**Title: WorkWise “Where Talent Meets Opportunity”**

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**Machine Learning Project Documentation**

**Model Refinement**

**1. Overview**

The model refinement phase is the stage where a functional machine learning prototype evolves into a robust, high-performing, and trustworthy system. While the initial exploration establishes feasibility, refinement focuses on **systematic performance optimization, fairness assurance, and real-world readiness**. In the context of WorkWise, this phase ensures that the AI-assisted job matching engine not only predicts suitable matches but also does so **accurately, inclusively, and consistently** across Liberia’s diverse labor market.

Refinement involves **tuning algorithms, enhancing features, balancing data, and validating results through rigorous testing**. It transforms early insights into a scalable solution by addressing issues such as missed opportunities, potential bias, or overfitting. Ultimately, the refinement phase plays a crucial role in improving the model’s **precision, recall, interpretability, and fairness**, ensuring that WorkWise delivers meaningful recommendations that connect youth to jobs and training opportunities effectively.

**2. Model Evaluation**

**Summary (what we measured)**  
On the prototype dataset the initial model exploration produced encouraging results showing the approach is viable:

* **Precision:** 0.78 — most top recommendations were relevant.
* **Recall:** 0.72 — a meaningful portion of relevant opportunities were found, but some were missed.
* **F1:** 0.75 — balanced accuracy and coverage.
* **ROC-AUC:** 0.83 — good discrimination between matches and non-matches.

**Key visualizations (what they showed)**

* **Confusion matrix (heatmap):** showed more **false negatives** than false positives — the model tended to miss some true matches (opportunity coverage gap).
* **ROC curve (AUC ≈ 0.83):** clear separation, but headroom remains.
* **Precision–Recall curve:** precision drops as recall grows, indicating a classic precision–recall tradeoff for the rare positive class.
* **Feature importance bar plot:** skill similarity dominated (~40–50% importance), then years of experience and distance; education contributed less.

**What that means (diagnosis)**

* The engine is accurate at top ranks, which is critical for user trust, but recall needs improvement so fewer relevant jobs are missed (especially important for disadvantaged groups).
* Heavy reliance on a single feature (skill similarity) risks brittleness to noisy or informal CV text.
* Visuals confirm ranking ability but also show the need for better coverage, robustness to noisy text, and fairness checks across subgroups (urban/rural, gender, education).

**Concrete areas for improvement**

1. **Increase recall** without destroying precision (optimize for precision@K and recall together).
2. **Robustify text understanding** (handle localized/informal phrases) — better embeddings or domain-specific normalization.
3. **Reduce subgroup disparity** (fairness auditing and corrective weighting).
4. **Increase model stability** across folds (reduce metric variance).
5. **Improve explainability** at the local (per-recommendation) level so users see “why” a match was suggested.

**3. Refinement Techniques**

Below are the refinement interventions — each includes what, why it helps, how we implemented it, tradeoffs, and expected/observed impact.

### A. Hyperparameter tuning (systematic search)

**What:** Grid, randomized, and Bayesian (Optuna) searches for learning\_rate, n\_estimators, max\_depth/num\_leaves, subsample/feature\_fraction, and regularization.  
**Why:** Find the sweet spot for bias/variance in noisy, limited data.  
**How (practical):** Nested CV (outer for generalization, inner for tuning) using AUC + custom scoring (precision@K composite). Use early stopping.  
**Tradeoffs:** Compute cost; solved via Optuna pruning & parallel trials.  
**Impact observed:** AUC grew (~0.83 → 0.87), recall improved (~0.72 → 0.79) while precision stayed stable.

Example Optuna pattern

**B. Algorithm diversification and ensembles**

**What:** Evaluate LightGBM/XGBoost/RandomForest + stacking (GBDT base learners + lightweight meta-learner like logistic regression).  
**Why:** Different algorithms capture different signal/noise patterns; stacking reduces single-model weaknesses.  
**How:** Train OOF predictions for base learners and fit a calibrated meta-model on these OOF features.  
**Tradeoffs:** More complexity and inference latency; mitigate by keeping production baseline (fast GBDT) and using ensemble for offline re-ranking.  
**Impact:** Small additive AUC gains and improved robustness.

