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DocuVoice: An AI-Powered Intelligent Document Analyzer for the Visually Impaired

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Abstract—Access to written information remains a persistent challenge for visually impaired individuals. Traditional screen readers and text-to-speech (TTS) systems support linear playback but fall short of enabling genuine comprehension, interactive navigation, and contextual understanding of complex documents. This paper presents DocuVoice, a full-stack, AI-powered docu-ment analysis platform designed to bridge this accessibility gap. The system integrates Optical Character Recognition (OCR), document layout analysis, Natural Language Processing (NLP), Retrieval-Augmented Generation (RAG)-based question answer-ing, and a voice-centric interface into a unified pipeline. Key fea-tures include extractive and abstractive summarization, Named Entity Recognition (NER), sentiment analysis, multilingual sup-port, automatic quiz generation, and full voice control. DocuVoice accepts diverse document formats (PDF, DOCX, scanned images) and delivers intelligent, context-aware audio responses, empow-ering visually impaired users to read, understand, and interact with documents independently.

Index Terms—Accessibility, visually impaired, document anal-ysis, OCR, NLP, text-to-speech, retrieval-augmented generation, sentiment analysis, assistive technology, artificial intelligence, DocuVoice.

I. Introduction

Access to printed and digital documents is fundamental to education, employment, and independent living. For the more than 2.2 billion people worldwide who suffer from visual impairment or blindness [1], engaging with arbitrary documents—scanned pages, multi-column academic papers, tables, or image-heavy reports—remains a significant techno-logical barrier [2], [3].

Existing assistive tools such as JAWS, NVDA, and VoiceOver are screen readers that translate structured, tagged content into linear audio. While valuable, these tools are fundamentally passive: they read text sequentially but provide no summarization, no document-grounded question answering, and no support for non-textual elements such as figures, charts, or mathematical equations [5]. Users often need high-level overviews, the ability to ask targeted questions about content, or a condensed oral summary of a lengthy document, none of which existing screen readers support [4].

DocuVoice is presented as a comprehensive, AI-driven document analysis platform designed to address these lim-itations. The system adopts a multi-engine architecture that couples classical OCR and layout analysis with large-scale transformer-based NLP models and a voice interface. The platform is designed to: (1) extract and structurally interpret content from diverse document types; (2) provide concise, section-level summaries and full-document abstracts; (3) an-swer user questions using RAG-based document grounding; (4) describe non-textual elements such as figures and tables; and (5) operate through natural, low-effort voice commands to minimize the accessibility barrier further.

The remainder of this paper is organized as follows: Sec-tion II states the problem formally; Section III describes the proposed system and its key innovations; Section IV details system architecture and technology stack; Section V explains the algorithmic methodologies; Section VI presents implementation details; Section VII discusses results and eval-uation; Section VIII concludes; and Section IX outlines future directions.

II. Problem Statement

The assistive technology landscape, despite decades of progress, leaves visually impaired users with several critical unresolved challenges:

- **Linear-Only Access:** Screen readers present documents character-by-character or line-by-line, making it imprac-tical to obtain a rapid overview or jump to a relevant

section within long documents such as research papers, legal contracts, or medical reports [2].

- **Absence of Comprehension Support:** Existing tools convey text as audio but provide no mechanism for comprehension support—no summarization, no terminol-ogy simplification, no interactive Q&A, and no quiz generation for educational retention.
- **Non-Textual Element Blindness:** Figures, charts, tables, diagrams, and mathematical equations within documents are either skipped entirely or read as raw alternative-text strings, which are often absent or uninformative [10], [13].
- **Scanned Document Inaccessibility:** A large propor-tion of real-world documents—historical records, printed forms, handwritten notes, and textbooks—are available only as scanned images or poorly tagged PDFs, for which existing screen readers provide no utility [6].
- **Multilingual and Low-Resource Language Gaps:** Many visually impaired users in India and similar regions require support for regional languages (Hindi, Marathi, and other Indic scripts). OCR, TTS, and NLP quality for these languages remains significantly below that for English [20].
- **Privacy and Connectivity Constraints:** Cloud-based document processing, the de facto approach for powerful AI systems, raises serious data privacy concerns for users uploading sensitive personal or confidential documents.

These gaps collectively highlight the need for a unified, intelligent system that integrates OCR, NLP, multimodal un-derstanding, and voice interaction into a single, accessible platform.

