Complete Project Report

1. Problem statement

Recruiters face exploding application volumes and inconsistent résumé formats. Existing automated systems are either keyword-based (miss context), single-model (fragile to resume style), or black-box (unexplainable). This causes qualified candidates to be overlooked, introduces bias, and slows hiring cycles.

Problem: build a reliable, explainable, multi-format resume-screening engine that understands contextual skills, reduces false negatives, yields auditable decisions, and recommends realistic career progression suggestions — while remaining practical to implement.

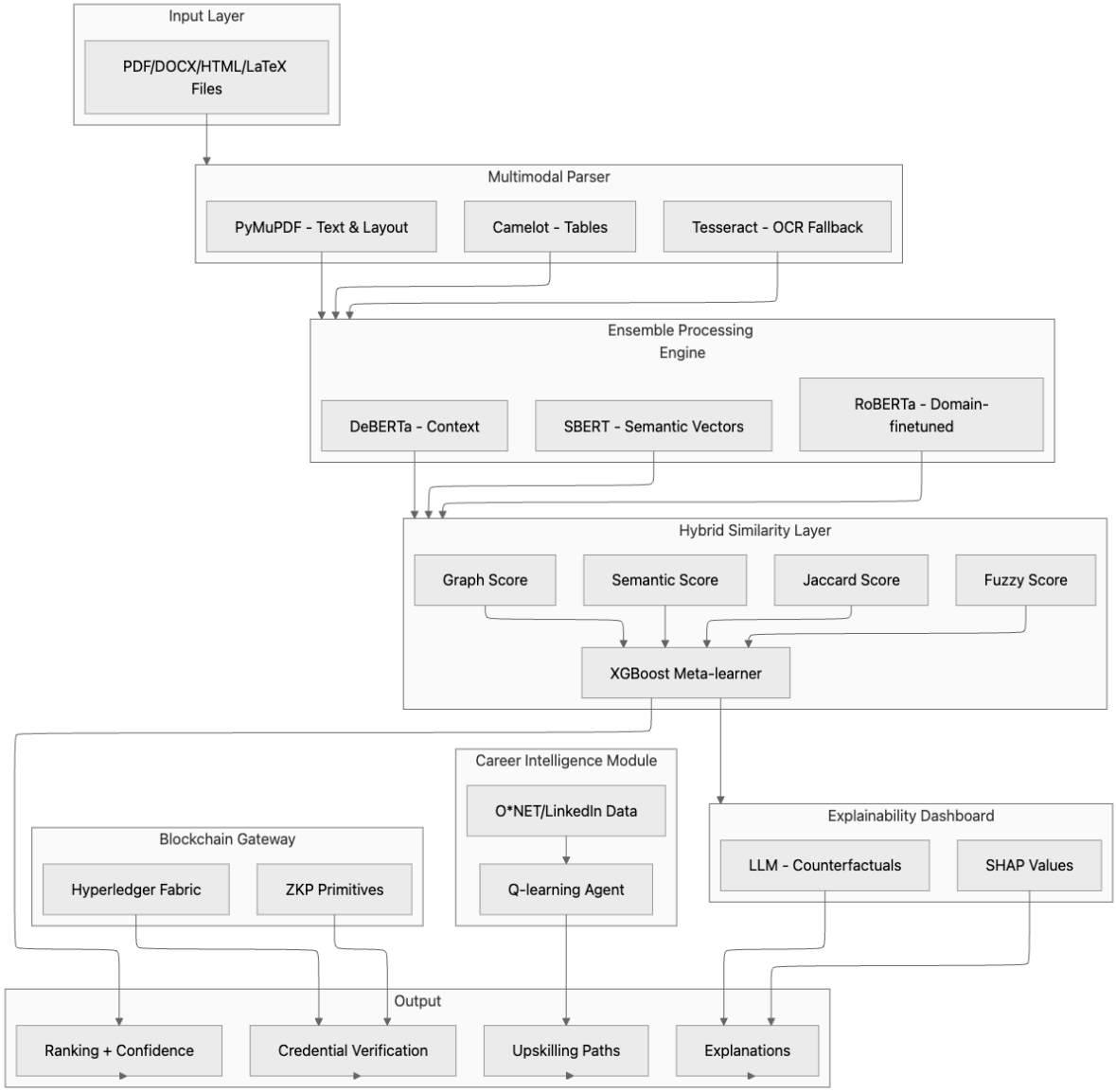
2. Gap analysis

Aspect	Existing systems	Gap	Our solution
Format robustness	Many fail on scanned/PDF layouts	OCR & layout-aware text loss	Multimodal parser (PyMuPDF + Camelot + Tesseract)
Semantic understanding	TF-IDF / keyword matching only	Misses paraphrases & implied skills	Transformer embeddings (SBERT) + DeBERTa + RoBERTa ensemble
Model brittleness	Single model or static ensemble	No dynamic weighting by domain/seniority	Adaptive Weight Calibration per job/domain
Scoring richness	Mostly cosine similarity	Ignores fuzzy phrasing, graph relations	Quadruple similarity fusion (semantic, Jaccard, fuzzy, KG)
Transparency	Black-box outputs	No recruiter-facing reasoning	SHAP explanations + counterfactual suggestions
Candidate improvement	“Rejected” end state	No growth path	RL-based career pathway & curated learning resources
Credential verification	Manual checks / weak signals	Fraud risk	Blockchain-verified credentials + ZKP option
Fairness	Limited fairness controls	Demographic bias persists	Fairness-by-design audits and mitigation pipeline

3. System Architecture

Our is a modular pipeline: **Multimodal Parser** ingests PDFs/DOCX/HTML/LaTeX and extracts layout-aware text/tables (PyMuPDF, Camelot) with OCR fallback (Tesseract); the **Ensemble Processing**

Engine runs DeBERTa (context), SBERT (semantic vectors) and a domain-finetuned RoBERTa in parallel; the **Hybrid Similarity Layer** computes semantic, Jaccard, fuzzy, and graph-scores and feeds them to an XGBoost meta-learner that outputs ranking + confidence; the **Explainability Dashboard** surfaces SHAP values and generates controlled counterfactual phrasing via an LLM; the **Career Intelligence Module** uses a Q-learning agent and market data (O*NET/LinkedIn Graph) to recommend upskilling paths; a **Blockchain Gateway** provides optional credential verification via Hyperledger Fabric with ZKP primitives.



