

THE ENIGMATIC RESEARCH OF DR. X

AI-Powered NLP Pipeline for OSOS

Project Overview

The Enigmatic Research of Dr. X is a detailed, multi-phase AI engineering project completed for OSOS, a pioneering AI company based in Oman. Centered around the fictional mystery of Dr. X's disappearance, the challenge was to create a robust, fully offline, NLP-driven Q&A system capable of reading, understanding, and interacting with Dr. X's research publications.

The system was built under strict local-only hardware constraints, emphasizing scalability, creativity, and real-world production quality throughout every phase.

Note on Model Downloads:

This project demonstrates two styles of local LLM usage — automatic model downloading (used in translation) and manual model setup (used in summarization).

Models requiring manual setup come with detailed instructions in their respective `models/<model_name>/instructions.md` folders, making the process clear and easy to follow.

Project Context & Execution

This entire project was conceptualized, engineered, and delivered in just 5 days (~30 working hours) — an extremely limited timeframe that reflects strong execution, prioritization, and engineering clarity.

Despite hardware constraints (CPU-only, 16GB RAM, no GPUs used), we built a complete proof-of-concept NLP pipeline demonstrating:

- Multi-format document support (.pdf, .docx, .txt, .csv, .xlsx)
- Chunking, embedding, retrieval, question answering, translation, and summarization — all done fully offline
- Smooth pipeline integration using local models and tools without reliance on cloud APIs or paid services

All scripts and outputs are kept within a flat directory structure for simplicity. In a production-grade refactor, this could be modularized into `src/`, `utils/`, `outputs/`, and `models/`, but current setup prioritizes pipeline chaining and ease of reuse.

The project demonstrates two practical methods for local model integration — automatic download on first run (used in translation) and manual setup (used in summarization). This design reflects thoughtful engineering to accommodate different deployment environments, including air-gapped systems and cases where model licenses or availability constraints apply.

All major phases — embedding, RAG, translation, and summarization — automatically log tokens processed, time taken, and speed (tokens/sec) into `performance_log.txt`. This offers transparency and benchmarking across experiments.

Where applicable, we implemented evaluation metrics such as ROUGE to test summary accuracy. Result tables and graphs are included to show comparative quality between models and techniques.

We tested multiple local LLMs (Flan-T5, LLaMA-2 GGML, LaMini-Flan, TinyLLaMA) and two different vector stores to showcase engineering flexibility. All scripts are commented and modular, written to be understandable and editable by both junior and senior developers.


Bonus Extension: Structured Data (Excel/CSV) Support

While the original assignment only required handling `.docx` and `.pdf` documents, this solution was extended to fully support structured Excel and CSV files (`.csv`, `.xlsx`, `.xls`, `.xslm`).

- Full pipeline support across extraction, chunking, embedding, and retrieval
 - Significantly boosts real-world scalability by including tabular sources
 - Minor QA accuracy drops were noted from tabular noise, but overall robustness improved
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Project Phases (Text Summary)

The following section offers a walk-through of each core phase in the pipeline — highlighting how they were built, improved, and connected to form a complete, end-to-end local NLP system.

 **Full Technical Guide:** For a more detailed engineering walkthrough, including folder structure, script names, and advanced setup notes — refer to the full README in the GitHub repository.

Phase 1: Text Extraction & Preprocessing

We began the pipeline by building modular extractors capable of handling `.pdf`, `.docx`, `.csv`, and `.xlsx` documents. Each extractor was developed to maintain pagination via `[PAGE X]` markers and simulate page structures in formats that lack true pagination. The system generated three output types — a dense `.txt` for token processing, a human-readable aligned `.txt`, and a structured `.json`. This early differentiation laid the groundwork for both LLM processing and manual inspection.

Phase 2: Chunking & Metadata Structuring

Once the documents were extracted, we implemented a token-based chunking approach using the `tiktoken` tokenizer, targeting chunks around 500 tokens. We ensured that each chunk included origin metadata — filename, page, and chunk ID — to allow traceability. The system also introduced fallback handling to break up oversized pages while preserving context. This formed a consistent and explainable intermediate format for embedding.

Phase 3: Embedding & Vector Database Construction

For the embedding stage, we selected a general-purpose HuggingFace embedding model and paired it with FAISS for vector storage. Using mean pooling and L2 normalization, we generated stable, semantically meaningful embeddings. A separate `metadata.json` file was maintained to decouple storage of text vectors from their source information. The pipeline also logged performance data such as total tokens processed and tokens/sec, allowing consistent benchmarking.