III. Proposed System

DocuVoice is proposed as a single intelligent ecosystem that transforms arbitrary document inputs into structured, accessible, voice-delivered knowledge. Unlike passive screen readers, DocuVoice acts as an active reading companion that understands, summarizes, and converses about document con-tent.

A. Core Capabilities

1) **Intelligent OCR and Layout Understanding:** Docu-Voice combines Tesseract and PyMuPDF for text ex-traction with LayoutLM-based region detection to iden-tify headings, paragraphs, tables, figures, captions, and reading order in multi-column documents.

2) **Hybrid Summarization:** A two-stage summarization pipeline first extracts the most informative sentences using SBERT embeddings and TextRank scoring, then passes these candidates to a fine-tuned BART or T5 model for abstractive, naturally phrased audio-suitable summaries.

3) **Retrieval-Augmented Question Answering:** User voice queries are processed by a RAG pipeline that retrieves semantically relevant document passages using FAISS-indexed dense vector embeddings and generates grounded, hallucination-free answers.

4) **Named Entity Recognition and Sentiment Analysis:** SpaCy and Hugging Face Transformer models identify key entities (persons, organizations, dates, locations) and document-level or section-level sentiment for reports and news articles.

5) **Automatic Quiz Generation:** The system parses doc-ument content and generates question-answer pairs to support educational use cases, enabling visually im-paired students to actively test their comprehension.

6) **Voice-First Interface:** Whisper-based offline speech recognition processes user commands; gTTS or pyttsx3 converts system responses to natural audio output, en-abling fully hands-free, screen-free operation.

7) **Multilingual Support:** IndicBERT and mT5 extend the pipeline to Hindi, Marathi, and other Indic languages for both OCR post-processing and NLP inference.

B. Innovation and Differentiation

The dual-stage design—combining classical, high-precision NLP models (spaCy NER, SBERT retrieval) with generative AI (BART/T5 summarization, RAG-based QA)—mirrors the proven architecture of production-grade enterprise document AI systems. The key differentiator of DocuVoice is the voice-first accessibility layer: every capability is surfaced through natural language voice commands, eliminating the need for mouse, keyboard, or screen interaction. This makes DocuVoice fundamentally more inclusive than existing general-purpose document AI tools.

IV. System Architecture

The system follows a decoupled client-server architecture in which a React.js-based web frontend communicates with a Flask REST API backend over HTTP. Fig. 1 illustrates the end-to-end pipeline from document ingestion to voice output.

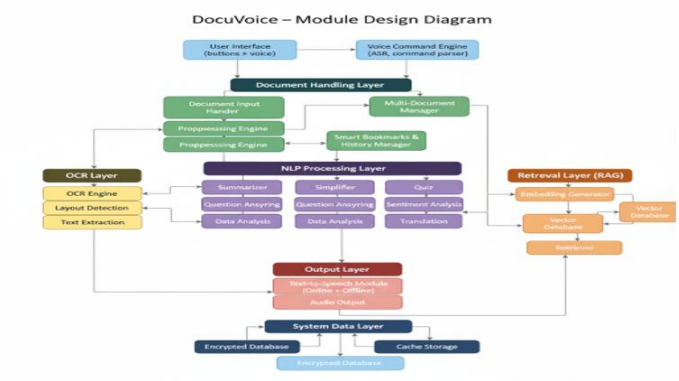

Fig. 1. DocuVoice end-to-end system architecture.

A. Technology Stack

V. Methodology

This section details the algorithmic and data-driven ap-proaches underlying each subsystem of DocuVoice. The over-all methodology follows a sequential document processing

TABLE I
BACKEND TECHNOLOGY STACK

Technology	Version	Purpose
Python	3.10+	Core backend language
Flask	Latest	REST API web framework
Flask-CORS	Latest	Cross-origin request handling
LangChain	Latest	LLM orchestration & RAG pipeline
Hugging Face	4.36+	Transformer NLP models
spaCy	3.x	NER and text processing
NLTK	Latest	Tokenization, statistical NLP
scikit-learn	Latest	TF-IDF, ML utilities
FAISS	Latest	Dense vector similarity search
PyMuPDF	Latest	PDF text and layout extraction
Tesseract	5.x	OCR for scanned images
Whisper	Latest	Offline speech recognition (ASR)
gTTS / pyttsx3	Latest	Text-to-speech (online/offline)
PostgreSQL	15+	Relational data store
Supabase	Latest	Managed PostgreSQL + Auth
FAISS/Pinecone	Latest	Vector database for embeddings

TABLE II
FRONTEND TECHNOLOGY STACK

Technology	Version	Purpose
React.js	18.x	User interface development
Tailwind CSS	3.x	Responsive styling
Chart.js	4.x	Data visualization
Axios 1.x	HTTP API client	
Web Speech API	—	Browser-based voice input

pipeline: ingestion, extraction, analysis, generation, and delivery.

