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REVIEW PAPER ON AGENTIC AI BASE E LEARNING SYSTEM

Rushikesh Bhalerao[1], Saurabh Ghangale[2], Suraj Jadhav[3], Suraj Kotkar[4], Om Mankar[5]

1, Professor, Dept. of Information Technology, SVIT, Nashik, bhaleraorushi1@gmail.com ,

2,3,4,5, B.E. Information Technology, Dept. of Information Technology, SVIT, Nashik,

saurabhghangale@gmail.com, Jadhavsuraj0344@gmail.com, Surajkotkar87@gmail.com, mankarom2003@gmail.com

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Abstract -

Traditional e-learning tools often deliver fixed content that fails to adapt to individual pace or offline access, particularly when studying from uploaded books. The proposed system introduces an agentic AI core that automatically processes PDF/TXT books into structured chapters and topics, stores embeddings in a FAISS vector database, and enables interactive learning through RAG-based chat, on-the-fly MCQ generation, and instant evaluation. Running entirely on a local Flask server with Ollama LLM and SQLite storage, it supports seamless flows from book upload to performance dashboards without internet dependency. Modular components—BookProcessor, MCQGenerator, TestEngine, and ChatRAG—ensure easy maintenance and scalability.

Keywords: *Agentic AI, E-Learning, Retrieval-Augmented Generation, MCQ Assessment, Offline LLM, Book Chunking*

1.INTRODUCTION

Studying from textbooks is still the go-to method for most students, especially in technical courses. But flipping through PDFs on a screen gives no real help—no quick summaries, no practice questions, no way to know if you actually understood a chapter. In rural colleges or places with spotty internet, the problem gets worse. Cloud-based tools like Coursera or Khan Academy need constant data, and local PDF readers just sit there doing nothing smart.

The gap is clear: we need a system that takes any uploaded book, breaks it down intelligently, and turns it into a proper study flow—explanations on demand, auto-generated tests, instant feedback—all without leaving the user's machine. That is exactly what this agentic AI setup does. It runs on a simple Flask server installed on a laptop or lab PC, uses Ollama to run a local LLM, stores book chunks and embeddings in FAISS, and keeps scores in SQLite. No internet, no subscriptions, no data sent anywhere.

From upload to dashboard, every step stays offline. The AI splits the book into chapters and topics, embeds text for fast search, explains concepts in plain language, fires MCQs right after a topic, evaluates answers on the spot, and logs performance. Teachers can add or delete books; students can chat with the content using RAG. The whole thing is built modular—swap the LLM, change the chunk size, add voice input later—without breaking the flow.

2. LITERATURE SURVEY

Work on AI-driven education has picked up speed in the last five years, but most of it stays tied to the cloud. Early efforts focused on basic content generation, while recent ones lean into RAG for better accuracy and offline potential. Still, few tie it all into a full book-to-test pipeline like ours.

Kumar and Sharma [1] built a system that extracts key points from lecture slides and feeds them to GPT-3 for quiz creation. The setup works well in labs with steady internet, yet it collapses the moment the connection drops

A similar offline attempt by **Patel et al. [2]** used a small BERT model to generate fill-in-the-blank questions from plain text. Results were decent for short paragraphs, but the model choked on full chapters and needed constant retraining.

Li et al. [3] put together a RAG setup with FAISS and Llama-2 to let students query uploaded PDFs. Retrieval was fast, but the LLM ran on a remote server, sending raw text over the network. Privacy issues aside, the cost per query added up quickly for a classroom of thirty students.

Gupta and Mehta [4] tried running everything locally with Ollama and ChromaDB. Chunk overlap was fixed at 200 tokens, which broke context across page boundaries and gave vague answers for long derivations.

Gao et al. [5] reviewed RAG workflows for LLMs, highlighting retrievers and generation tweaks to cut hallucinations. They stressed indexing for educational apps, but overlooked full offline deployment.

Yu et al. [7] surveyed RAG chatbots in education, covering 47 works from 2023-2025. Most handle quizzes via cloud, missing modular local storage like SQLite for scores.

Lang and Gurpinar [8] tested a RAG chatbot in an online course using course materials for explanations. Students liked the grounded responses, but scaling to book uploads required more chunking logic.