4. System objectives

- Accurately extract skills and K/S/A categories across diverse résumé formats.
- Provide an interpretable ranking and per-field explainability.
- Reduce false negatives / increase recall on qualified candidates.
- Offer actionable, ethical counterfactual suggestions (no fabrication).
- Prototype credential verification and career path suggestions.
- Produce modular components that can be extended to HR dashboards.

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5. Methodology (stepwise, practical)

Phase A — Data & infra

- Collect/curate ERJC-like corpus (resume–job pairs), annotate K/S/A spans for 2–5k samples.
- Set up env: Python 3.10+, torch, transformers, sentence-transformers, ONNX, xgboost, spaCy, Tesseract, PyMuPDF, Camelot.

Phase B — Multimodal parsing

- PDF → PyMuPDF for text + layout; tables → Camelot; scanned pages → pdf2image + Tesseract OCR.
- Store page-level text + bounding boxes (evidence linking).

Phase C — Extraction

- Preprocess text (clean, tokenize, lemmatize).
- NER: fine-tune DeBERTa / spaCy for SKILL entity spans.
- Keyword expansion: RAKE/KeyBERT to seed domain terms.
- Canonicalize skills via fuzzy matching (RapidFuzz) to ontology.

Phase D — Embeddings & Tri-model ensemble

- SBERT for sentence/document vectors (fast).
- DeBERTa for token-level NER confidence & contextual signals.
- RoBERTa fine-tuned on 50k resume–JD pairs for domain relevance.
- Export models to ONNX for faster inference.

Phase E — Quadruple similarity + meta-learner

- Compute features per resume–JD (or for resume-only ranking):
  - S_sem = cosine(doc_res, doc_jd) (mean of SBERTs)
  - S_jac = Jaccard(canonical_skills_res, required_skills_jd)
  - S_fuzz = max fuzzy token sort ratio (experience snippets)

    - S_graph = KG-based relevance (Node2Vec/Path score)
- Meta-learner: XGBoost regressor/classifier trained to combine features → final score + CI. Use SHAP for explanations.