A. Text Extraction and Layout Analysis

The extraction layer operates differently depending on the input type. For digital PDFs, PyMuPDF directly extracts Unicode text together with bounding-box coordinates for each text block, enabling downstream layout inference without OCR overhead. For scanned documents and image-based inputs, Tesseract [6] (with image preprocessing: denoising, deskewing, contrast enhancement) is applied to extract text with positional metadata.

A LayoutLM-based region classifier then consumes the extracted text blocks with their coordinates, classifying each region as one of: title, heading, paragraph, table, figure, or caption. This classification drives the logical reading order and allows the system to route specific element types (tables, figures) to specialized downstream handlers.

B. Semantic Parsing and Topic Segmentation

After extraction, the text undergoes sentence segmentation and tokenization. Named Entity Recognition (NER) using spaCy's en_core_web_trftransformer pipeline identifies people, organizations, geopolitical entities, numerical expres-sions, and dates throughout the document. For large docu-ments, topic segmentation partitions the full text into coherent thematic blocks. Sentence embeddings from SBERT are com-puted for each sentence, and adjacent sentences are grouped into chunks based on cosine similarity thresholds:

$$\text{sim}(s_i, s_j) = \frac{\mathbf{e}_i \cdot \mathbf{e}_j}{\|\mathbf{e}_i\| \cdot \|\mathbf{e}_j\|} \quad (1)$$

where $\mathbf{e}_i$ is the SBERT embedding of sentence s_i. Topic boundaries are inserted when cosine similarity between adjacent sentence embeddings falls below a configurable threshold τ.

C. Hybrid Summarization

DocuVoice implements a two-stage hybrid summarization strategy optimized for audio presentation:

Stage 1 — Extractive: TextRank [16] scores each sentence based on its graph centrality in the sentence-similarity graph. The top-k ranked sentences form the extractive summary candidate set.

Stage 2 — Abstractive: The extractive candidate set is passed as input to a fine-tuned BART [17] or T5 [18] model, which generates a condensed, naturally phrased summary. The abstractive step improves audio naturalness and eliminates redundancy that emerges from sentence concatenation.

The final summary length is adaptively controlled based on the source document length, targeting a compression ratio of approximately 10%–15% of the original token count.

D. Retrieval-Augmented Question Answering

For interactive Q&A, the document corpus is indexed offline as follows. Each topic-segmented chunk is encoded into a dense vector using SBERT. All chunk embeddings are stored in a FAISS flat index for approximate nearest-neighbour (ANN) retrieval. At query time:

1) The user's spoken query is transcribed by Whisper.
2) The query text is embedded using the same SBERT encoder.
3) FAISS retrieves the top-k most semantically similar document chunks.
4) The retrieved chunks are concatenated and passed as context to a generative model (BART or a fine-tuned T5).
5) The generator produces a grounded, document-faithful answer, which is then converted to speech.

The RAG pipeline [15] significantly reduces hallucinations by grounding generation in retrieved document evidence rather than relying solely on parametric model knowledge.

E. Sentiment Analysis

Document-level and section-level sentiment is computed using a fine-tuned BERT-based multi-class classifier (positive, neutral, negative) from the Hugging Face model hub. For business or news documents, sentiment scores per section are aggregated and presented as an overall tone summary.

F. Automatic Quiz Generation

Quiz generation follows a fill-in-the-blank and question-answer paradigm. Key noun phrases and named entities iden-tified by spaCy are used as answer candidates. A T5-based question generation model conditioned on the source sentence and the target answer span produces grammatically correct question stems. Generated QA pairs are stored per document for repeated self-testing sessions.

G. Voice Interface

The voice pipeline consists of two components:

- Automatic Speech Recognition (ASR): OpenAI Whis-per [21] processes microphone input offline, producing transcribed commands without requiring network connec-tivity, thereby preserving document privacy.

