

Project Report: AI-Powered Candidate Screening Backend Service

Candidate Information

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Repository Link

- <https://github.com/zendParadox/backend-ai-screener>
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1. Approach & System Design

Initial Plan

I divided this challenge into several main components:

1. **API Layer:** Building a clear RESTful API for external interaction.
2. **Asynchronous Processing:** Identifying that AI evaluations take time, so the process must be separated from the main HTTP request-response flow.
3. **RAG (Retrieval-Augmented Generation):** Designing a workflow for storing and retrieving reference documents (ground truth) to provide accurate context to the LLM.
4. **LLM Integration:** Connecting the system with a generative AI service to perform the final analysis.

System & Database Design

API Endpoints: The system exposes three main endpoints:

- **POST /upload:** Accepts multipart/form-data (CV and Report), stores them on the server, and returns the filenames as unique IDs.
- **POST /evaluate:** Accepts file IDs and job details, then enqueues an evaluation task (queue) and immediately returns a `job_id`.
- **GET /result/{id}:** Allows clients to check the job status (queued, processing, completed, failed) and retrieve the final result when available.

Job Queue: To handle long-running evaluation processes, I used **BullMQ with Redis** as the backend. This ensures the `/evaluate` endpoint can respond quickly without waiting for the LLM call to complete. It also lays a strong foundation for scalability and future fault-tolerance.

Vector Database: I chose **Qdrant** as the vector database. Reference documents such as Job Descriptions, Case Study Briefs, and Evaluation Rubrics are ingested into a Qdrant collection. This allows efficient semantic search to retrieve the most relevant context for each evaluation.

LLM Integration

LLM Choice: I used **Google AI's gemini-2.5-flash** model, selected for its balance of speed, ability to follow complex instructions (such as producing strict JSON outputs), and cost efficiency.

RAG Strategy: The Retrieval-Augmented Generation pipeline was implemented as follows:

1. When an evaluation starts, the candidate's CV content is converted into vector embeddings using the local model `Xenova/all-MiniLM-L6-v2`.
2. These embeddings are used to query Qdrant for the most relevant reference documents.
3. The retrieved documents (context) are then injected into the prompt sent to Gemini.

Prompting Strategy: The prompt was carefully designed to ensure consistent and structured output:

1. **Persona:** The AI is instructed to act as an *"Expert HR Assistant."*
 2. **Strict Instructions:** Explicitly requires the AI to use contextual documents as the sole source of truth.
 3. **Output Structure:** Defines a mandatory JSON schema.
 4. **Data Injection:** Context from RAG and candidate CV/Report data are provided separately with clear markers.
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2. Results & Reflection

Results:

The asynchronous architecture with BullMQ worked very well. The system was able to accept jobs, process them in the background, and deliver results without blocking the client. The RAG pipeline successfully retrieved relevant context, significantly improving Gemini's output quality compared to evaluations without context.

Reflection:

The biggest challenge was ensuring version compatibility across all components (Qdrant server, Node.js client, etc.). Additionally, the quality of embeddings strongly influenced the success of RAG. Using a locally running embedding model provided advantages in privacy and cost, though it required additional initialization time during the first run.

3. Future Improvements

With more time, the following areas could be enhanced:

- **Error Handling:** Implement more advanced retry logic with exponential backoff for Gemini API calls.
- **Testing:** Add unit tests and integration tests to ensure reliability of each component.
- **Frontend:** Build a simple user interface to streamline document upload and result checking.

4. Screenshots of Real Responses

