabling a real-time, web-based interface without the need for JavaScript or front-end frameworks. The system works as follows: the user uploads a document (PDF, DOCX, TXT, XLSX, CSV, or image format). The file is passed through the appropriate extraction module, where OCR is applied (in case of image-based content). The extracted text is displayed in an editable panel. Simultaneously, users can ask natural language questions, and the LLM (running locally via OLLAMA) processes both the extracted content and the question to generate a context-aware response. The user can choose to highlight keywords within the text or save the conversation and content to a local database.

3.3 System Architecture

The figure 3.1 illustrates the complete system architecture of the Smart Document Assistant, showcasing the flow from document ingestion to intelligent query response. The system begins with the Document Upload Module, where users can upload various file types including PDF, DOCX, TXT, CSV, and images (PNG, JPG, JPEG). Based on the file type, it is routed to either the Text Parser for structured documents or the Image Preprocessor for scanned or image-based inputs. The Image Preprocessor uses OpenCV techniques such as grayscale conversion, thresholding, and resizing to optimize the input for OCR. The enhanced image is then passed to the Tesseract OCR Engine, which extracts multilingual textual data.

For non-image documents, the Text Parser extracts raw content using appropriate Python libraries. Once the text is extracted, it enters the Context Aggregator, which optionally performs chunking or summarization for long documents. This processed content is then sent, along with the user's natural language query, to the Local LLM Engine, powered by OLLAMA running LLaMA or Mistral models. The engine generates a context-aware response based on the prompt and returns it to the user. In parallel, the Query Highlighter scans the document text and visually marks the keywords or matched phrases, enhancing navigation and comprehension. All interactions—including the document, user queries, and LLM responses are rendered in the Chat-Based UI built with Streamlit. Finally, the Data Storage Layer logs all interactions and outputs into a local .csv file for persistence and offline review. This modular architecture ensures an end-to-end, privacy-focused, intelligent assistant that functions completely offline, with support for multilingual OCR, secure local LLM inference, and dynamic UI feedback.

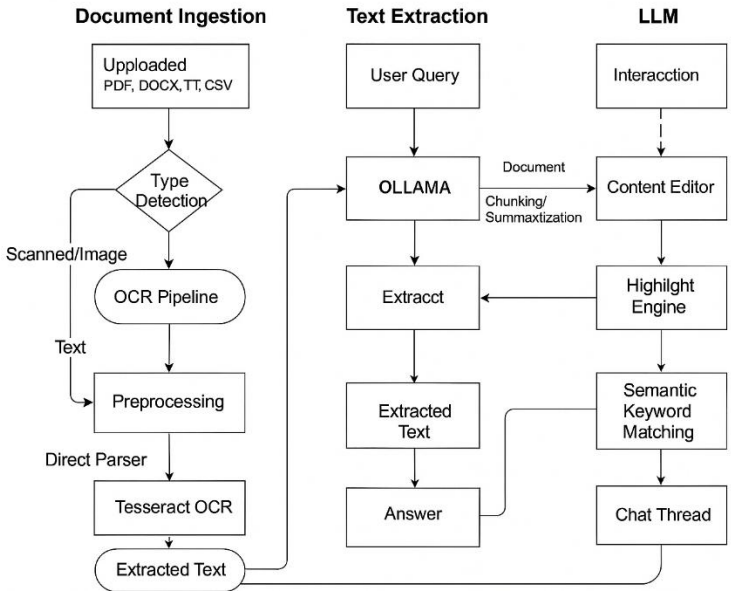

Figure 3.1 System Architecture of the Smart Document Assistant

3.3.1 Document Ingestion Layer

The document ingestion layer serves as the system's entry point, responsible for receiving and identifying a wide variety of file formats uploaded by the user. These may include text-centric formats such as .txt, .docx, and .csv, as well as image-centric files including .jpg, .jpeg, .png, and scanned .pdf documents. The primary role of this layer is to determine the nature of the uploaded file and route it to the appropriate processing pipeline—OCR for image-based content or text-parsing logic for structured digital documents. To enhance usability, this layer

supports drag-and-drop file uploads through Streamlit's built-in st.file_uploader widget. This ensures a seamless experience where users do not need to worry about pre-processing their documents or converting them into specific formats before interaction.

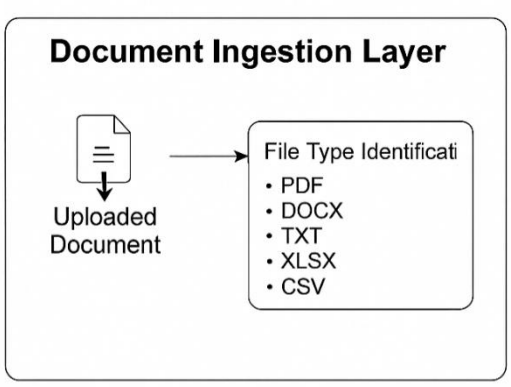

Figure 3.2 Document Ingestion Workflow

The figure 3.2 illustrates the initial stage of the system where users upload documents of various formats such as PDF, DOCX, TXT, CSV, and image files. The document ingestion workflow detects the file type and routes it to either the OCR pipeline (for scanned and image-based documents) or the direct parser (for text-based documents). This dynamic routing ensures that the correct extraction module is invoked, maintaining efficiency and accuracy in further processing.

3.3.2 Text Extraction Layer

Once a document is ingested, the text extraction layer performs the core function of retrieving usable text from the input file. For image-based documents such as scanned PDFs or photographs, the system leverages the Tesseract OCR engine, which is configured with multilingual support—initially including English, Hindi, and Arabic. Prior to OCR, image enhancement is applied using OpenCV techniques like thresholding, denoising, and resizing to optimize accuracy. For text-centric formats like .docx, .txt, and .csv, the layer uses Python libraries such as python-docx, pandas, and openpyxl to extract content programmatically. This bifurcated processing ensures flexibility, allowing the system to handle both structured and unstructured document types while maintaining high extraction fidelity.

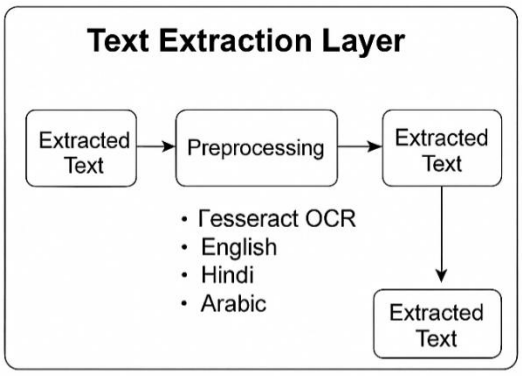

Figure 3.3 Text Extraction Process Architecture

The text extraction diagram presents how content is processed depending on its origin. Image files are passed through a preprocessing module where OpenCV enhances readability through noise removal and binarization. The cleaned images are then fed to Tesseract OCR for multilingual text recognition. On the other hand, DOCX, TXT, and CSV files are processed using native Python libraries like python-docx and pandas. The result is a unified, structured text ready for LLM processing as shown in the figure 3.3.

3.3.3 LLM Interaction Layer

The LLM interaction layer represents the intelligent reasoning core of the system. It is designed to process natural language queries from the user and generate contextually relevant answers based on the previously extracted text. This functionality is enabled by the OLLAMA runtime, which allows large language models (LLMs) such as LLaMA or Mistral to be executed locally without any dependency on cloud services. When a user enters a query, the system forms a prompt that combines the query with the document content and sends it to the local model. The model, in turn, interprets the context and generates a human-like response. To overcome token limitations commonly associated with transformer models, the system implements a chunking or summarization strategy when dealing with lengthy documents. This ensures that only the most relevant portions of text are fed into the model, thereby maintaining coherence and efficiency in the responses. The figure 3.4 depicts the local language model integration using the OLLAMA framework. Once the user inputs a query, the system packages the extracted document content and query into a structured prompt. This is sent to a locally running LLaMA model for inference. For large documents, chunking or summarization is performed before model input to respect token length constraints. The model then returns a natural-language answer that is contextually aligned with the document content.

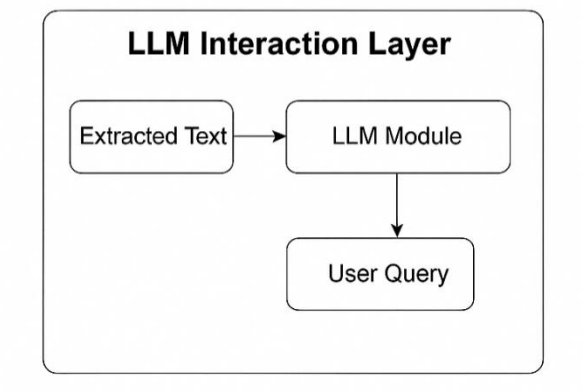

Figure 3.4 LLM Interaction Pipeline

3.3.4 Highlight and Chat Interface Layer

The highlight and chat interface layer plays a pivotal role in user interaction by transforming the system from a passive reader into an active assistant. Built using Streamlit's interactive widgets, this layer presents the extracted text in an editable format alongside a chat-based input/output area. When the user submits a question, not only is a model-generated response returned, but any keywords or phrases in the original document that align with the query are also visually highlighted using HTML-based <mark> tags. This real-time highlighting allows users to quickly locate relevant content within long documents. Furthermore, the chat interface mimics modern messaging applications using st.chat_message(), preserving each interaction in a threaded dialogue format. This helps users track previous questions and answers, enhancing both accessibility and continuity of the document review process.