Phase 4: RAG Q&A System Development

To support question answering, we developed a Retrieval-Augmented Generation system. Our initial version used **Flan-T5** (small, base, large) and featured static prompt templates and top-3 context retrieval. We then added dynamic context budgeting, which ensured that the prompt stayed within model limits. A memory-based variant using **LLaMA-2 GGML** was also explored, allowing 3-turn conversational memory while keeping the model entirely local.

Smart Prompt Control: We introduced structured prompts like *"Answer ONLY based on the context below"* and used tokenizer-safe truncation to avoid semantic cut-offs. Token budgeting helped balance the number of retrieved chunks with answer quality.

Flexible Model Switching: Models were made swappable with one-line code edits, supporting rapid iteration and benchmarking. The pipeline supported strict per-query inference, disabling memory where needed for consistent answers.

This phase highlighted model-switching flexibility and safe retrieval-question integration under local compute constraints.

Phase 5: Multilingual Translation

We initially experimented with the **Qwen2-1.5B** model, which performed well in terms of structure preservation but introduced several hallucinations and instability in language switching. To mitigate this, we tested Meta's distilled **NLLB-200** model which gave highly stable translations, but failed to retain layout fidelity. As a solution, we implemented a line-by-line **NLLB** translator that offered the best of both — stable language control and improved structural accuracy.

Version Testing & Tuning: Three script versions were developed — one using full-document NLLB (fast but loses layout), one with Qwen2 (fluent but unstable), and a final one that translated line-by-line with perfect ROUGE balance.

Manual Evaluation Loop: We used native-language readers and backtranslation scoring (Arabic to English and Bangla) to assess clarity, terminology accuracy, and formatting. Final translations scored above 90% accuracy in Arabic and around 87% in Bangla. These scores were achieved without GPU use, on a fully offline CPU setup, demonstrating strong baseline capability even under constrained conditions.

This method proved reliable for translation between English, Arabic, and Bangla, and validated the system's language extensibility and performance tuning workflow.

Phase 6: Document Summarization

The summarization phase explored various local models to determine feasibility within our resource limits. We started with LLaMA-2 GGML 7B, which had difficulty due to aggressive chunking and weak output fluency. Then we tested TinyLLaMA for speed, but found it too limited to produce coherent summaries.

Eventually, we adopted LaMini-Flan-T5-248M, a newer lightweight model that delivered high-quality, ROUGE-evaluated summaries when paired with LangChain loaders and intelligent chunking. The model was integrated manually to demonstrate pipeline flexibility, and the final output quality reached 85–90% accuracy on structured academic text. These results were especially strong considering the limited 512-token context and no GPU acceleration. Summarization on `.txt`, `.pdf`, or `.docx` using LaMini-Flan-T5. Evaluated via ROUGE and visualized. Model must be downloaded manually to showcase flexibility. Performs better on paragraph-style text vs slide-format or hyperlinked documents.

Engineering Insight: Manual model integration demonstrates pipeline adaptability. LangChain's chunking and HuggingFace summarizer combine for a lightweight, high-performing offline summarization solution.

Final Notes & Future Outlook

This implementation is already feature-complete and performs above 50%+ accuracy on real-world scientific content. The architecture supports future integration of GPUs, frontend interfaces, cloud automation, and fine-tuning of models.

The system was designed as a proof of concept, but it is already production-aligned in:

- Modularity and pipeline handoff between phases
- Local-only operation with API-free deployment
- Use of real LLM engineering practices like evaluation metrics, speed benchmarking, layered chunking, and controlled context building

With more time and compute, we can also focus on data pre/post-processing, fine-tuned evaluation, multilingual support, and detailed analytics dashboards.

Future Directions: Overcoming Current Constraints

While the current implementation runs on a CPU-only, low-resource environment, the pipeline was designed with future extensibility in mind:

- Upgrading to higher-end GPUs (e.g., RTX 4090, A100) would significantly reduce inference time and support larger LLMs (e.g., LLaMA-13B, flan-t5-xl).
- Frontend development (starting with Streamlit, then full web) will offer user-friendly access and demo interfaces.
- Integration with cloud storage and automation services (e.g., Azure triggers, GCP workflows) could enable continuous data pipelines.
- Domain-specific fine-tuning will be critical to make the summarization and Q&A responses more context-aware and medically grounded.
- Adding indexing and hybrid retrieval strategies (e.g., semantic + keyword) would further improve system precision.

These directions are all achievable thanks to the strong modular and explainable architecture demonstrated throughout the phases.

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