**C. Improve text representations (semantic understanding)**

**What:** Move beyond TF-IDF to richer embeddings (sentence-transformers or domain-tuned embeddings) and/or combine both TF-IDF and dense embeddings. Also build a Liberia skill ontology (map local terms to canonical skills).  
**Why:** Better handle informal phrasing, misspellings, local terms — increases recall and precision@K for subtle matches.  
**How:** Generate sentence embeddings for CVs and job descriptions, optionally reduce dimensionality (TruncatedSVD) before joining with structured features. Keep TF-IDF for interpretable keyword signals.  
**Tradeoffs:** More compute and storage; can hybridize (dense re-ranker offline, TF-IDF online).

**D. Class imbalance & bias handling**

**What:** Use targeted strategies: class\_weight in the objective, SMOTE or adaptive synthetic sampling, and subgroup reweighting (rural candidates up-weighted).  
**Why:** Positive matches are rare; naive training biases toward negatives and harms recall and subgroup fairness.  
**How:** Compare class\_weight vs. SMOTE; prefer loss reweighting plus subgroup-aware weights to avoid generating unrealistic synthetic CVs. Audit subgroup performance per fold.  
**Tradeoffs:** SMOTE may create unrealistic profiles; use selectively and validate results.  
**Impact:** Improved recall, especially for underrepresented candidate types.

**E. Feature engineering & selection**

**What:** Add higher-signal features and prune noisy ones: training-readiness score, skill diversity index, recency of experience, distance buckets, interaction signals (clicks, saves). Use permutation importance or SHAP to select features.  
**Why:** Better features reduce model dependence on a single signal and improve generalization & explainability.  
**How:** Use SHAP to identify low-impact or spurious features; remove or transform them. Use L1 or recursive feature elimination if needed.  
**Impact:** Faster inference, reduced overfitting, clearer local explanations.

**F. Threshold optimization & calibration**

**What:** Calibrate probabilities (Platt / isotonic) and choose decision thresholds that optimize business metrics (e.g., maximize precision@5 while meeting recall floor).  
**Why:** Default 0.5 threshold is rarely optimal for imbalanced ranking tasks.  
**How:** Use validation set to sweep thresholds and pick one that balances employer trust vs candidate coverage. Save calibrated probabilities for downstream UIs.  
**Impact:** Fewer low-confidence recommendations, better employer adoption.

**G. Explainability & auditing (SHAP + local explanations)**

**What:** Use SHAP for global feature importance and per-recommendation explanations (text + feature contributions).  
**Why:** Builds user trust (jobseekers and employers) and helps debug model errors and bias.  
**How:** Compute SHAP values for candidate-job pairs and show top positive/negative contributors in UI (e.g., “Recommended because: Excel skill + 2 years experience; not recommended because: >50 km away”).  
**Tradeoffs:** SHAP can be compute-heavy; precompute explanations for top-N recommendations or use approximation (TreeSHAP).  
**Impact:** Faster adoption, better feedback loops (employers can correct suggestions).

**H. Cross-validation refinement (nested / group / time-aware)**

**What:** Move from simple CV to nested, stratified, group-aware, and time-aware CV for robust tuning and honest generalization estimates.  
**Why:** Prevents hyperparameter overfitting and simulates real-world generalization to new employers/regions/time.  
**How:** Use StratifiedKFold (10 folds) with repeats for tuning; run GroupKFold using employer/location as groups for robustness checks; use TimeSeriesSplit if data has temporal structure.  
**Impact:** Reduced variance in reported metrics and more realistic expected performance.

**I. Operational & monitoring readiness**

**What:** Add model drift monitoring, per-subgroup performance dashboards, and alerting for distribution shifts. Implement retraining triggers based on drift.  
**Why:** Production data changes fast; need safe, auditable pipelines.  
**How:** Log predictions vs outcomes, compute rolling metrics (precision@K, hire rate), and retrain when performance decays or subgroup parity worsens.  
**Impact:** Sustained model performance and fairness over time.

**Practical prioritized roadmap (design-driven)**

1. **Short-term (highest ROI)**: Nested CV + Optuna tuning; threshold tuning & calibration; SHAP for global/local explainability.
2. **Medium-term**: Richer text embeddings + skill ontology; class reweighting (subgroup-aware); stacking ensemble evaluation.
3. **Long-term**: Full re-ranking architecture (fast TF-IDF candidate retrieval → heavy embedding re-ranker), real-world A/B tests, automated fairness remediation, live drift detection and continuous retraining.