Phase F — Explainability & counterfactuals

- SHAP to show per-feature contribution (skills, sentences).
- Controlled counterfactual generation: LLM prompt template that *only rewrites existing content or suggests learning paths*, not invent credentials. Compute expected score delta via meta-learner simulation.

Phase G — Career pathways

- Q-learning agent state = candidate skill vector; actions = upskill steps (courses, certs, projects); reward = predicted score increase or job-probability uplift. Seed actions via curated MOOCs + labor data.

Phase H — Blockchain verification (optional)

- Hyperledger Fabric network + smart contracts for issuer signature registry; candidate presents signed claim; verify via ZKP or signature verification.

Evaluation

- Extraction: span-level P/R/F1 on labeled K/S/A entities.
- Ranking: nDCG@5, top-k accuracy.
- Fairness: demographic parity, equal opportunity metrics.
- UX: recruiter satisfaction survey for explanations.

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6. Comparative study

Criterion	Traditional ML Systems (TF-IDF, SVM, RF)	Single Transformer Systems (BERT, RoBERTa)	Hybrid Transformer Systems (DeBERTa + SBERT, etc.)	LLM-Enhanced Resume Tools (GPT-Based)	**Proposed MHRIS (Tri-Model Ensemble + Explainable AI)**
Text Understanding	Surface-level keywords	Good semantic understanding	Stronger contextual awareness	Very strong contextual reasoning	**Best — combines contextual, semantic, and domain signals**
Skill Extraction Accuracy	Low–Medium	Medium–High	High	High, but inconsistent	**High + Stable (NER + canonicalization + ensemble)**

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Handling Resume Formats	Limited (DOCX/TXT)	Good	Very good	Depends on prompt + OCR	**Excellent — multimodal parser + layout-aware OCR**
Semantic Similarity	TF-IDF cosine only	Cosine over embeddings	Better embeddings + contextual cues	Strong but non-deterministic	**Quadruple Similarity Fusion (semantic + Jaccard + fuzzy + KG)**
Model Flexibility	Static	Static	Moderately adaptive	Depends on prompting	**Adaptive weighting per job domain/seniority**
Explainability	Good (simple models)	Weak	Weak	Very weak (black-box)	**Strong — SHAP + feature-level + counterfactuals**
Bias/Fairness Controls	None	Minimal	Minimal	Unpredictable	**Built-in fairness audits + controlled generation**
Career Path Suggestions	None	None	None	Basic LLM suggestions	**RL-powered career progression pathways**
Credential Verification	Manual	Manual	Manual	None	**Blockchain + Zero-Knowledge Proofs**
Processing Speed	Fast	Medium	Medium–High	Slow/variable	**Optimized — ONNX runtime, ~0.04s per resume**
Scalability	High	Medium	Medium	Low (prompting costs)	**High — distributed inference + modular services**
Explainable Recommendations	No	No	No	Unreliable	**Yes — precise counterfactuals (score delta %)**