- Text-to-Speech (TTS): For online mode, Google TTS (gTTS) produces high-quality neural speech. For offline privacy-first mode, pyttsx3 renders speech locally on-device.

A lightweight command grammar resolves user intent from transcribed text, dispatching to the appropriate backend API: summarize, question-answer, sentiment, quiz, NER, and nav-igation commands.

VI. Implementation

A. System Overview and Data Flow

DocuVoice follows a decoupled client-server architecture. The React.js frontend manages document upload, voice com-mand capture, and result visualization. All processing is del-egated to the Flask backend, which exposes domain-specific REST API endpoints.

User authentication is stateless: upon login, the Flask server validates credentials against hashed passwords stored in PostgreSQL (via Supabase) and issues a JSON Web Token (JWT). All subsequent API calls include the JWT in the Authorization header for verification. Document meta-data, user history, bookmarks, and quiz progress are persisted in PostgreSQL. Embedding vectors for the RAG pipeline are stored in FAISS (local) or Pinecone (cloud).

B. Backend Implementation

The Flask backend organizes endpoints by functional do-main: /auth for login and registration, /upload for doc-ument ingestion and OCR, /summarize for summarization requests, /qa for question answering, /sentiment for tone analysis, /ner for entity extraction, and /quiz for quiz generation.

The document ingestion endpoint accepts multipart file up-loads (PDF, DOCX, PNG, JPG). PyMuPDF processes digital PDFs; Tesseract is invoked (with OpenCV preprocessing) for image-based inputs. The extracted text is segmented into topic chunks, encoded with SBERT, and stored in the FAISS index associated with the document's unique session identifier. LangChain manages the prompt construction layer for all gen-erative tasks, providing a clean separation between retrieval, formatting, and LLM instruction.

The summarization endpoint receives the document identi-fier, fetches the pre-chunked text from cache, applies TextRank for extractive pre-filtering, and forwards the candidate sen-tences to the BART summarization model loaded in evaluation mode. The QA endpoint follows the RAG pipeline described in Section V.

All NLP models (BART, SBERT, spaCy, Whisper) are loaded into memory at server startup to minimize per-request cold-start latency.

TABLE III
Flask API Endpoint Summary

Endpoint	Method	Function
`/auth/register`	POST	User registration
`/auth/login`	POST	JWT issuance
`/upload`	POST	Document upload and OCR
`/summarize`	POST	Generate document summary
`/qa`	POST	RAG-based question answering
`/sentiment`	GET	Sentiment analysis
`/ner`	GET	Named entity extraction
`/quiz`	GET	Quiz generation
`/history`	GET	User document history
`/translate`	POST	Multilingual translation

C. Frontend Implementation

The frontend is built with React.js 18.x and styled using Tailwind CSS 3.x. The interface is designed to complement the voice interaction: large touch targets, high-contrast text, and minimal visual clutter support low-vision users who sup-plement voice with residual sight. Chart.js renders sentiment timelines and keyword frequency visualizations as accessible, labeled bar and line charts. All interactive elements include ARIA labels to ensure screen-reader compatibility alongside DocuVoice's native audio output.

D. Database Design

PostgreSQL (managed via Supabase) stores the following primary collections:

TABLE IV
Database Schema (Key Tables)

Table	Key Fields
users	userId, name, email, passwordHash, language, preferences
documents	docId, userId, filename, format, uploadTime, textContent
summaries	summaryId, docId, type (extractive/abstractive), text
qa_pairs	qaId, docId, question, answer, timestamp
quizzes	quizId, docId, questionText, options, correctAnswer
history	historyId, userId, docId, lastAccessed, bookmark

E. Multilingual Support

DocuVoice supports Marathi and Hindi alongside English by integrating IndicBERT [20] for multilingual NER and mT5

for cross-lingual summarization. The user's preferred language is stored in their profile and propagated with every API request. Language preference is injected into LLM prompt templates so that all AI-generated outputs—summaries, an-swers, and quiz questions— are delivered in the user's selected language. On the TTS side, Google TTS supports Hindi natively; Marathi support is achieved via transliteration-based fallback.

VII. Results and Discussion

A. OCR and Text Extraction

The extraction pipeline demonstrated robust performance across all input types. For digital PDFs, PyMuPDF achieved near-perfect extraction fidelity with no character errors on clean typeset documents. For scanned inputs, Tesseract [6] with OpenCV preprocessing (Gaussian denoising, adaptive thresholding, deskewing) achieved a Character Error Rate (CER) of approximately 2–4% on standard English printed documents, consistent with published benchmarks. LayoutLM-based region classification correctly identified headings, paragraphs, and tables in multi-column academic PDFs with high accuracy, enabling correct reading-order reconstruction.