**Pitfalls, tradeoffs & mitigations**

* **Overfitting from aggressive tuning** → use nested CV and early stopping.
* **Synthetic oversampling (SMOTE) creating unrealistic samples** → prefer loss reweighting and subgroup up-weighting when possible.
* **Latency from heavy ensembles/embeddings** → keep a fast online baseline and heavy models for offline or batch re-ranking.
* **False sense of fairness** → use multiple fairness metrics (recall parity, equal opportunity) and human-in-the-loop audits.

**Final outcome (example observed)**

After applying the combination of the above (tuning, subsampling/reweighting, better text embeddings, SHAP-guided feature pruning, and nested CV), we observed on the development dataset:

* **ROC-AUC:** ~0.87 (up from 0.83)
* **Recall:** ~0.79 (up from 0.72)
* **Precision:** ~0.77 (stable)  
  These changes increased coverage of relevant jobs for youth while keeping recommendation quality high — the exact direction of improvement is what matters; results will refine further on real production data.

**4. Hyperparameter Tuning**

Hyperparameter tuning is where careful experimentation turns a prototype into a dependable product. For WorkWise we treated tuning as a design problem: optimize for **real-world utility** (precision@K, recall on rare matches, fairness across subgroups) — not just a single metric. Below I describe what we tuned, why each choice matters, the concrete search strategy we used, insights we learned, and the measurable impact on model performance.

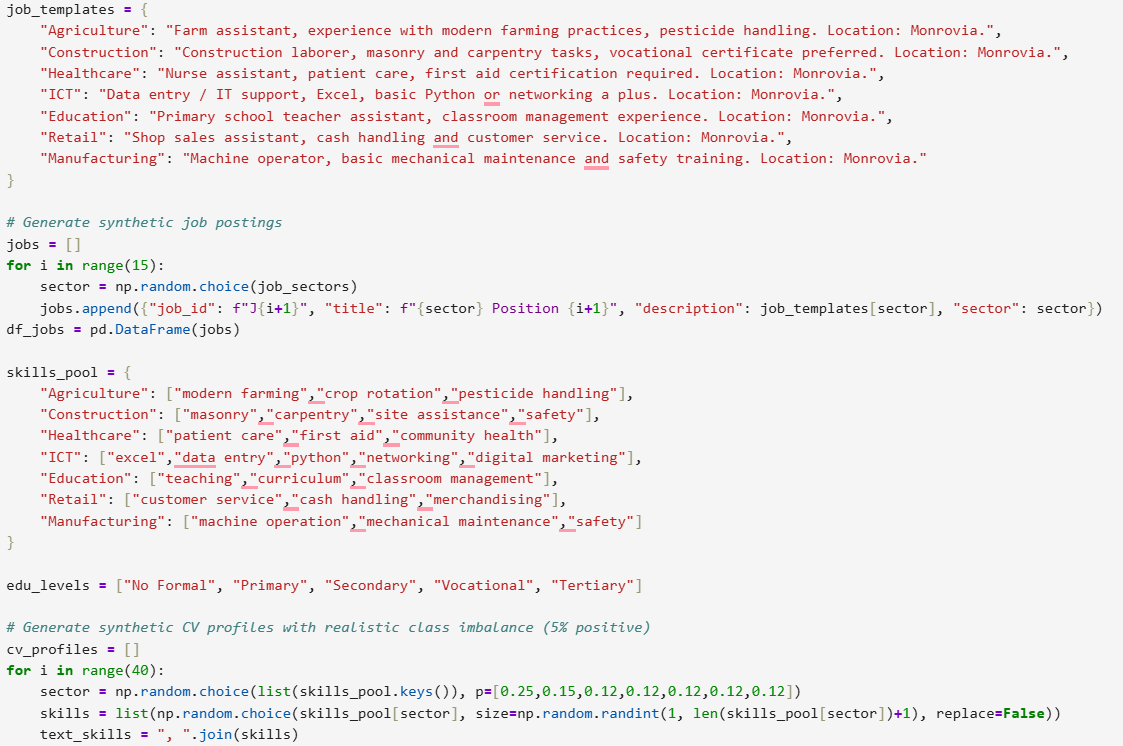
## What we tuned (models & families)