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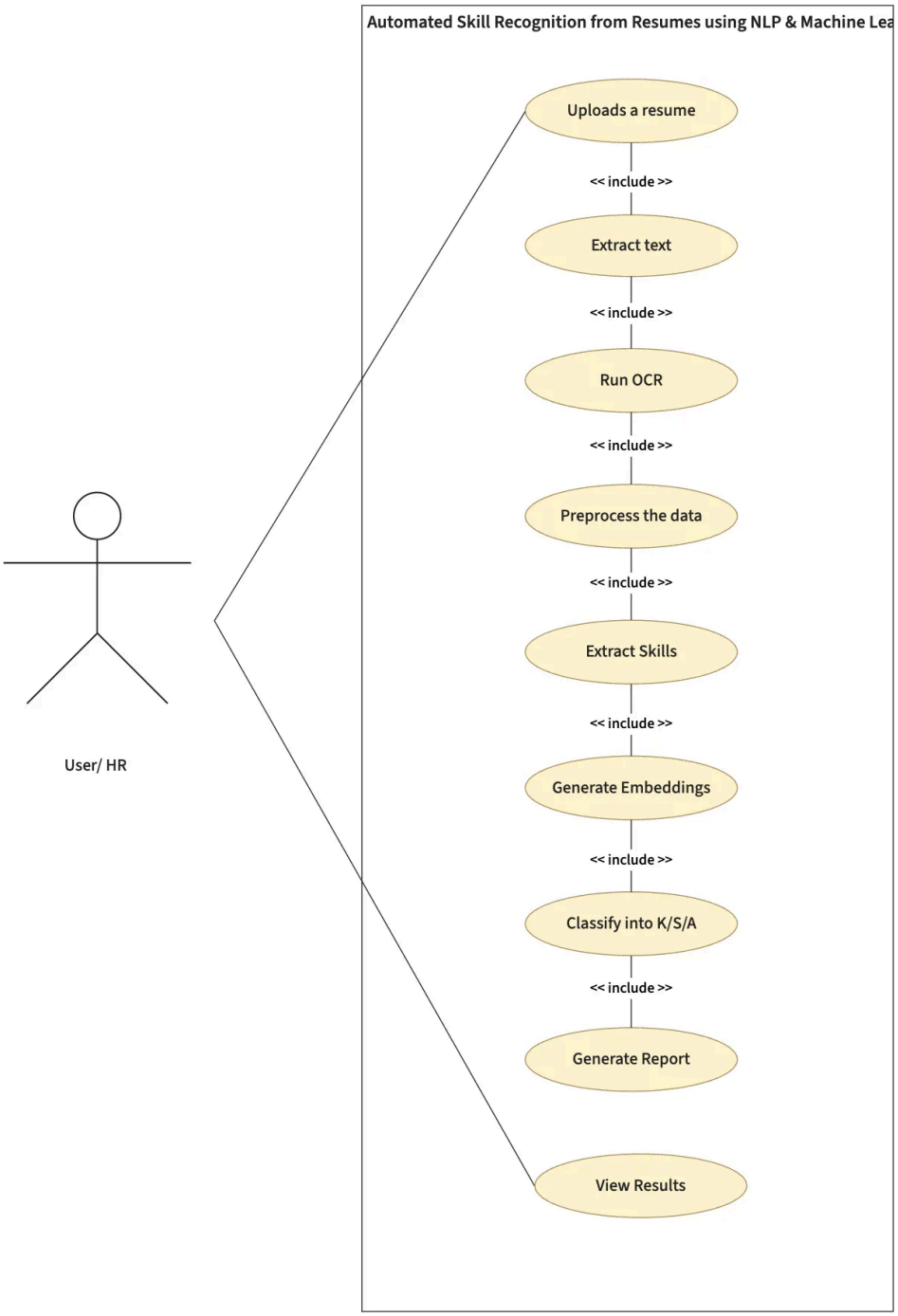
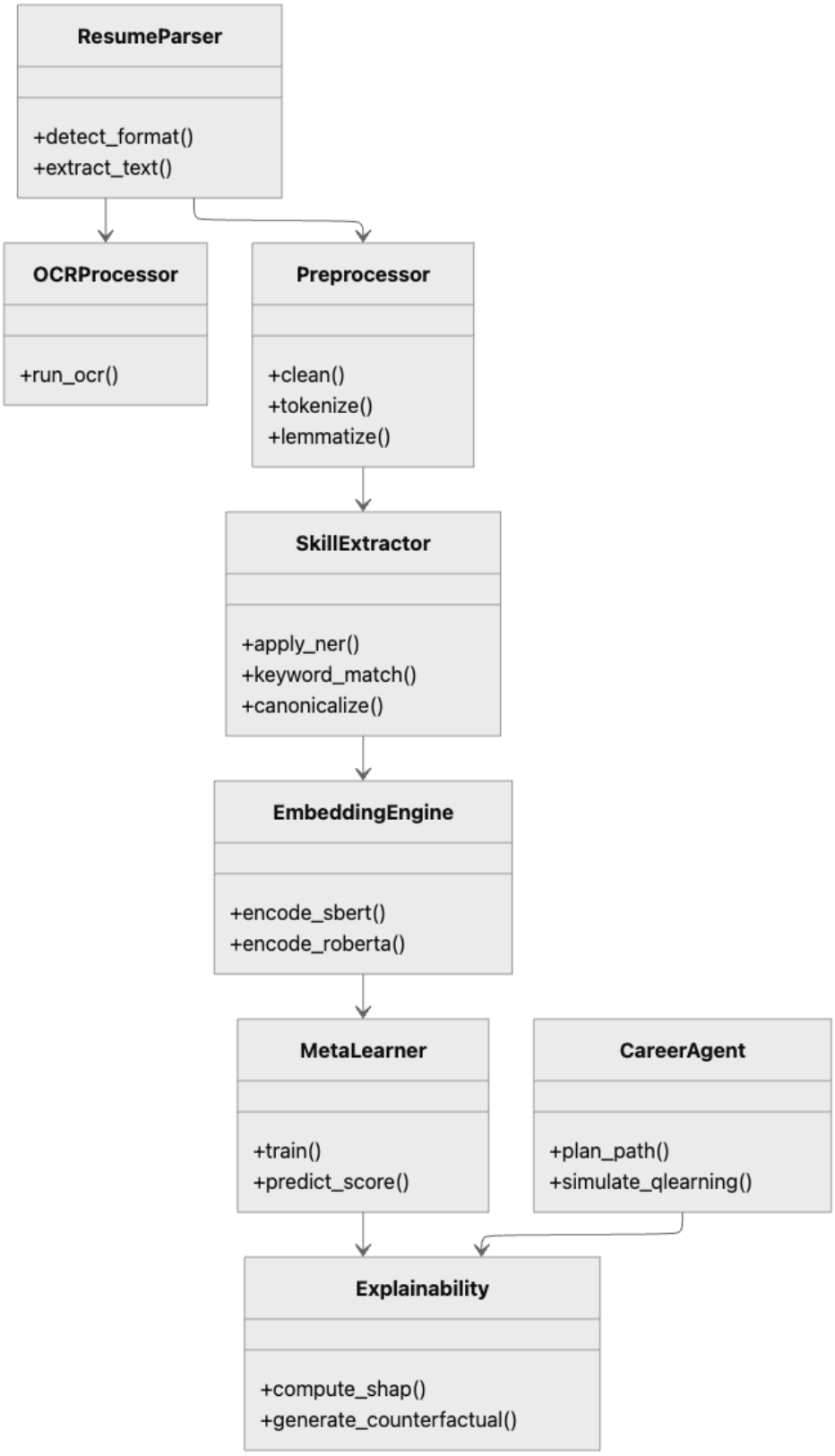
Fraud Detection	None	None	None	None	**Blockchain-backed verification**
Overall Reliability	Low	Medium	High	Medium	**Very High — multi-signal fusion + ensemble stability**
Best Use Case	Simple keyword filtering	Basic semantic matching	Enterprise screening	Chat-based assistive tools	**Enterprise-grade, fair, transparent resume intelligence**