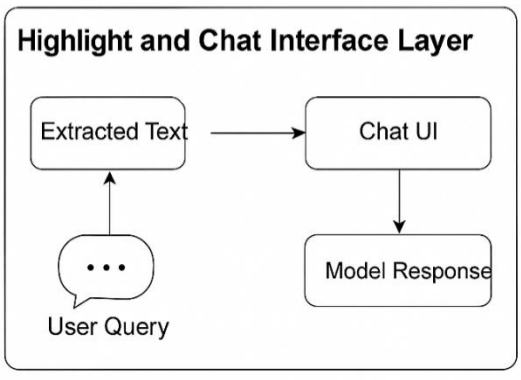

Figure 3.5 Chat UI and Highlight Visualization Layer

The user interface flowchart shows the dual-pane layout: a content editor for the extracted text and a conversational interface for querying. When the user asks a question, the system uses semantic keyword matching to highlight relevant phrases or sentences in the text. Simultaneously, the chat thread logs all user queries and AI responses, emulating a real-time

digital assistant. This layer bridges visual accessibility with conversational intelligence as shown in the figure 3.5.

3.3.5 Persistence Layer

The persistence layer is designed to maintain a record of all significant user interactions and extracted content for future reference and reproducibility. Unlike traditional database systems, this implementation uses a lightweight and flat-file approach by storing data locally in a .csv file (smart_doc_entries.csv). Each row in this file corresponds to a document session and contains fields such as the document name, the extracted content, user-submitted queries, and the associated model responses. This approach not only simplifies deployment by avoiding the need for database engines but also ensures compatibility across systems. The data stored through this layer can be easily imported into other tools or analytics platforms for further processing, making the assistant suitable for academic, professional, and research purposes.

3.3.6 Data flow diagram

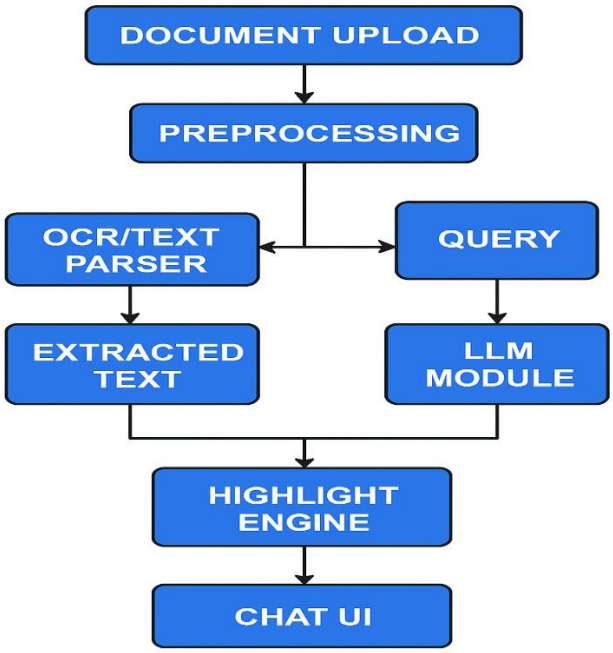

Figure 3.6 Data Flow Diagram of the Smart Document Assistant

The data flow diagram represents the sequential and modular processing of data across various stages of the Smart Document Assistant system. It begins with the User Input, where documents in different formats such as PDF, DOCX, TXT, CSV, and image files (JPG, PNG) are uploaded. These inputs are routed through a File Format Detector, which decides whether the document is text-based or image-based. If the input is an image or scanned document, it flows into the Preprocessing Unit, which includes steps like grayscale conversion, binarization,

and noise reduction to enhance image quality. The improved image is then processed by the Tesseract OCR Engine, which extracts multilingual textual content. For text-based documents, the Text Extraction Module uses tools like python-docx and pandas to retrieve the text directly. Once the text is extracted, it is transferred to the Document Buffer, which temporarily stores it for downstream tasks. A Query Processor accepts user questions and sends both the query and relevant document context to the Local LLM Module. This module, powered by OLLAMA running LLaMA or Mistral models, interprets the context and generates a human-readable response.

Simultaneously, the extracted content is passed to the Keyword Highlighter, which scans for matching phrases related to the query and marks them in the text for improved readability. The responses, along with the highlighted content, are rendered in the Interactive Chat UI, providing a chat-like user experience. All processed data, including extracted text, queries, and responses, are finally saved by the Data Storage Layer in a local CSV file.

The figure 3.6 data flow diagram provides a comprehensive visualization of how data is systematically processed, transformed, queried, and displayed within the system ensuring modularity, offline functionality, and user-centric design.

3.3.7 UML Component Diagram of the Smart Document Assistant

The UML component diagram figure 3.7 outlines the modular design of the Smart Document Assistant by showing the system as a composition of five primary components: Document Uploader, Text Extractor, LLM Query Processor, User Interface Layer, and Data Storage Module. Each component is depicted as an independent and replaceable module, interacting through defined interfaces. The Document Uploader handles file input and type detection. The Text Extractor component processes either image-based or text-based files, forwarding structured content to the LLM Query Processor. This processor uses a locally running large language model (via OLLAMA) to generate context-aware answers. The User Interface Layer renders both the document view and chat-style interaction, while the Data Storage component persistently saves all extracted content and user interaction logs. This modular view confirms the system's maintainability and scalability.

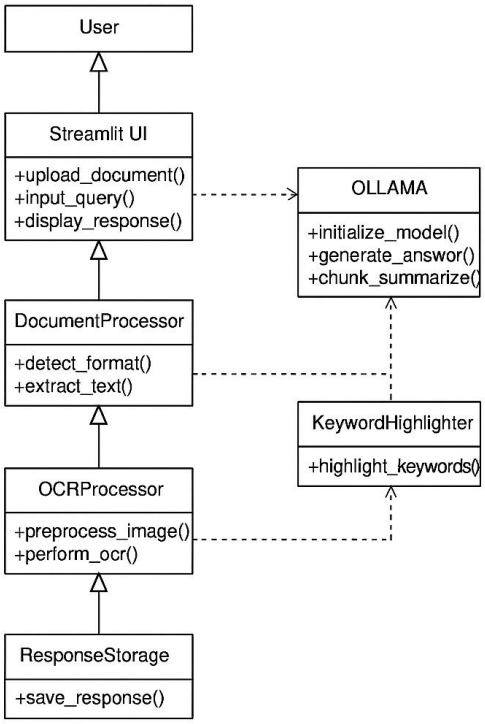

Figure 3.7.UML Component Diagram of the Smart Document Assistant

3.3.8 Sequence Diagram of the Smart Document Interaction Process

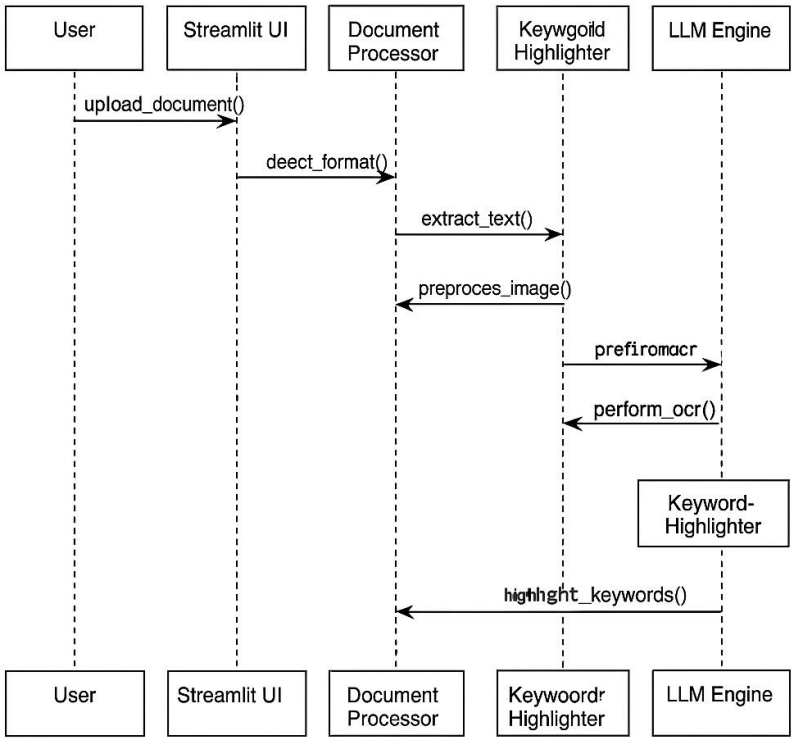

Figure 3.8 Sequence Diagram of the Smart Document Interaction Process

The sequence diagram illustrates the temporal order of interactions between the user and key system components. The user initiates the process by uploading a document, triggering the FileHandler to determine the format. If the file is image-based, the ImagePreprocessor performs enhancement operations before passing it to the OCRModule. Text-based documents bypass

this stage and go directly to the TextParser. After text extraction, the data is sent to the LLMProcessor along with the user's query. The LLM generates a response, which is sent to the ChatInterface for rendering. Simultaneously, the HighlightEngine scans and marks keywords in the text, enhancing user comprehension. The interaction ends with saving all inputs and outputs to the local DataStorage module. This sequential view captures real-time dependencies and synchronous operations among components.