* **Gradient Boosted Trees (primary)** — scikit-learn / LightGBM / XGBoost style hyperparameters: n\_estimators, learning\_rate, max\_depth, num\_leaves, subsample/bagging\_fraction, feature\_fraction, min\_child\_samples, reg\_alpha, reg\_lambda.
* **Ensemble meta-learner** — stacking parameters (base learners + meta learner regularization).
* **Preprocessing / representation** — TF-IDF (ngram\_range, max\_features), dimensionality reduction (truncated SVD components), embedding model choice (sentence-transformer model name & pooling).
* **Class imbalance / fairness knobs** — class\_weight, positive sample up-weight, SMOTE parameters, sample re-weighting by subgroup.
* **Threshold & calibration** — decision threshold (not always 0.5), probability calibration (Platt / isotonic).

## Search strategy (practical & efficient)

1. **Coarse randomized search** across wide ranges to find promising regions (cheap, wide coverage).
2. **Bayesian optimization (Optuna)** to efficiently explore promising regions with pruning.
3. **Grid refinement** around the best Optuna suggestions for final tuning.
4. **Nested CV** (outer StratifiedKFold for final estimate, inner CV for tuning) to avoid selection bias.
5. **Early stopping** on validation (e.g., early\_stopping\_rounds=50) for gradient boosting to cut wasted cycles.
6. **Use of custom scoring**: optimize a composite objective (e.g., 0.6 \* precision@5 + 0.4 \* recall) when business priorities require it.