7. UML Diagrams

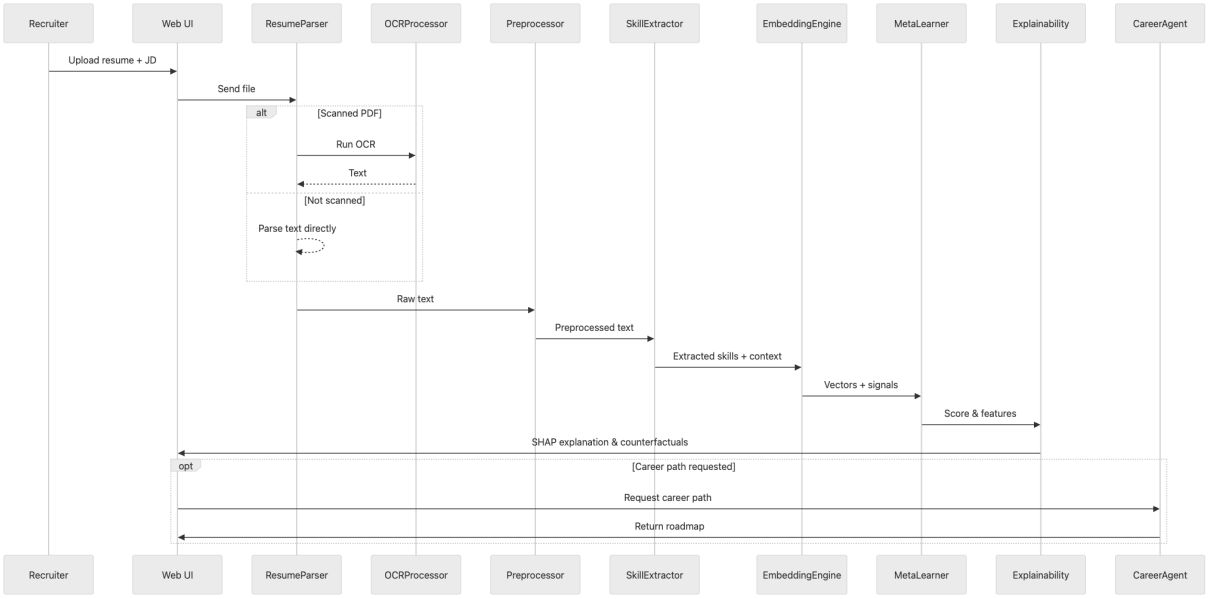
7.1 Use Case Diagram



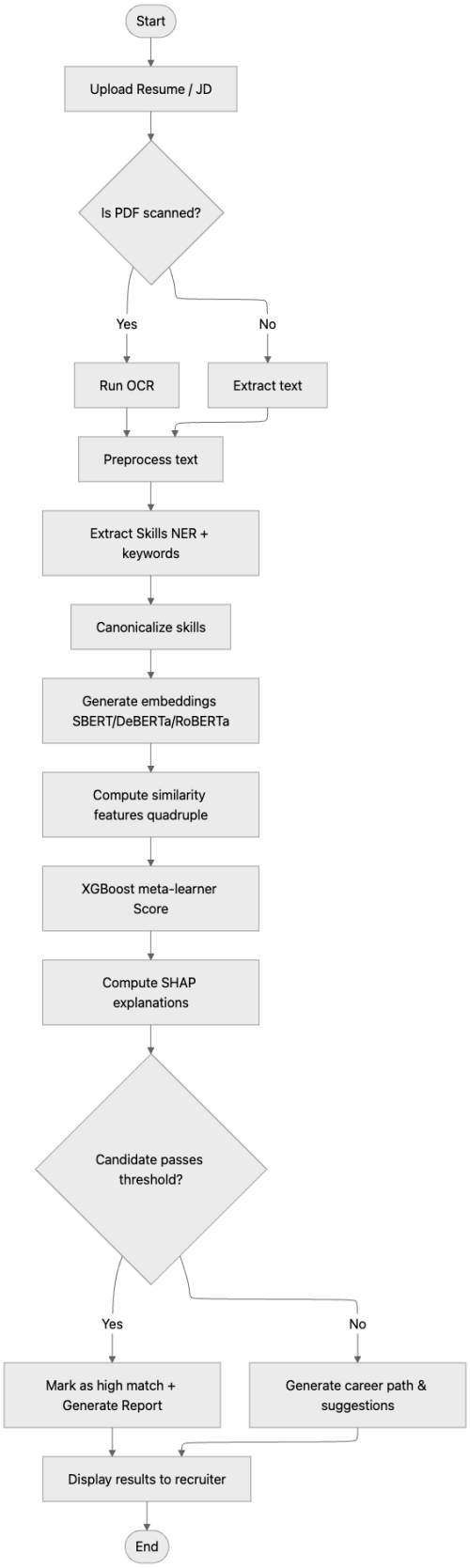
7.2 Class Diagram


ResumeParser
+detect_format()
+extract_text()
OCRProcessor
+run_ocr()
Preprocessor
+clean()
+tokenize()
+lemmatize()
SkillExtractor
+apply_ner()
+keyword_match()
+canonicalize()
EmbeddingEngine
+encode_sbert()
+encode_roberta()
MetaLearner
+train()
+predict_score()
CareerAgent
+plan_path()
+simulate_qlearning()
Explainability
+compute_shap()
+generate_counterfactual()