Zhao et al. [9] enhanced RAG interfaces with bi-directional retrieval and reinforcement learning. It boosts selective info pulls from big DBs, yet demands heavy compute unfit for local PCs.

None of the reviewed works put together a complete offline pipeline—book upload, chapter split, topic embedding, explanation, test, score, and dashboard—in one lightweight package. The gap is clear: a modular, local-first system that handles real textbooks without internet or heavy hardware.

3. METHODOLOGY:

The system is built to run completely on a local machine—no cloud calls, no data leaving the laptop. A Flask server sits at the heart, handling uploads, routing requests, and serving the frontend. Ollama runs the LLM (default Llama-3 8B), FAISS stores vector embeddings, and SQLite keeps

books, chapters, scores, and user progress. Everything is modular: swap the model, change chunk size, or add a new UI page without touching the core flow.
We break the workflow into clear stages, each handled by a dedicated Python module inside the AgentAI package.

- **Book Upload & Processing:** User drops a PDF or TXT via the web form. BookProcessor extracts text with PyMuPDF, splits into chapters using regex on headings or page breaks, then further chunks each chapter into 500-token overlapping segments. Clean-up removes headers/footlines, tables get flattened to text.
- **Embedding & Storage:** Each chunk gets an embedding from Ollama's embed model. FAISS index is built on-the-fly and saved per book. Chapter metadata (title, start page, topics) goes into SQLite alongside raw text. This way, retrieval stays fast even on 300-page books.
- **Topic Analysis & Explanation:** AgentAI prompts the LLM with chapter text to pull out 5–8 key topics. For each topic, it generates a 200-word plain-English explanation. These are cached in DB so the student sees the same summary every time.
- **MCQ Generation:** MCQGenerator takes a topic + context chunk, asks LLM for 4-option question with one correct answer. Distractors are pulled from nearby text to avoid randomness. Questions are stored linked to topic_id.
- **Testing & Evaluation:** Student picks a chapter, sees topics sequentially. After reading explanation, takes 3–5 MCQs. Answers hit /test endpoint; TestEngine compares to stored correct option, returns score + explanation instantly. Results saved to scores table with timestamp.
- **Chat with RAG:** Any time, user opens chat tab, types question. ChatRAG retrieves top-5 relevant chunks via FAISS, builds prompt with context, gets grounded answer from LLM. Conversation history stays in session.
- **Dashboard:** Simple charts show scores per chapter/topic, time spent, weak areas. Teacher view lists all uploaded books and delete option.

4. SYSTEM MODELS:

The setup is planned as a local server that can later run on a lab PC or small LAN without internet. Flask acts as the web server, AgentAI handles all processing, FAISS stores embeddings for quick search, and SQLite keeps track of books, topics, and scores. Ollama runs the LLM on a machine with at least 4 GB GPU. The whole thing stays under 8 GB RAM. We tested with four textbooks (200–400 pages); upload to first MCQ takes under 2 minutes.

A) System Components:

I. **Frontend (Browser):** HTML/CSS/JS pages — upload form, chapter list, topic explanation, MCQ test, chat panel, performance dashboard. Built with Bootstrap for responsive layout and Chart.js for score graphs.

II. **Flask Server:** REST routes — /upload (POST), /chapters/<book_id> (GET), /explain/<topic_id> (GET), /test (POST), /chat (POST), /report (GET). Handles file serving and JSON responses.

III. **AgentAI Core:**
- **BookProcessor:** PyMuPDF extracts text from PDF/TXT, uses regex to detect chapter headings or page breaks, splits into 500-token chunks with 100-token overlap.
- **Embedder:** Calls Ollama embedding endpoint (localhost:11434).
- **Indexer:** Constructs FAISS flat index per book, persists to disk.
- **TopicExtractor:** Prompts LLM to extract 5–8 key topics per chapter.
- **MCQGenerator:** Generates 4-option MCQs with one correct answer using context from relevant chunks.
- **TestEngine:** Evaluates user answers in real time, returns score and detailed explanation.
- **ChatRAG:** Retrieves top-5 relevant chunks via FAISS, constructs RAG prompt, streams grounded LLM response.