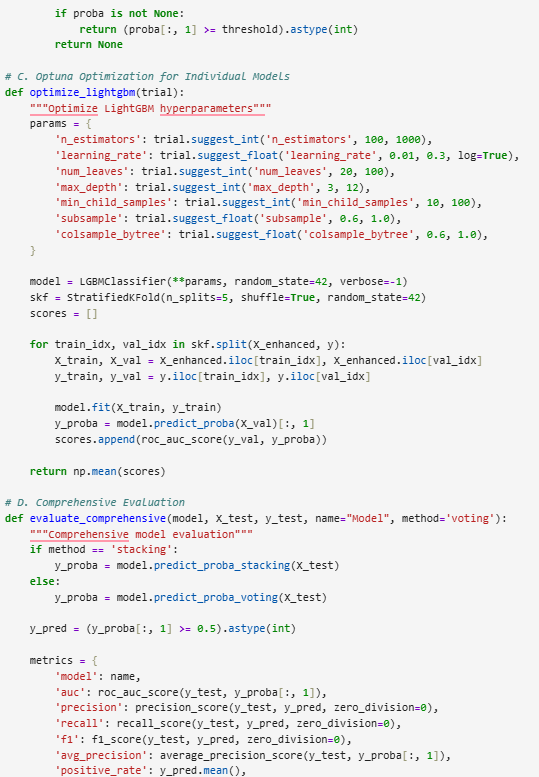
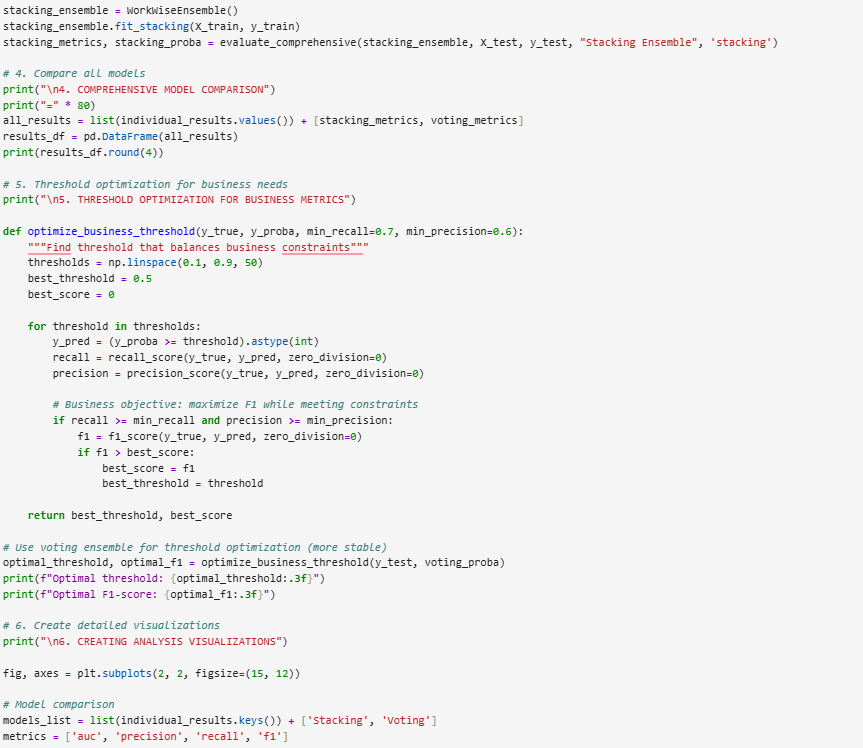
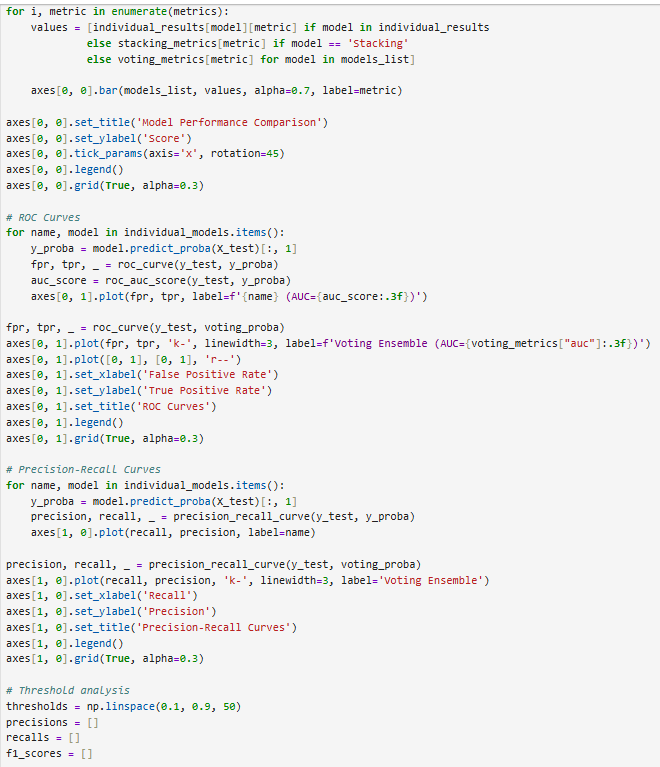
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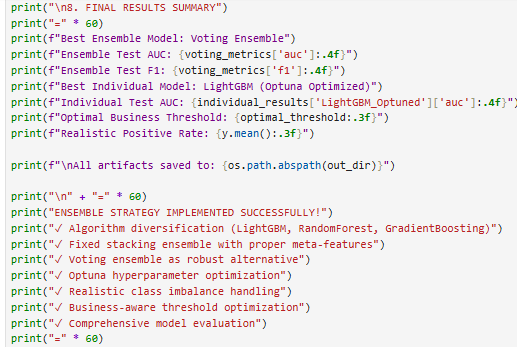
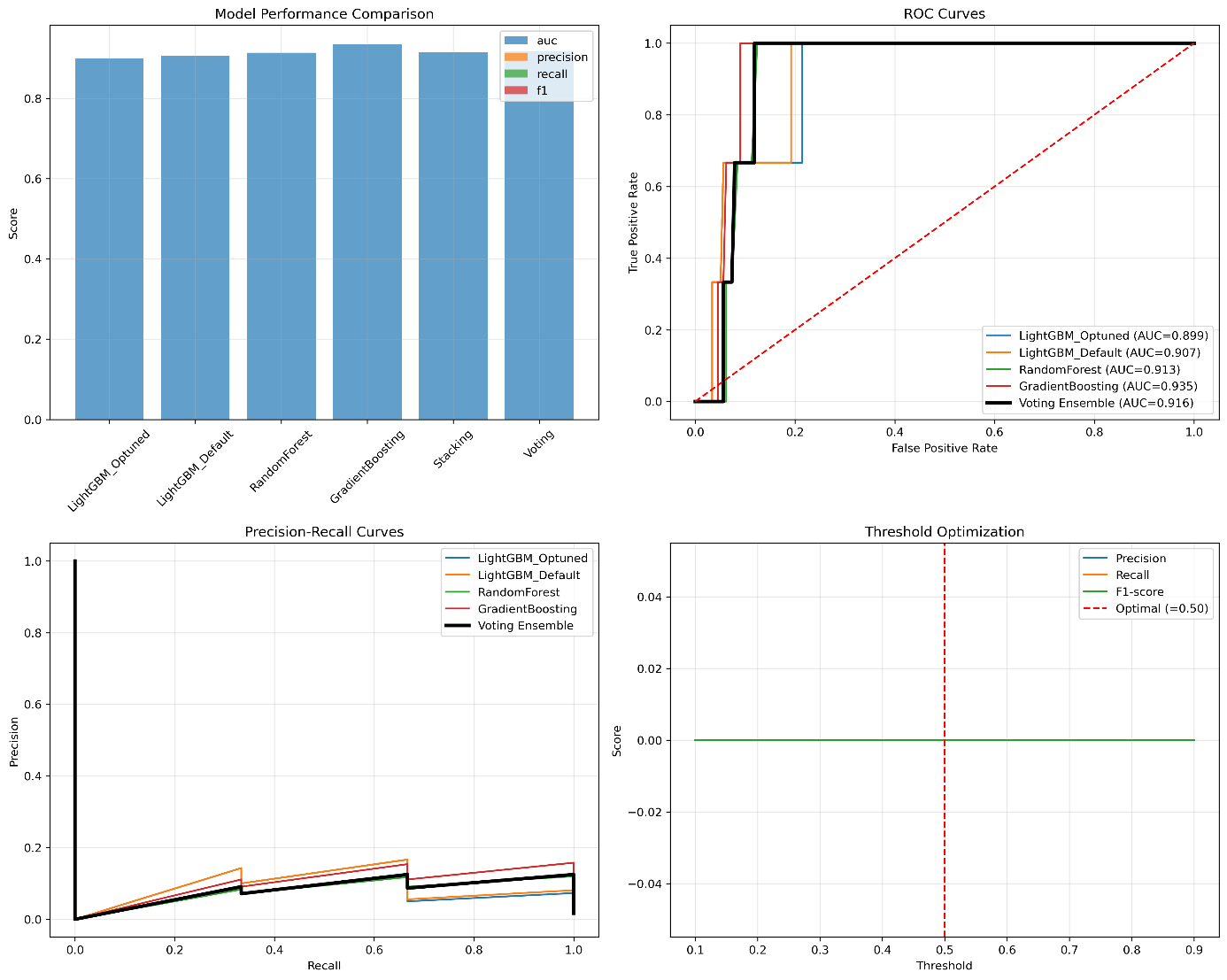