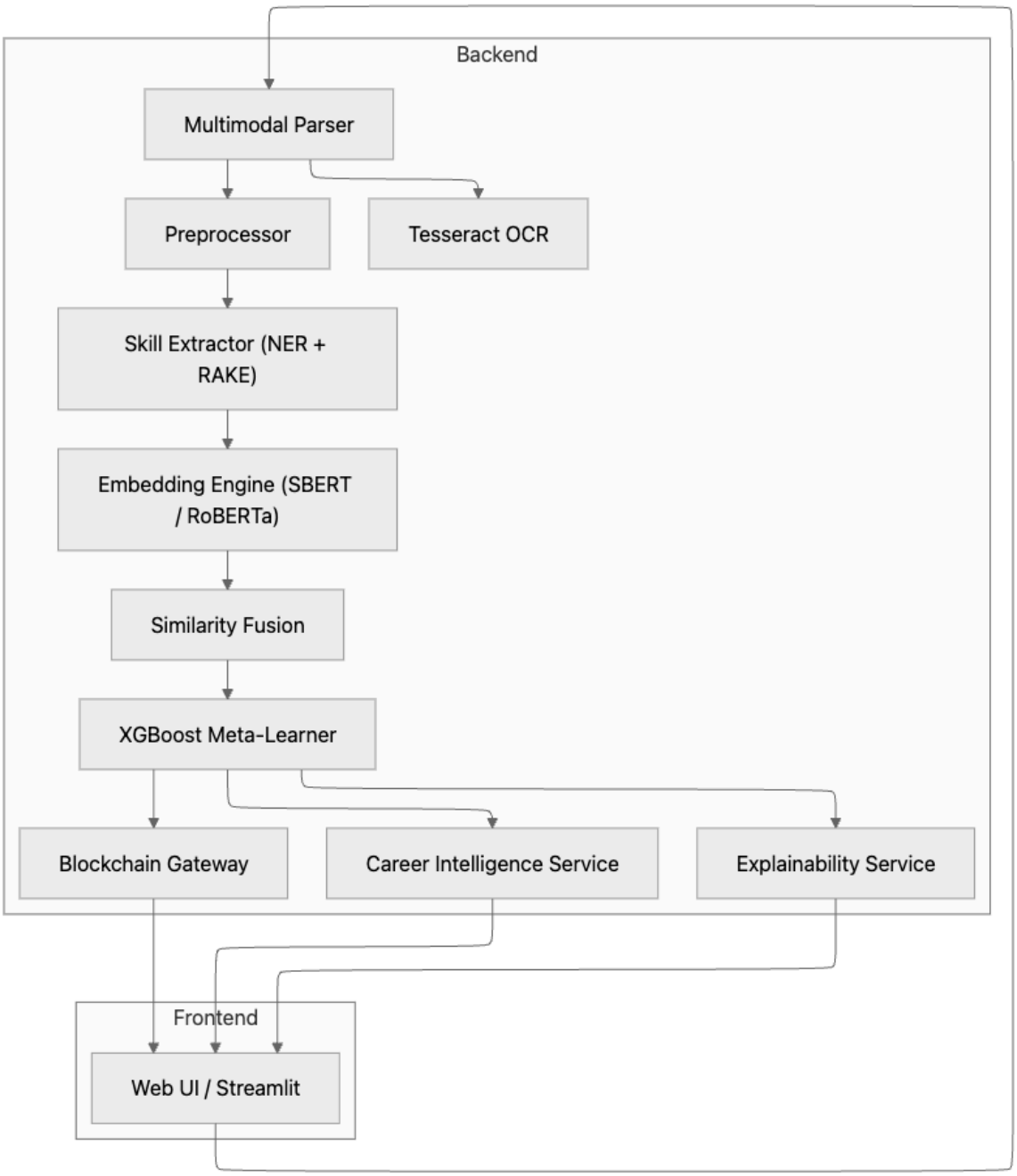
7.3 Sequence Diagram



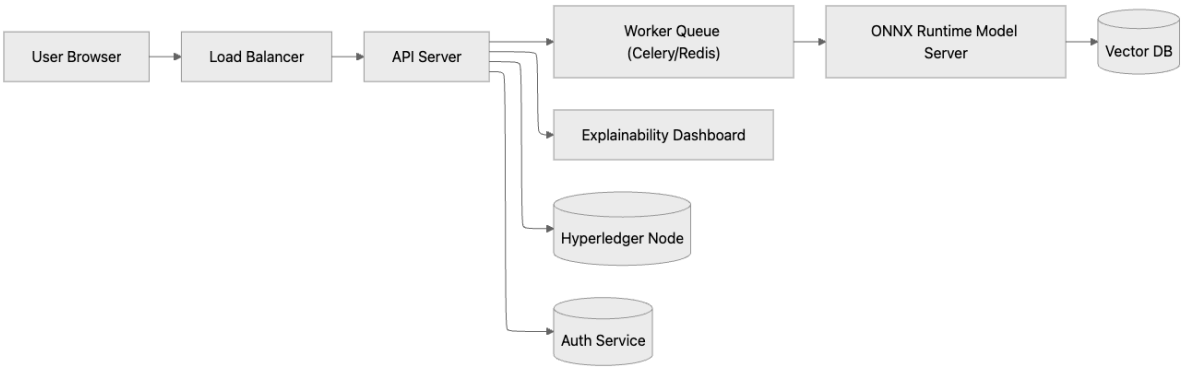
7.4 Activity Diagram


Start
Upload Resume / JD
Is PDF scanned?
Yes
No
Run OCR
Extract text
Preprocess text
Extract Skills NER + keywords
Canonicalize skills
Generate embeddings SBERT/DeBERTa/RoBERTa
Compute similarity features quadruple
XGBoost meta-learner Score
Compute SHAP explanations
Candidate passes threshold?
Yes
No
Mark as high match + Generate Report
Generate career path & suggestions
Display results to recruiter
End

7.5 Component Diagram



7.6 Deployment Diagram



8. UI screens (descriptions + elements)

Design for a Phase-1 Streamlit / React UI — simple, demo-ready.

Screen 1 — Landing / Upload

- File upload control (drag/drop, multi-file)
- Job description text box (paste JD)
- Start button
- Small note: supported formats (PDF, DOCX, TXT; scanned PDFs OK)

Screen 2 — Extraction Preview

- Left pane: extracted text with page selector + highlighted OCR confidence
- Right pane: quick stats (num pages, tables detected, OCR pages)

Screen 3 — Skill Extraction

- Extracted skills listed grouped: Technical | Soft | Certifications
- Each skill shows: source snippet (click to show evidence), confidence score, canonical mapping
- Buttons: Accept / Reject / Edit skill mapping (human-in-loop)

Screen 4 — Classification & Score

- K/S/A classification view (table + filtered view)
- If JD supplied: show match score card (final score, confidence interval)
- SHAP waterfall widget (top positive/negative contributors)
- Counterfactual suggestions (text snippets + estimated score uplift) with “apply suggestion” toggle (for applicant UI)

Screen 5 — Career Path & Resources

- If candidate below threshold, show prioritized skill gaps with severity bars
- Curated course list (time, cost, provider) and recommended micro-projects
- Timeline slider to show estimated months-to-qualification

Screen 6 — Admin / Model View (optional)

- Update skill ontology (upload CSV)
- Trigger model re-train / view model metrics
- Credential verification: show blockchain-verified badges

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9. Conclusion

Our solution is a practical, research-aligned framework that upgrades resume screening from brittle keyword matching to a **multimodal, explainable, career-forward** system. Its combination of tri-model ensemble, quadruple similarity fusion, SHAP explanations, career pathway guidance, and optional blockchain verification addresses precision, fairness, transparency, and anti-fraud — while remaining modular so teams can adopt the core extraction + KSA classifier first, and progressively integrate advanced features.