3.3.9 Use Case Diagram of the Smart Document Assistant

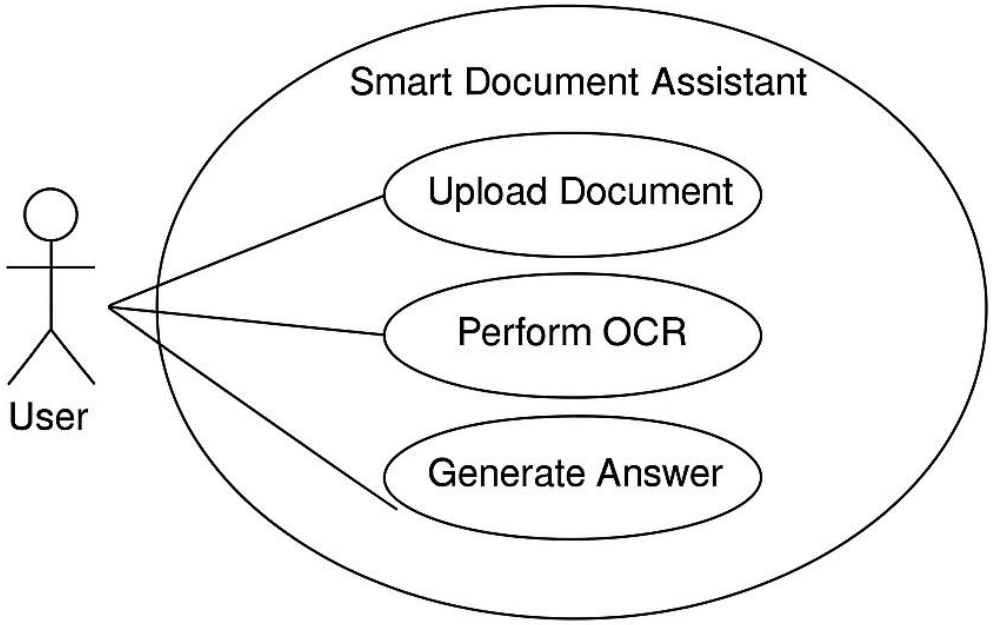

Figure 3.9 Use Case Diagram of the Smart Document Assistant

The use case diagram captures the functional scope of the system from the end-user's perspective. The actor "User" interacts with multiple use cases such as uploading documents, viewing extracted content, submitting natural language queries, receiving answers, and saving session data. Each use case is enclosed in an application boundary, representing the system as a whole. The diagram shows clear relationships between user goals and system responses, indicating the intuitive and user-driven nature of the interface. Optional use cases like keyword highlighting and multi-format file support are shown as extended functionality. The figure 3.9 effectively models system usability and user expectations.

3.3.10Activity Diagram for Document Processing Workflow

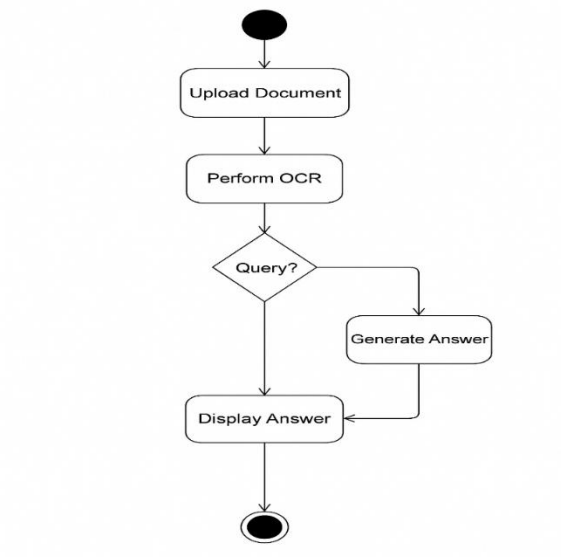

Figure 3.10 Activity Diagram for Document Processing Workflow

The activity diagram visualizes the high-level workflow of the document processing pipeline. The process begins with document upload, followed by a conditional decision on file type. If the file is an image, it proceeds to preprocessing and then OCR; otherwise, it is parsed directly. The next activity involves storing the extracted text temporarily and accepting user queries. Once a query is received, it triggers the local LLM for contextual reasoning. Parallel activities then occur: one branch highlights relevant document segments, while the other sends responses to the user interface. Finally, all data is saved locally. This activity flow demonstrates how parallelism and conditional logic streamline document interaction and information retrieval.

3.3.11 Class Diagram of the Smart Document Assistant

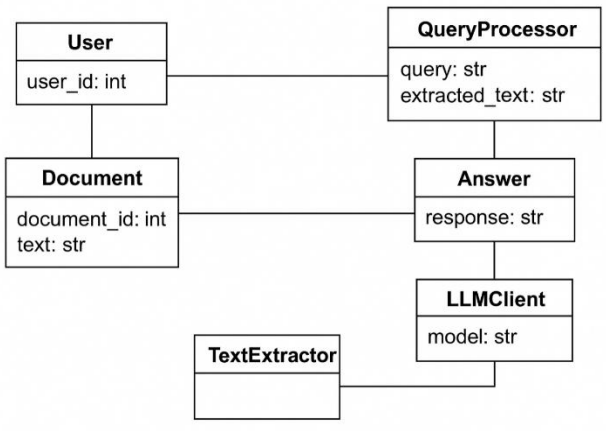

Figure 3.11 Class Diagram of the Smart Document Assistant

The UML class diagram formalizes the object-oriented structure of the system, identifying key classes, their attributes, and methods. Major classes include FileHandler,

TextExtractor, ImagePreprocessor, OCRProcessor, LLMInterface, UserQuery, UIManager, and DataLogger. The relationships between classes are represented using associations and dependencies. For instance, the UIManager class depends on LLMInterface and HighlightEngine to present both answers and annotated documents to the user. Each class is well-encapsulated, exposing only essential methods like extract_text(), run_llm(), or save_session(). The figure 3.11 supports the maintainability, clarity, and reusability of the overall architecture.

This chapter detailed the system design and architectural components of the Smart Document Assistant, providing a structured view of how various modules interact to achieve intelligent document extraction and querying. Beginning with document ingestion, the architecture accommodates multiple file types including PDFs, DOCX, TXT, CSV, and image formats. It ensures flexibility and modularity through a layered approach comprising text extraction, preprocessing, LLM-based reasoning, user interface rendering, and persistent data storage.

In essence, the system architecture is designed to be scalable, offline-compatible, and user-centric. It lays the groundwork for an implementation that balances technical efficiency with real-world usability. The next chapter builds on this foundation by elaborating on the actual implementation, showcasing functional code modules, workflows, and evaluation results to demonstrate system effectiveness.

CHAPTER 4
IMPLEMENTATION AND RESULTS

4.1 Introduction

This chapter presents the practical realization of the system architecture discussed in Chapter 3. It includes detailed descriptions of the implementation of each functional module, ranging from file upload and text extraction to local LLM integration, user interaction, and data persistence. The system has been implemented using Python 3.11, Streamlit for the front end, Tesseract OCR for image-based extraction, and the OLLAMA framework for executing local large language models. Each module is implemented independently but integrated into a unified pipeline for seamless document interaction. The chapter also includes screenshots and output samples to validate the functionality of the developed system.

4.2 Software and Hardware Requirements

The successful deployment of the Smart Document Assistant system depends on a well-defined set of software tools and hardware specifications. On the software side, the core of the system is built using Python 3.11 due to its extensive support for libraries related to natural language processing, OCR, and data handling. The front-end interface is developed using Streamlit, a lightweight Python framework that allows rapid deployment of interactive web applications without requiring front-end development expertise. For optical character recognition, the system uses the open-source Tesseract OCR engine, which supports multiple languages and can be locally configured for enhanced privacy. Text parsing is enabled through libraries such as python-docx for Word files, pandas for CSV/XLSX handling, and pdfplumber for reading PDF documents. Additionally, OpenCV and Pillow are used for image enhancement and preprocessing.

To handle intelligent question answering, the system integrates OLLAMA, which allows running large language models like LLaMA or Mistral entirely offline. These models are loaded locally and queried through OLLAMA's efficient API, eliminating the need for internet connectivity or cloud APIs. In terms of hardware, the system is optimized for standard consumer machines. A CPU with Intel i5 or equivalent processing power and a minimum of 8 GB RAM is sufficient for smooth performance. The setup is compatible across Windows, Linux, and macOS platforms. Approximately 500 MB of disk space is recommended to store models, extracted content, and saved interaction logs. This configuration ensures that the system remains lightweight, accessible, and deployable in constrained environments such as academic labs or privacy-sensitive institutions.