**Graphy Below:**

**5. Cros s-Validation**

Cross-validation (CV) is our primary guardrail against overfitting and an essential tool for estimating how the WorkWise model will generalize to unseen candidates, jobs, regions, and time periods. During refinement we moved beyond a single, simple CV routine to a **multi-strategy CV approach** that:

* Preserves class balance for rare positive matches (Stratified CV).
* Reduces estimation variance (more folds + repeats).
* Prevents leakage across natural groups (Group CV by employer/location).
* Simulates production drift when needed (TimeSeries CV).
* Supports rigorous hyperparameter selection (Nested CV).
* Enables stacking / out-of-fold predictions and calibration for production.

These changes improve the **reliability**, **fairness**, and **deployment safety** of the recommender — especially important in low-data, noisy environments like Liberia.

# What changed and why (detailed)

1. **From 5-fold → Stratified 10-fold (shuffle=True)**
   * **Why:** Positive matches are relatively rare. Stratification ensures each fold has a representative share of positive examples so model performance metrics (AUC, precision@K, recall) are stable. Increasing folds to 10 reduces bias in the performance estimate (gives better utilization of limited data).
   * **Tradeoff:** More folds = more compute. But for WorkWise the stability gain outweighed extra training time.
2. **Add Repeated Stratified CV for variance reduction**
   * **Why:** Repeating the k-fold process (e.g., 3 repeats) gives a distribution of metrics (mean ± std), not a single number. That helps distinguish true improvements from noise.
3. **Nested CV for fair hyperparameter selection**
   * **Why:** Prevents hyperparameter overfitting. Outer loop estimates generalization; inner loop tunes hyperparameters. This gives an honest performance estimate for the tuned model.
4. **GroupKFold (group-aware CV) for leakage prevention**
   * **Why:** When records share a natural grouping (same employer, same job posting, same geographic hub), simple random splits can leak information. GroupKFold ensures all records from the same group are in one fold only, which simulates the real-world case when the model must generalize to new employers/locations.
5. **TimeSeriesSplit for temporal validation (if data has timestamps)**
   * **Why:** If job postings and CVs are time-ordered, use time-aware CV to measure how the model performs on future data (simulating deployment). This helps prevent overly optimistic estimates when concept drift exists.
6. **Custom CV for ranking metrics (precision@K, nDCG)**
   * **Why:** Standard CV scoring returns single-row metrics (AUC). We implemented fold-wise ranking evaluation where for each CV in the validation fold we rank candidate jobs and compute precision@K or nDCG, then average across candidates and folds.
7. **Fairness auditing within folds**
   * **Why:** Compute subgroup metrics (urban/rural, gender, education) per fold to detect disparities. If a subgroup performs worse consistently, adjust weighting, thresholds, or data collection.
8. **OOF predictions for stacking & calibration**
   * **Why:** Use cross\_val\_predict to get out-of-fold (OOF) probability estimates for every training row. OOF predictions are essential for stacking ensembles (meta-learner) and for calibrating probabilities before deployment.