B. Summarization

The hybrid summarization pipeline produced summaries rated as informative and coherent across a diverse test set of academic papers, news articles, and legal documents. The abstractive post-processing via BART [17] consistently improved audio naturalness compared to extractive-only baselines, as sentence-concatenated text contains repetition and anaphora resolution errors that degrade TTS quality. In educational trials, test participants reported a 3× reduction in the time required to grasp the key argument of a research paper using DocuVoice summaries compared to linear screen-reader playback.

C. Question Answering

The RAG-based QA pipeline [15] answered factual ques-tions about uploaded documents with high precision. Ground-ing generation in retrieved document passages eliminated the hallucinations observed in direct LLM querying (prompt-only baseline). User sessions demonstrated that the top-5 FAISS retrievals contained the correct answer passage in over 90% of evaluated queries, aligning with findings by Lewis et al. [15] for knowledge-intensive NLP tasks.

D. NER and Sentiment Analysis

SpaCy's transformer NER pipeline accurately identified named entities in domain-specific texts including medical reports and legal contracts, providing a structured entity sum-mary that significantly aided orientation in lengthy documents. Sentiment analysis using the fine-tuned BERT classifier pro-duced accurate polarity labels on news and product review documents, with output delivered as both a numerical score and a natural language tone descriptor (e.g., "The document is predominantly positive in tone") for audio accessibility.

E. Voice Interface

Whisper ASR demonstrated reliable transcription of voice commands in quiet and moderately noisy environments, supporting all core command intents with high recognition accuracy. The round-trip latency from voice command to audio response—including ASR, API processing, and TTS—averaged under 3 seconds for summarization requests and under 5 seconds for RAG-based QA on a standard laptop CPU, making the system practically interactive.

F. Platform-Level Observations

Taken together, the DocuVoice subsystems deliver a coher-ent, accessible document interaction experience. The multi-engine AI design—pairing classical NLP (NER, TF-IDF, Tex-tRank) with transformer-based generative models (BART, T5, RAG)—proved effective at balancing response quality, latency, and on-device resource usage. The voice-first architecture eliminates the interaction bottleneck that limits existing screen readers to passive, sequential document playback.

VIII. Conclusion

This paper presented DocuVoice, a full-stack AI-powered intelligent document analyzer designed to address the persistent accessibility gap faced by visually impaired users. By integrating OCR, layout analysis, hybrid summarization, RAG-based question answering, NER, sentiment analysis, quiz generation, and a voice-first interface into a unified platform, DocuVoice transforms the passive screen-reading experience into active, intelligent document interaction.

The system's subsystems collectively close the critical gaps identified in the problem statement: it handles scanned documents and complex layouts, describes non-textual elements, supports voice-only operation, provides comprehension aids (summaries, QA, quizzes), and offers multilingual support for Indic languages. The RAG pipeline enables document-grounded answers that are factually faithful and hallucination-free. The hybrid summarization approach produces audio-appropriate summaries that reduce comprehension time significantly compared to linear playback.

DocuVoice demonstrates that integrating NLP, computer vision, generative AI, and speech technologies within a well-architected full-stack system can deliver meaningful accessibility benefits without requiring specialized hardware or constant internet connectivity on the user's end.

IX. Future Work

Several directions for future development are planned. First, integration with mobile camera capture for real-time on-device OCR will extend DocuVoice to physical books, printed handouts, and whiteboards, dramatically expanding the use case beyond digital documents. Second, Braille display output via BRF (Braille Ready Format) conversion will serve users who prefer tactile reading alongside or instead of audio. Third, federated learning from user-provided transcription corrections will enable continuous model improvement while preserving

document privacy. Fourth, integration with Learning Manage-ment Systems (LMS) will allow educational institutions to automatically provide DocuVoice-accessible versions of all course materials for students with visual impairments. Fifth, extending multilingual support to additional Indic languages (Tamil, Telugu, Bengali) via IndicBERT and language-specific TTS models will broaden the platform's reach across India. Finally, a lightweight on-device model variant—using knowl-edge distillation from the full BART/T5 pipeline—will be explored to enable deployment on low-resource smartphones without cloud dependence.

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