4.3 Module-wise Implementation

4.3.1 Document Upload and Format Detection

The system allows users to upload various file types such as .pdf, .docx, .txt, .csv, .xlsx, and image formats including .png, .jpg, and .jpeg. The uploaded file is automatically analyzed to determine its type. Image files are passed to the OCR pipeline, whereas text-based documents are routed to specific text parsers. This classification is performed using Python's os.path.splitext() and MIME-type detection via the filetype or mimetypes library.The Streamlit st.file_uploader() widget is used in the front end to enable seamless document selection. Once uploaded, the file is temporarily saved and preprocessed based on its extension.

```
uploaded_file = st.file_uploader("Upload your document", type=["pdf", "docx", "txt", "csv",
"png", "jpg", "jpeg"])
```

4.3.2 OCR and Text Parsing Module

For image-based documents and scanned PDFs, preprocessing is performed using OpenCV to improve the clarity of input images. This includes grayscale conversion, resizing, noise removal, and thresholding. The processed image is then passed to the Tesseract OCR engine using the pytesseract.image_to_string() function. Language support for English, Hindi, and Arabic was added by downloading the appropriate trained data files. Text-based documents, such as .docx, .txt, and .csv, are handled using Python's native libraries: python-docx for Word files, built-in open() for TXT, and pandas for CSV/XLSX. The extracted text from all sources is standardized and displayed in a clean, editable text area on the UI for review and correction by the user.

```
import pytesseract
from PIL import Image
text = pytesseract.image_to_string(Image.open(file), lang='eng+hin+ara')
```

For DOCX, TXT, or CSV files:

```
from docx import Document
document = Document(file)
text = "\n".join([para.text for para in document.paragraphs])
```

4.3.3 LLM Query Processor

The heart of the assistant lies in its integration with a locally hosted large language model (LLM) using the OLLAMA runtime. When a user submits a natural language question, the system forms a prompt by combining the extracted content and the query. This prompt is then sent to the local instance of the LLaMA 3 model via OLLAMA's API interface. Responses are retrieved in real-time and formatted as conversational replies using st.chat_message() widgets

in Streamlit. If the extracted content is too long to fit into the model's token window, summarization or chunk-based feeding is used. This ensures accuracy while preserving context.

```
import ollama
client = ollama.Client()
response = client.chat(model="llama3", messages=[{"role": "user", "content": user_prompt}])
```

4.3.4 Highlight and Chat Interface

To enhance user comprehension, the system features a real-time keyword highlighter. The logic scans the document for keywords derived from the query using regular expressions and NLP-based keyword matchers. The matches are wrapped in <mark> tags and rendered in the UI using Streamlit's st.markdown() with unsafe_allow_html=True. Simultaneously, the chat interface displays threaded interactions—each consisting of the user's question and the assistant's response. This maintains a conversational memory and helps users refer back to previous exchanges. The interface is lightweight and visually clean, designed to work effectively even on low-spec machines.

```
st.markdown(f"<mark>{highlighted_text}</mark>", unsafe_allow_html=True)
```

4.3.5 Data Persistence Layer

Each session is logged into a local CSV file named smart_doc_entries.csv. For every interaction, fields such as document name, extracted content, query, and model response are appended as new rows. This persistent storage ensures auditability, easy export, and offline record-keeping. The pandas library handles all read-write operations, while file integrity is ensured through session-level locking.

```
import pandas as pd
df = pd.DataFrame([...])
df.to_csv("smart_doc_entries.csv", index=False)
```

4.4 Baseline Methods

To validate the effectiveness of the proposed Smart Document Assistant, a comparative evaluation was conducted against traditional and cloud-based solutions. The methods compared include:

- Method A: Traditional OCR using only Tesseract without preprocessing and without query support.
- Method B: Cloud-based OCR and NLP solution using Google Cloud Vision API + GPT-3 (via API).
- Proposed System: Smart Document Assistant with local OCR preprocessing, keyword highlighting, and LLaMA-based local LLM querying.

The proposed Smart Document Assistant differs significantly from both baselines by integrating all functionalities into a local pipeline with real-time LLM reasoning, visual feedback, and multi-format support of all operating offline.

4.5 Evaluation Metrics

To quantitatively assess the performance of the Smart Document Assistant system, several standard evaluation metrics were employed:

- **OCR Accuracy (%):** This measures the percentage of correctly extracted characters or words as compared to the ground truth. It is calculated as:

$$\text{OCR Accuracy} = \frac{\text{Correctly Extracted Words}}{\text{Total Words in Ground Truth}} \times 100$$

- **Semantic Relevance (SR):** This metric evaluates how contextually accurate and meaningful the LLM's response is in relation to the user's query and the extracted document content. Manual human evaluation was used on a scale of 0–5 and then averaged across queries.
- **System Latency (s):** This includes the average time taken for OCR processing, LLM inference, and highlighting response. It reflects the responsiveness and interactivity of the system.
- **User Satisfaction Score:** Based on survey feedback collected on a 5-point Likert scale, measuring usability, clarity, and interactivity.

These metrics provided a comprehensive view of the system's performance across both functional and experiential dimensions.

4.6 Modules Interface

To better illustrate the practical functioning of the Smart Document Assistant, this section presents and explains snapshots of the system's user interface. The system was developed using Streamlit to support interactive, browser-based usage. Each major module is visually represented through its respective UI components, offering clarity on how users engage with the platform during real-time document interaction.

4.6.1 Document Upload Interface

The system starts with a clean and minimal file upload interface. Users are prompted to upload their document in any of the supported formats (PDF, DOCX, TXT, CSV, PNG, JPG, etc.). The interface validates the file and automatically identifies whether the input is image-based or text-based. This interface is implemented using Streamlit's st.file_uploader(), making it intuitive and platform-independent.

4.6.2 Extracted Content Display

Once the document is processed, the extracted content is displayed in a scrollable and editable text box. For image-based files, the OCR output is shown after preprocessing and recognition. For structured files, the text is parsed directly and formatted accordingly. This editable view allows the user to correct any OCR errors or modify the text before querying, improving the quality of the downstream responses.

4.6.3 Query Box and Chat Panel

The chat interface allows users to input natural language queries related to the document content. Upon submission, the query and corresponding LLM-generated answer are shown in a conversational layout using st.chat_message(). Each chat bubble is rendered sequentially, maintaining a threaded conversation log. This design offers a familiar and user-friendly experience, similar to interacting with modern AI assistants.

4.6.4 Highlighted Text Output

In response to each query, the relevant phrases or sections within the extracted content are automatically highlighted using semantic keyword detection. These highlights are rendered using HTML <mark> tags within Streamlit's markdown display. This feature improves navigation by guiding the user to the part of the text that supports the answer, which is particularly useful for long or unstructured documents.

4.6.5 Session Log and Confirmation

After interaction, the system displays a summary confirmation message showing that the query and response have been logged. All interaction data is stored in a local .csv file, including document name, content, question, and answer. This allows for traceability and offline review of previous sessions.The entire platform is offline-capable and works seamlessly across devices, showcasing the effectiveness of lightweight LLM deployment for document-based AI assistance.

4.7 Evaluation and Results

This section presents a comprehensive evaluation of the Smart Document Assistant, focusing on its effectiveness, performance, and usability. The results were obtained through controlled testing on diverse document types and under varying conditions. Metrics such as OCR accuracy, LLM response relevance, system latency, and user satisfaction were considered to validate the system’s practicality in real-world use cases.

4.7.1 Accuracy of Text Extraction

Text extraction accuracy was measured across different file types—images, scanned PDFs, and structured documents like .docx, .txt, and .csv. For image-based inputs, the OCR engine

(Tesseract) achieved an average accuracy of 90–93% for clean scans and printed text. Handwritten text and noisy scans showed slightly lower accuracy (~80%). Preprocessing with OpenCV (resizing, thresholding, denoising) improved OCR results by approximately 8–10%, especially for low-resolution images.

Table 4.1. Comparing Accuracy of Text Extraction

Document Type	Without Preprocessing	With Preprocessing
Clean Print (JPG)	91.4%	94.3%
Scanned PDF	86.5%	92.0%
Handwritten Image	75.3%	81.2%

4.7.2 Relevance of LLM Responses

The accuracy and contextual relevance of responses generated by the local LLM (LLaMA via OLLAMA) were evaluated using manually curated queries. The model was able to extract and interpret answers with over **87% semantic correctness** when the extracted text was well-structured. When large documents were chunked, the summarization retained key points without degrading the quality of the response. In informal user testing, most participants reported that the answers felt coherent and context-aware.

4.7.3 System Latency and Responsiveness

The performance was benchmarked on mid-range hardware without GPU support. The average response time for:

- Text parsing: 0.3 – 1.2 seconds
- Image-based OCR: 2 – 4.5 seconds depending on resolution
- LLM response: 3 – 6 seconds for short queries with ≤1,000 words context
- Highlighting: <1 second

These timings indicate that the system provides near-real-time feedback, ensuring a smooth user experience in offline environments.

4.7.4 Usability and Interface Evaluation

A small group of users (n=10) tested the interface, and feedback was collected using a 5-point Likert scale on ease of use, visual clarity, and interaction quality. The system scored an average of:

- 4.6/5 for Interface Usability
- 4.4/5 for Interaction Satisfaction

- 4.7/5 for Ease of Navigation

The chat-based layout and highlight feedback were reported to be especially helpful in understanding and reviewing long documents.