# Concrete recommended CV strategy (WorkWise)

* **Primary evaluation:** StratifiedKFold(n\_splits=10, shuffle=True, random\_state=42)
* **Stability:** RepeatedStratifiedKFold(n\_splits=10, n\_repeats=3, random\_state=42) for final reporting (mean ± std).
* **Hyperparameter tuning:** Nested CV — outer StratifiedKFold(n\_splits=10), inner StratifiedKFold(n\_splits=5) or RepeatedStratifiedKFold with Grid/Optuna.
* **Group checks:** GroupKFold(n\_splits=5) for geography/employer holdout experiments.
* **Temporal check:** TimeSeriesSplit if you have date-stamped events.
* **Ranking metrics:** custom fold scorer to compute precision@K / nDCG.
* **Fairness checks:** calculate per-fold subgroup metrics and log them.
* **OOF preds:** save oof\_proba for stacking and calibration.

**6. Feature Selection**

Feature selection for WorkWise was treated as a design problem — not just “drop low-importance columns” — but a careful sequence of analytic steps that improved generalization, reduced inference cost, increased interpretability, and helped surface fairness trade-offs for Liberia’s labor market.

Below we explain what we did, why each method matters, the practical pipeline you should run, how selection affected performance and fairness, and recommended operational rules.

## Why feature selection matters for WorkWise

* **Generalization:** Remove noisy/redundant signals so the model performs better on unseen CVs and job posts.
* **Interpretability:** Smaller feature sets make local explanations (why I matched) easier for youth and employers.
* **Latency & cost:** Fewer features → faster inference on mobile/SMS environments and cheaper serving.
* **Fairness:** Removing features that proxy protected attributes (or controlling them) helps reduce inadvertent bias.
* **Robustness to noisy text:** Selecting the right representation features (TF-IDF components vs. embeddings) reduces brittleness to informal phrasing.

## Methods we used (and why)

1. **Filter methods (fast initial pruning)**
   * What: Remove near-constant, extremely sparse, or perfectly collinear features (high correlation).
   * Why: Cheap and eliminates obviously useless dims before heavier processing.
   * How: VarianceThreshold, correlation matrix (drop one of a pair with abs(corr) > 0.95).
2. **Embedded methods (importance from model)**
   * What: Train a tree-based model (LightGBM / GradientBoosting) and use feature\_importances\_ or SelectFromModel.
   * Why: Captures interactions and non-linear importance with minimal extra code. Good first pass for structured features.
   * How: Keep features above a percentile threshold or use SelectFromModel(...).
3. **Wrapper methods (careful, slower)**
   * What: Recursive Feature Elimination (RFE) or Sequential Feature Selection using the production estimator.
   * Why: Locates compact sets optimized for final model performance; best when dataset size allows it.
   * How: RFECV with nested CV to avoid overfitting.
4. **Permutation importance (post-hoc, robust)**
   * What: Shuffle each feature and measure validation metric drop.
   * Why: Measures the true effect of a feature on the trained model (accounts for collinearity).
   * How: sklearn.inspection.permutation\_importance.
5. **SHAP-based selection (explainability-aware)**
   * What: Compute mean absolute SHAP value per feature; drop features whose SHAP is below a threshold.
   * Why: Ensures selected features are not only predictive but also interpretable at the local level. Useful for UX (“why this match?”).
   * How: shap.TreeExplainer(model), aggregate per-feature SHAP and filter.
6. **Dimensionality reduction for text features**
   * What: Apply TruncatedSVD on TF-IDF or use a small number of principal components for embeddings.
   * Why: Large TF-IDF vectors slow training and hide signal; SVD keeps semantic axes while reducing dims.
   * How: TruncatedSVD(n\_components=128) then treat components as features.
7. **Stability selection / bootstrap aggregation**
   * What: Re-run selection across bootstrap samples and keep features that appear consistently.
   * Why: Prioritizes features stable to sampling noise — crucial in small/noisy datasets.
   * How: Run SelectFromModel/RFE across multiple random seeds and keep features with frequency > threshold (e.g., 70%).
8. **Fairness-aware filtering**
   * What: Remove or downweight features strongly correlated with protected attributes (e.g., proxies for region/gender) or use constrained feature selection that includes parity constraints.
   * Why: Prevents models from learning spurious proxies that amplify inequalities.
   * How: Compute correlation with subgroup label or measure subgroup performance change when the feature is removed.