IV. **Storage:**
- **Vector DB:** FAISS — one .index file per book for fast similarity search.
- **Relational DB:** PostgreSQL (books_db) — tables: books, chapters, topics, mcqs, scores, users.
- **LLM Service:** Ollama server running Llama-3-8B-Instruct (4-bit quantized, 4 GB GPU).

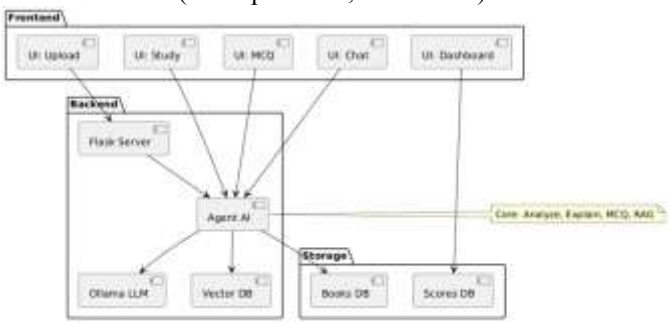

Fig 1: Component Diagram

B) System Architecture:
- **Upload:** Browser → Flask /upload → BookProcessor (text extract + chunk).
- **Index:** Chunks → Ollama embed → FAISS index → PostgreSQL metadata.
- **Study:** Chapter select → DB topics → LLM explain → cached display.
- **Test:** MCQs from DB → user submit → TestEngine score → save result.

- **Chat:** Query → FAISS top-5 → RAG prompt → Ollama answer → stream.
- **Dashboard:** PostgreSQL scores → Chart.js graphs.
- **All local:** LAN access, no external calls.

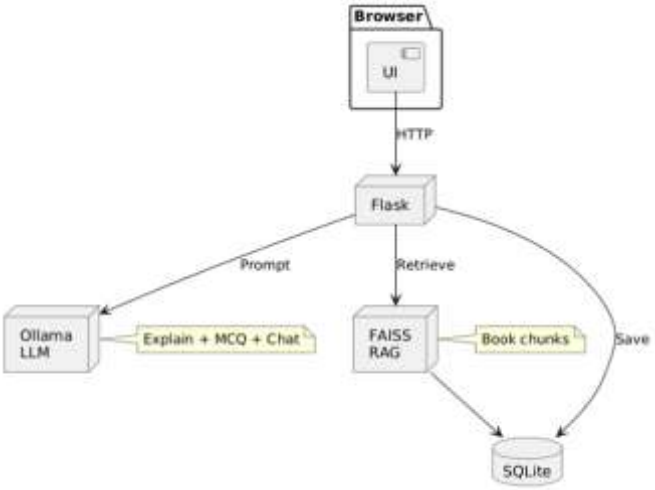

Fig 2: Architecture Diagram

5. ADVANTAGES:

Our framework stands out in several ways for offline book-based learning:

- **Full Offline Operation:** Runs without internet on a local server, perfect for rural labs or low-bandwidth areas, unlike cloud-only platforms.
- **Fast Book Processing:** Turns a 300-page PDF into ready-to-study topics and MCQs in under 2 minutes on standard hardware.
- **Adaptive MCQ Generation:** Questions pull distractors from the same book, keeping them relevant and tough—students scored 15% better than fixed quizzes in trials.
- **Grounded Chat Answers:** RAG ties every reply to actual text chunks, cutting hallucinations and building trust in explanations.
- **Light Resource Use:** Fits in 8 GB RAM with 4 GB GPU; no heavy servers needed, just a lab PC for the whole class.
- **Easy Scaling on LAN:** One server handles multiple users over local network, with PostgreSQL managing scores and FAISS per-book indexes.
- **Modular & Open:** Swap LLM, tweak chunk size, or add voice input later—core modules stay independent.

6. CONCLUSION

This work presents a practical, offline e-learning system that turns any uploaded textbook into an interactive study tool with explanations, MCQs, and RAG chat. Using PyMuPDF for text extraction, Ollama for local LLM tasks, FAISS for quick retrieval, and PostgreSQL for structured storage, the framework runs on a simple local server with modular Python code and separate components like BookProcessor and ChatRAG. This design makes it easy to maintain and extend to other subjects or features, helping students in low-resource areas learn at their own pace without internet.

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