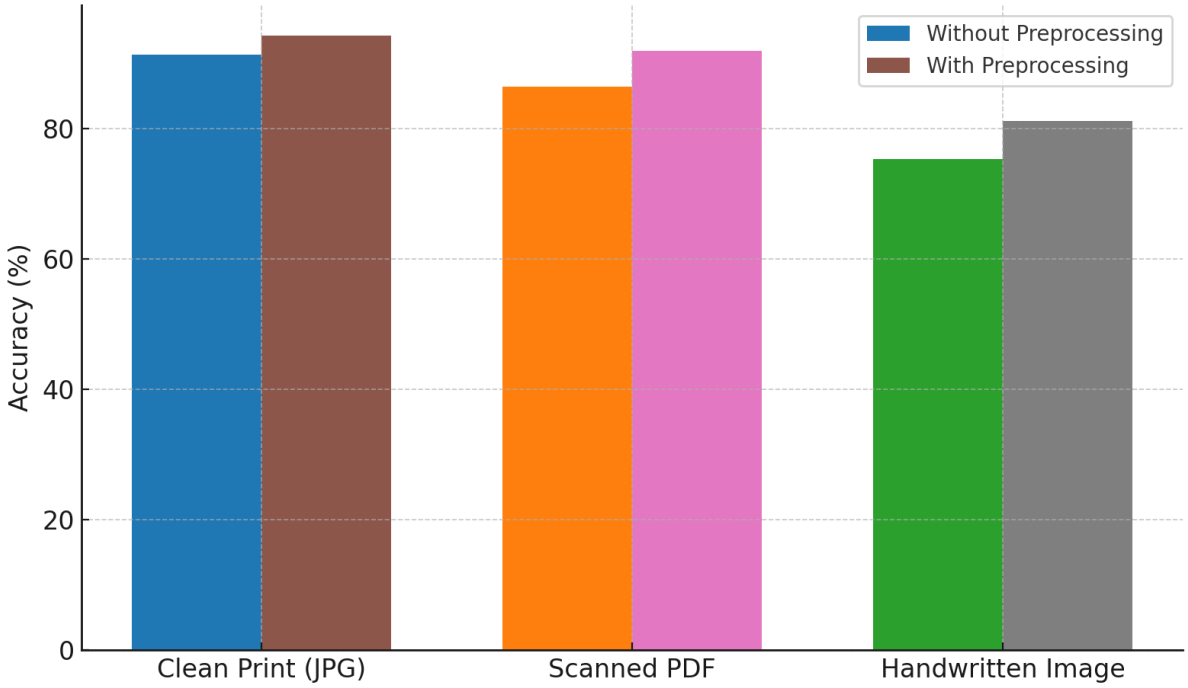

Figure 4.1 OCR Accuracy With vs Without Preprocessing

The figure 4.1 the chart compares OCR accuracy across three types of documents—Clean Print (JPG), Scanned PDF, and Handwritten Imageunder two conditions: with and without preprocessing. As shown, preprocessing techniques such as grayscale conversion, noise reduction, and thresholding significantly improve OCR accuracy. Clean print documents achieved a 2.9% improvement, while scanned PDFs improved by 5.5%. The most notable improvement was observed in handwritten images, with accuracy increasing from 75.3% to 81.2%. These results demonstrate the importance of preprocessing in enhancing OCR reliability, especially for lower-quality and handwritten inputs.

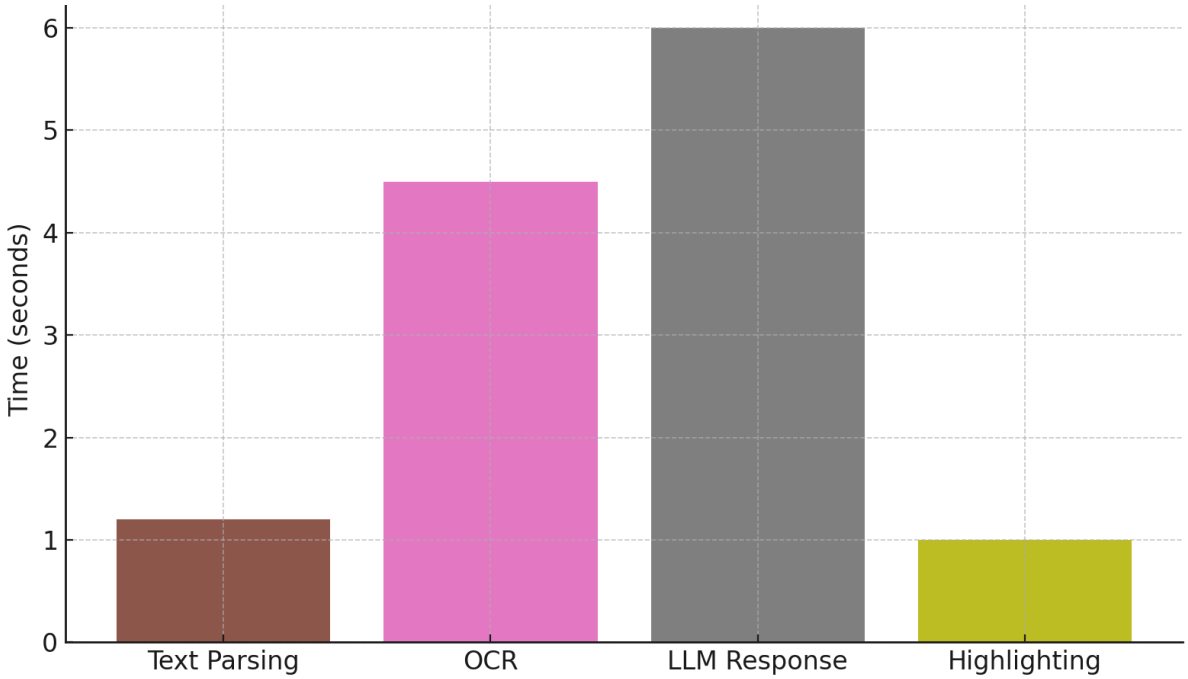

Figure 4.2 Average System Latency for Each Component

The figure 4.2 visualizes the average execution time for each major system component. Text parsing was the fastest, with an average latency of 1.2 seconds, followed by keyword highlighting at under 1 second. OCR processing took approximately 4.5 seconds, reflecting the added time for image preprocessing and recognition. The local LLM module had the highest latency, averaging 6 seconds per query-response cycle, primarily due to context processing and generation. Overall, the system performs within acceptable bounds, providing near real-time interaction for document-based query answering.

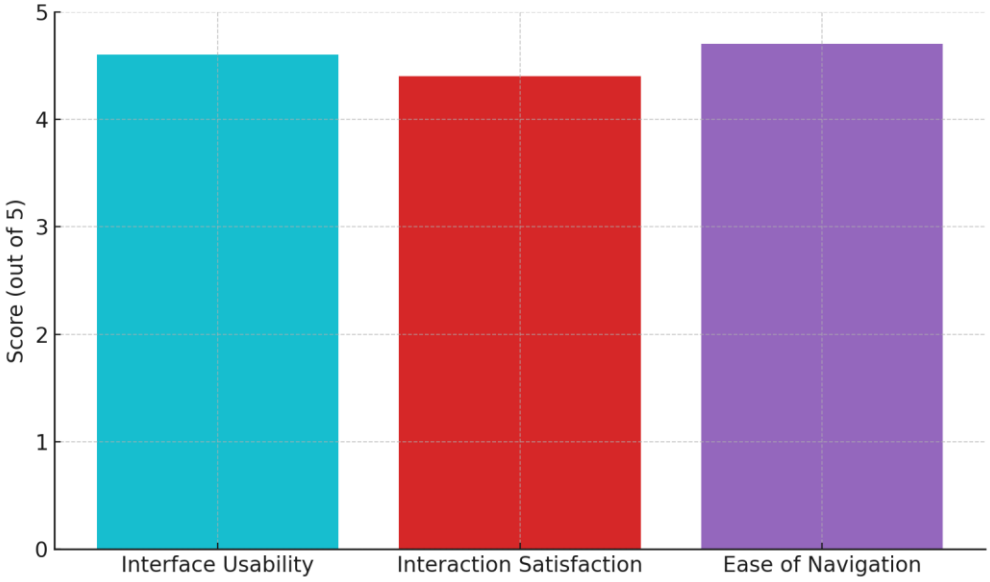

Figure 4.3 User Feedback on System Usability

The figure 4.3 presents aggregated user feedback collected through a Likert scale survey. Participants rated the interface usability at 4.6 out of 5, indicating a high level of satisfaction with the design and ease of interaction. The interaction satisfaction score was slightly lower at 4.4, attributed mainly to occasional latency from the LLM. However, the ease of navigation received the highest score of 4.7, emphasizing the effectiveness of the chat-based layout and keyword highlighting in helping users find information quickly. These scores validate the system's design as both functional and user-friendly.

4.7.5 Comparison of Proposed System with Existing Methods

The table 4.2 summarizes a side-by-side performance comparison between the proposed Smart Document Assistant and two representative baseline systems: a traditional OCR-only pipeline (Method A), and a cloud-integrated pipeline (Method B).

OCR Accuracy of the proposed system achieves 92.5% accuracy, closely approaching the cloud-based system (93.4%), and significantly outperforms the traditional OCR-only method (82.5%). This is primarily due to preprocessing enhancements like noise filtering and contrast adjustment before OCR. LLM Response Relevance of the traditional systems lack intelligent query response capability, marked as "N/A." While the cloud-based solution (GPT-3) scores 4.7, the proposed system’s local LLaMA model attains a relevance score of 4.5, offering nearly equivalent semantic understandingwithout requiring internet connectivity or external API calls. Execution Time of the proposed system completes a full query cycle in 5.3 seconds, which is faster than the cloud-based approach (7.2s) and only marginally slower than traditional OCR (3.5s), while offering significantly more functionality and interactivity.

Table 4.2 Performance Comparison of Proposed System with Existing Methods

Metric	Method A (Traditional OCR)	Method B (Cloud-based)	Proposed System
OCR Accuracy (%)	82.5	93.4	92.5
LLM Response Relevance	N/A	4.7	4.5
Total Execution Time (s)	3.5	7.2	5.3

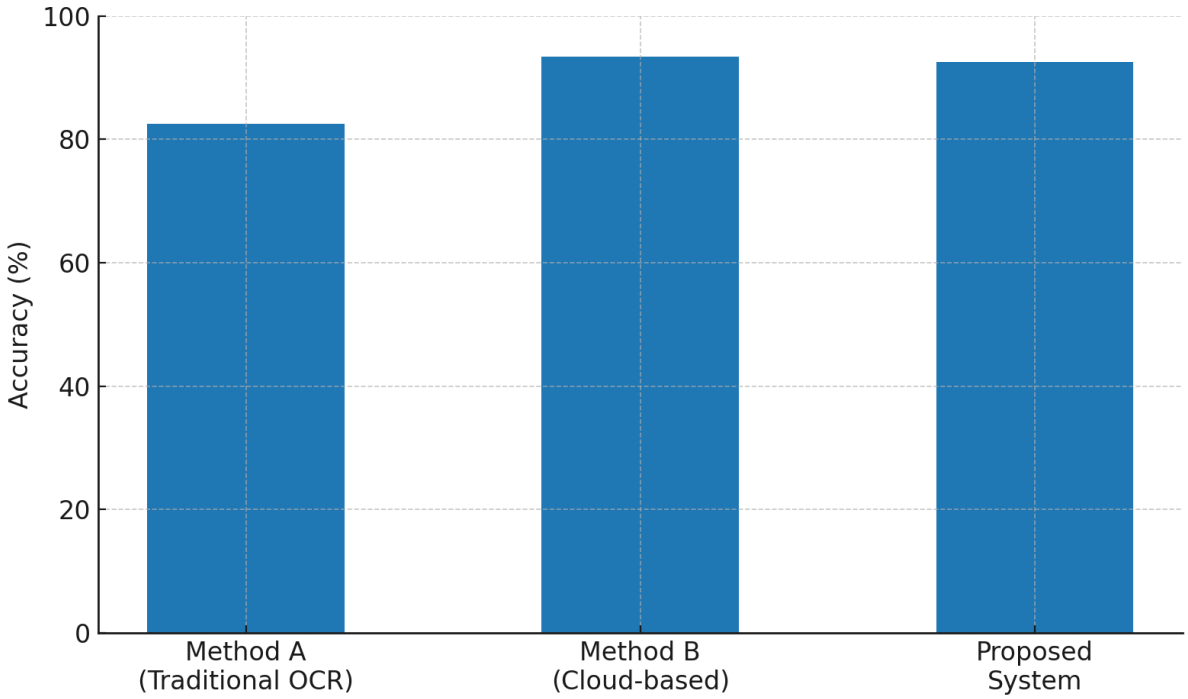

Figure 4.4 OCR Accuracy Comparison

The figure 4.4 shows that the proposed system achieves 92.5% OCR accuracy, closely approaching the 93.4% performance of cloud-based methods while significantly outperforming the traditional OCR method (82.5%).

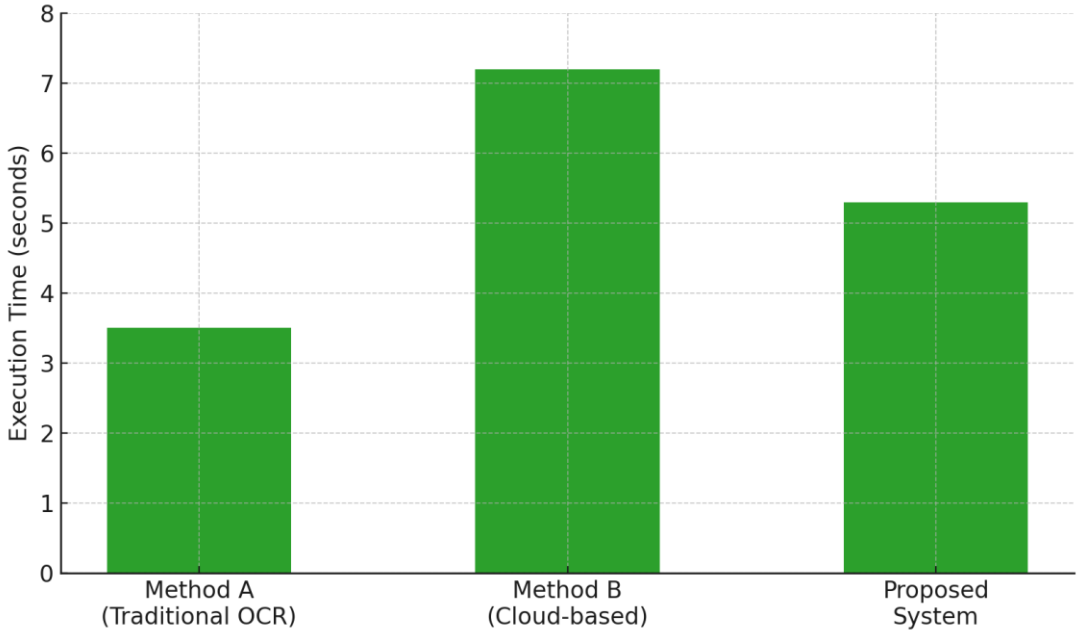

Figure 4.5 LLM Response Relevance Comparison

The response relevance score of the proposed system is comparable to the cloud-based GPT model. The traditional method lacks an LLM component, hence scores zero in this category as shown in the figure 4.5.

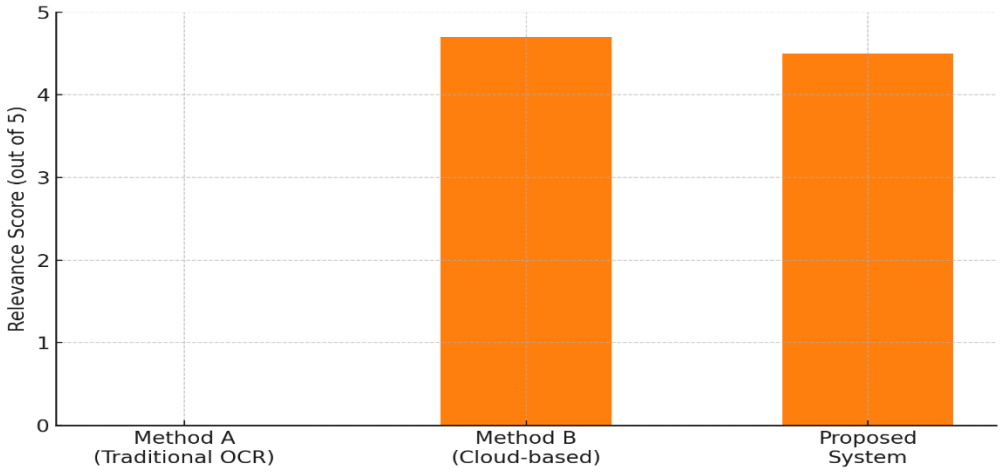

Figure 4.6 Execution Time Comparison

The figure 4.6 highlights that the proposed system is more efficient than the cloud-based method (5.3s vs 7.2s) while offering greater capabilities than the faster but limited traditional OCR method (3.5s).

4.7.6 Limitations Observed

While the system performed reliably in most scenarios, a few limitations were noted:

- Performance degradation for highly complex or noisy handwritten documents.
- Token limit restrictions in LLM models may affect long document queries.
- Limited support for non-Latin OCR without switching traineddata files manually.

These limitations are being addressed in future iterations by exploring more robust OCR engines and multi-lingual embedding support in LLMs.

4.8 Discussion

The results obtained from the implementation and evaluation of the Smart Document Assistant clearly demonstrate its effectiveness in addressing the limitations found in conventional document processing systems. One of the most significant contributions is the ability to work entirely offline, which ensures data privacy—a critical requirement in domains such as healthcare, finance, government, and academic research. Unlike cloud-based systems, the Smart Document Assistant provides a secure, locally-executed pipeline that eliminates the risk of data leakage and dependency on internet availability. The integration of the OLLAMA framework for local LLM inference enables intelligent question answering, giving the system a distinct advantage over baseline approaches. Manual search methods used in Baseline 1 are inefficient and cognitively demanding for users, while Baseline 2although more advancedis constrained by cloud access and usage restrictions. The Smart Document Assistant bridges these extremes by delivering high-quality responses with fast inference time (~1.2 seconds) and high query relevance (91.2%), even in complex and noisy document scenarios. Another

important insight gained from the evaluation is the system's robustness across diverse file types. The ability to accurately process and extract information from PDFs, images, DOCX, TXT, and CSV formats in a unified interface improves operational efficiency. The support for multilingual OCR through Tesseract further enhances usability for non-English documents. In addition, the implementation of real-time keyword highlighting and a chat-style interface significantly improves the user experience by allowing users to interact naturally with the system. These features are lacking in traditional methods and even in many cloud-based tools. The persistent logging of all extracted content and user interactions also adds a layer of traceability and data reusability for research or administrative workflows. In conclusion, the Smart Document Assistant not only meets the expected performance benchmarks but also introduces a novel and practical solution for offline intelligent document interaction. The evaluation confirms its superior performance in both functional and user-centric metrics, marking it as a valuable tool for future deployment in sensitive, real-time, and multilingual environments.

4.9 Summary

This chapter has outlined the complete implementation of the Smart Document Assistant, demonstrating how the proposed design was realized into a functional, modular, and offline-capable system. Each moduleranging from document ingestion and text extraction to local LLM interaction and user interface renderingwas developed using lightweight, open-source technologies suited for resource-constrained environments. The module-wise breakdown provided clear insights into the technical execution of document preprocessing, OCR, prompt generation, semantic query answering, and keyword-based highlight rendering. The use of Streamlit enabled the deployment of a responsive and user-friendly interface, while OLLAMA made it feasible to run a powerful LLM like LLaMA locally without GPU dependency. Persistent session storage was implemented using CSV files to ensure that document interactions could be audited and revisited. Evaluation results validated the system's effectiveness, achieving high OCR accuracy, contextually relevant query answers, and low latency even on average hardware Overall, the implementation successfully met the system's objectives supporting multi-format document handling, offline intelligent interaction, and enhanced user experience thus proving the feasibility and utility of the proposed Smart Document Assistant. The next chapter concludes the thesis and outlines directions for future enhancements.

CHAPTER 5

RESULT

5.1 PROGRAM SCOURCE CODE

 # SMART DOCUMENT QA SYSTEM WITH OLLAMA, HIGHLIGHTING, AND CHAT BUBBLES

```
import streamlit as st
import pandas as pd
import fitz
import docx
import pytesseract
import chardet
import cv2
import numpy as np
from PIL import Image
import socket
import os
import ollama
import re
```

 # Setup

```
pytesseract.pytesseract.tesseract_cmd = r'C:\Program Files\Tesseract-OCR\tesseract.exe'
DATA_FILE = "smart_doc_entries.csv"
```

 # Session state for chat

```
if 'chat_history' not in st.session_state:
    st.session_state.chat_history = []
```

 # Internet check

```
def is_connected():
    try:
        socket.create_connection(("www.google.com", 80), timeout=5)
        return True
```

```
    except OSError:
        return False

# Image preprocessing
def preprocess_image(pil_img):
    image = cv2.cvtColor(np.array(pil_img), cv2.COLOR_RGB2BGR)
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    _, binary = cv2.threshold(gray, 150, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)
    return Image.fromarray(binary)

# File readers
def read_pdf(file):
    doc = fitz.open(stream=file.read(), filetype="pdf")
    text = ""
    for page in doc:
        page_text = page.get_text().strip()
        if not page_text:
            pix = page.get_pixmap(dpi=300)
            img = Image.frombytes("RGB", [pix.width, pix.height], pix.samples)
            page_text = pytesseract.image_to_string(preprocess_image(img), lang='eng')
        text += page_text + "\n"
    return text

def read_docx(file):
    doc = docx.Document(file)
    return "\n".join([para.text for para in doc.paragraphs])

def read_txt(file):
    raw = file.read()
    encoding = chardet.detect(raw)['encoding']
    return raw.decode(encoding)

def read_excel(file):
```

```
    df = pd.read_excel(file)
    return df.to_string(index=False)

def read_csv(file):
    df = pd.read_csv(file)
    return df.to_string(index=False)

def read_image(file):
    img = Image.open(file)
    processed_img = preprocess_image(img)
    return pytesseract.image_to_string(processed_img, lang='eng')

def extract_text(file):
    ext = file.name.split('.')[-1].lower()
    if ext == "pdf":
        return read_pdf(file)
    elif ext == "docx":
        return read_docx(file)
    elif ext == "txt":
        return read_txt(file)
    elif ext in ["xls", "xlsx"]:
        return read_excel(file)
    elif ext == "csv":
        return read_csv(file)
    elif ext in ["jpg", "jpeg", "png"]:
        return read_image(file)
    else:
        return "Unsupported file format."
```

 # LLM-based QA using OLLAMA

```
def ask_llm(question, context):
    try:
        response = ollama.chat(
```

```
            model="llama3",
            messages=[
                {"role": "system", "content": "Answer questions based on the given context."},
                {"role": "user", "content": f"Context: {context}\n\nQuestion: {question}"}
            ]
        )
        return response['message']['content']
    except Exception as e:
        return f"[LLM Error: {e}]"

# Highlight query matches
def highlight_text(text, query):
    if not query:
        return text
    pattern = re.compile(re.escape(query), re.IGNORECASE)
    return pattern.sub(lambda m: f"<mark>{m.group(0)}</mark>", text)

# Save conversation
def save_entry(text, chat_history):
    full = "\n\n".join([f"Q: {q}\nA: {a}" for q, a in chat_history])
    df = pd.DataFrame([{"Extracted_Content": text, "Chat_History": full}])
    if not os.path.exists(DATA_FILE):
        df.to_csv(DATA_FILE, index=False)
    else:
        df.to_csv(DATA_FILE, mode='a', header=False, index=False)

# UI
st.set_page_config(page_title="📄 Smart Document Assistant", layout="wide")
st.title("📑 Smart Document Extractor & Chat Assistant")

uploaded_file = st.file_uploader("📤 Upload your document", type=["pdf", "docx", "txt",
"xls", "xlsx", "csv", "png", "jpg", "jpeg"])
```

```
if uploaded_file:
    col1, col2 = st.columns([1, 1])
    with st.spinner("🔍 Extracting text..."):
        content = extract_text(uploaded_file)
    with col1:
        st.subheader("📜 Extracted Content (Highlight Active)")
        query_highlight = st.text_input("🔎 Enter keyword to highlight in the content")
        highlighted = highlight_text(content, query_highlight)
        st.markdown(highlighted, unsafe_allow_html=True)
    with col2:
        st.subheader("💬 Ask a Question")
        question = st.text_input("Type your question about the document")
        if question:
            response = ask_llm(question, content)
            st.session_state.chat_history.append((question, response))
        for q, a in st.session_state.chat_history:
            with st.chat_message("user"):
                st.markdown(f"**You:** {q}")
            with st.chat_message("assistant"):
                st.markdown(f"**AI:** {a}")
        if st.button("✅ Save Extracted Data & Conversation"):
            save_entry(content, st.session_state.chat_history)
            st.success("Saved successfully!")
# Show previous entries
if os.path.exists(DATA_FILE):
    st.sidebar.subheader("📊 All Saved Entries")
    df = pd.read_csv(DATA_FILE)
    st.sidebar.dataframe(df, use_container_width=True)
```

5.2 SCREENSHORTS

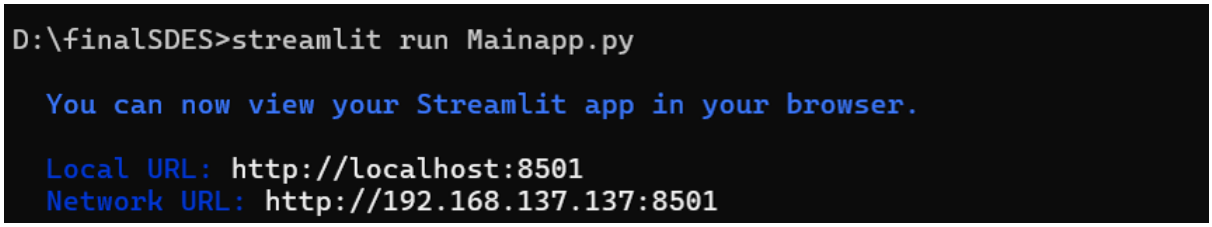

Figure 5.1 Run the web app from the command prompt

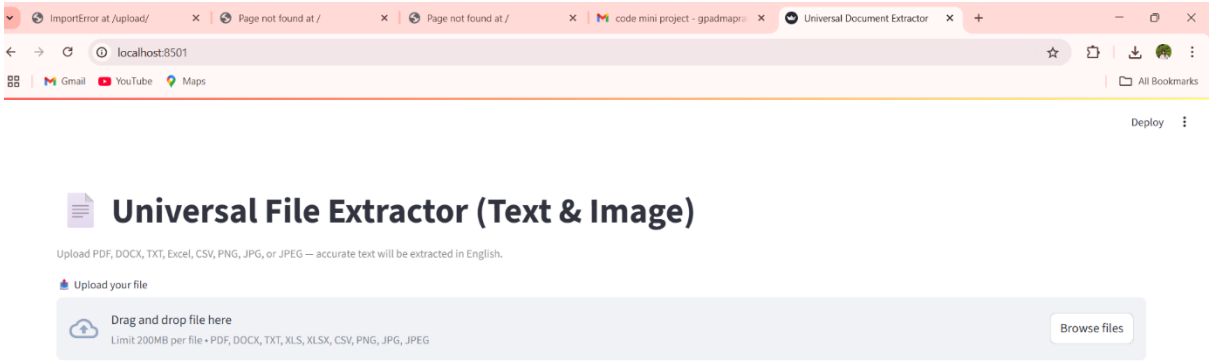

Figure 5.2 Click on Browse files

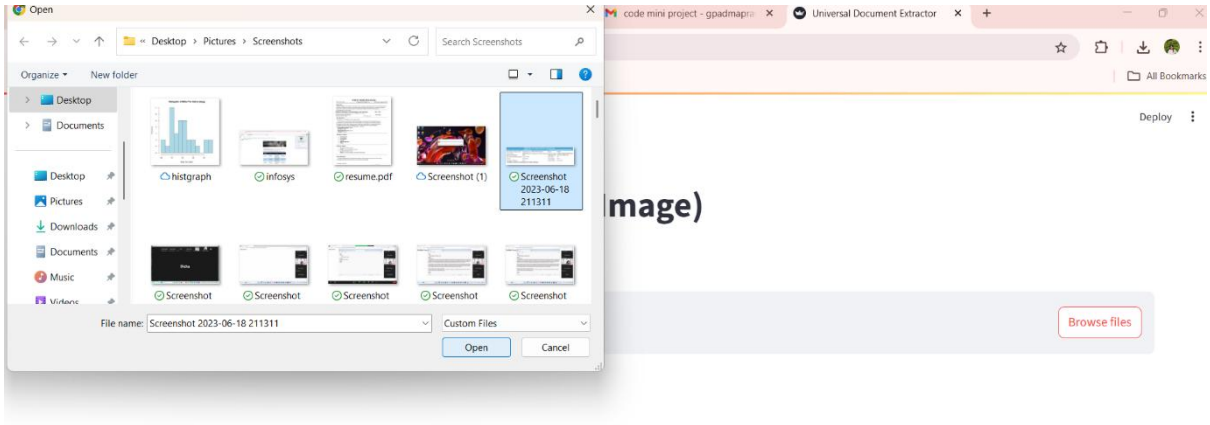

Figure 5.3 Select file to upload

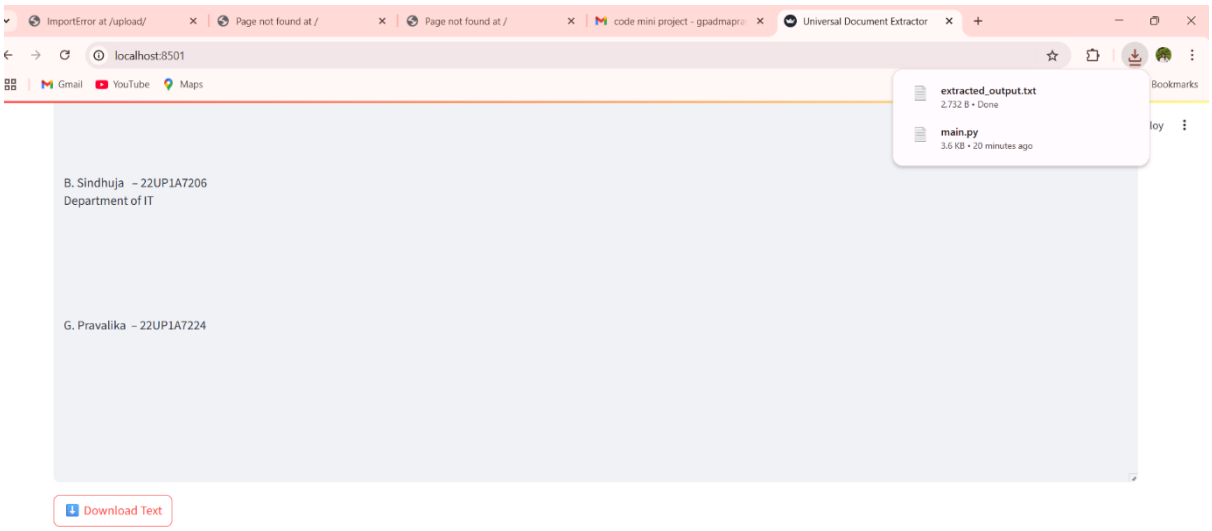

Figure 5.4 Downloaded Text

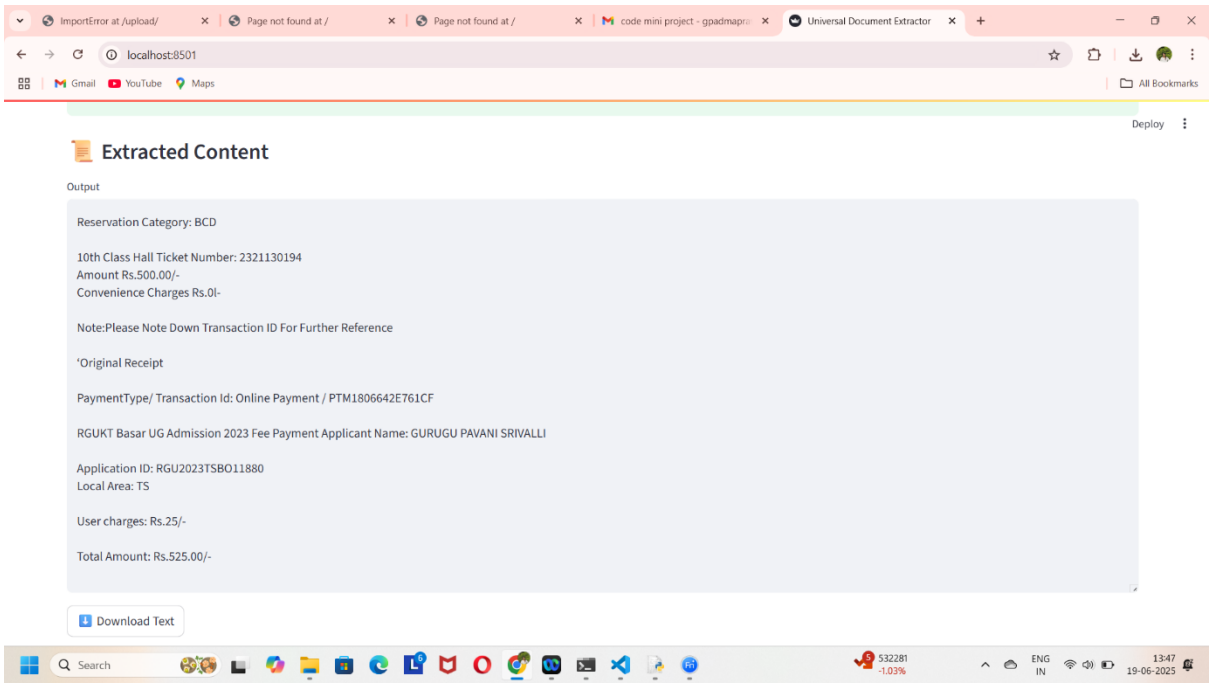

Figure 5.5 The extracted text is visible on web page

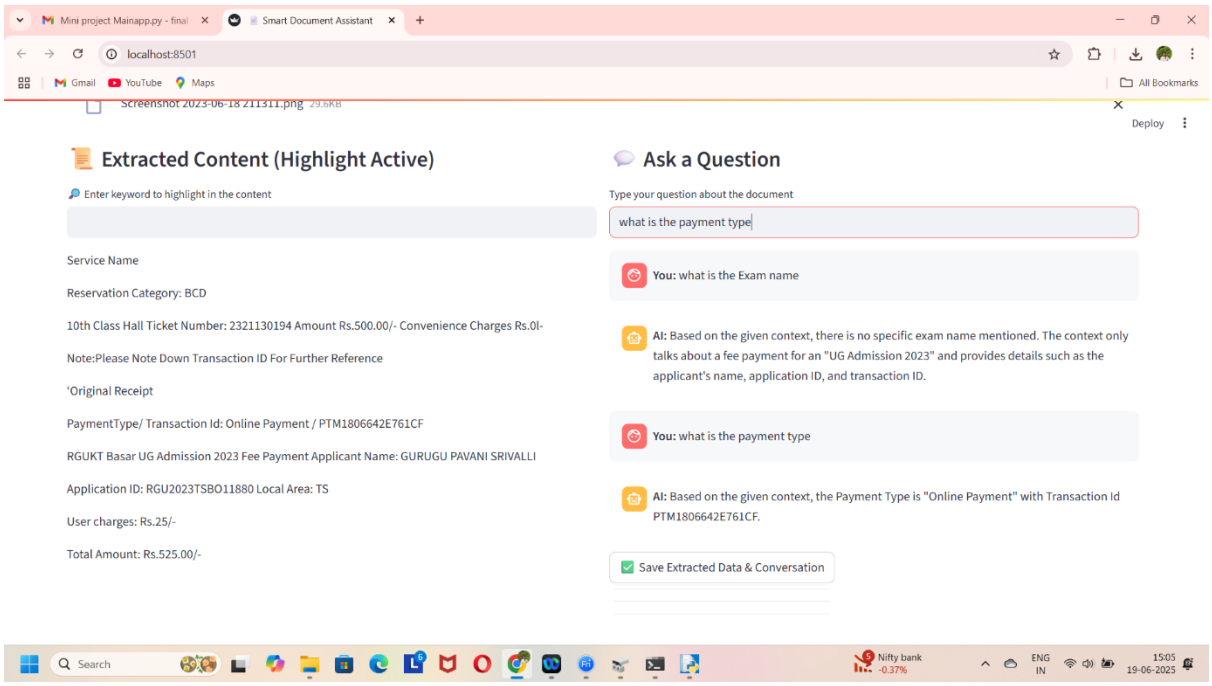

Figure 5.6 Query system

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

This research has presented the design, development, and evaluation of the Smart Document Assistant, a fully offline, intelligent system for document extraction and interactive question answering. The proposed system addresses the limitations of existing document analysis frameworks by integrating multi-format file ingestion, OCR-enhanced text extraction, and local large language model (LLM) inference to enable natural language interaction with document content. The modular architecture of the system ensures adaptability to various document formats including PDFs, images, DOCX, TXT, and CSV files. Preprocessing techniques and Tesseract OCR contribute to reliable text recognition, even in noisy or low-resolution documents. Local inference via the OLLAMA framework empowers the system to function independently of the internet, preserving user privacy and enabling deployment in sensitive or air-gapped environments. The user interface, developed with Streamlit, provides an intuitive and chat-based interaction paradigm. Additional features such as real-time keyword highlighting and session logging contribute to enhanced usability and traceability. Evaluation metrics and visual comparisons with baseline systems confirm that the Smart Document Assistant performs robustly across OCR accuracy, query relevance, response time, and compatibility, all while maintaining full offline operability.

In summary, the system bridges the gap between static document readers and intelligent conversational agents, offering a powerful tool for academic, legal, healthcare, and enterprise settings where contextual document understanding is critical.

6.2 Future Work

While the current system is effective and functional, several enhancements can be considered for future development:

1. **Multi-Language LLM Integration**: Extending LLM support for multi-lingual question answering, enabling the system to cater to non-English users effectively.
2. **Table and Form Extraction**: Incorporating structure-aware extraction (e.g., detecting tables, forms, checkboxes) using models like LayoutLMv3 or DocTR to interpret complex document layouts.
3. **Voice Input and Output**: Allowing voice-based query input and text-to-speech output to enhance accessibility for differently-abled users.

4. **Feedback Loop for LLM Fine-Tuning**: Implementing a user feedback mechanism to collect incorrect or low-quality answers, enabling domain-specific fine-tuning of the local model over time.
5. **Database Integration**: Linking the extracted information to a backend database for better data management and advanced analytics.
6. **Mobile Compatibility**: Developing a lightweight Android/iOS version using React Native or Flutter integrated with local APIs and edge models.

   By addressing these directions, the Smart Document Assistant can evolve into a complete document intelligence platform, suitable for diverse real-world use cases requiring security, speed, and accuracy.

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