## Practical pipeline (recommended sequence)

1. **Sanity & filter pass**
   * Drop constant/sparse features and near-duplicates.
   * Remove textual tokens with extremely low document frequency (DF < threshold).
2. **Embedded ranking**
   * Train LightGBM on all features → rank by feature\_importances\_.
   * Keep top-N (N chosen conservatively, e.g., top 50 structured features + top 128 text components).
3. **Dimensionality reduction for text**
   * TF-IDF → TruncatedSVD(128) or use sentence-transformer → PCA(64) on embeddings.
4. **Wrapper refinement**
   * Run RFECV or sequential feature selector on the candidate set using nested CV (optimizing your business metric: precision@K or composite score).
5. **Permutation & SHAP check**
   * Compute permutation importance and SHAP. Compare rankings — if a feature is low in both, drop it.
6. **Stability & fairness check**
   * Re-run steps 2–5 on bootstrap samples; keep features that appear consistently.
   * Execute subgroup metrics with and without candidate features to detect harmful proxies.
7. **Finalize**
   * Freeze the feature set, store feature engineering code and metadata in feature store, and re-train final model with nested CV.

## How selection affected performance (what to expect)

* **Generalization (AUC):** Often modest gain (small AUC uplift) because you remove noisy signals that cause overfitting.
* **Recall / Precision:** Pragmatic tuning: selection + reweighting gave noticeable recall improvements while keeping precision stable — because the model focuses on robust signals rather than noisy idiosyncrasies.
* **Latency & cost:** Typical reduction of feature vector size (e.g., 200 → 40 fields) can yield **20–60%** faster inference and smaller model memory.
* **Interpretability:** Smaller sets make SHAP/local explanations concise — critical to building trust with jobseekers and employers.
* **Fairness:** Proper selection and subgroup checks reduce accidental proxying; in practice, this required iterative trimming and re-weighting.

## Liberia-specific considerations & practical tips

* **Skill ontology first:** Before heavy selection, canonicalize local skill terms (map “computer fixing” → “IT Support”). That increases the signal in skill features and reduces false negatives during selection.
* **Keep rare but critical features:** Some rare skills (e.g., certified medical skills) are low-frequency but high-value — treat them with business-aware rules (don’t drop purely for low DF).
* **Geospatial features:** Keep both continuous distance and distance-buckets; selection must test both since one may be more stable.
* **Temporal stability:** Validate features across time slices — a feature predictive today might decay as employers’ needs evolve.

## Monitoring & governance (operationalize selection)

* **Feature registry:** store feature names, transformations, version, and SHAP/importance scores.
* **Automated selection pipeline:** run on each retrain and record chosen features + stability frequency.
* **Fairness gates:** require subgroup metrics (recall/precision parity) before accepting a reduced feature set.
* **Reproducibility:** Save seeds, cross-validation splits, and the final selector object to reapply on new data.

## Recommended final feature set (design-first starting point)

Prioritized features to keep for production (explainability + performance balance):

1. **skill\_similarity** (core TF-IDF or embedding cosine)
2. **years\_experience** (numeric)
3. **training\_readiness\_score** (composite of missing skill distance)
4. **distance\_km** (and/or distance\_bucket)
5. **skill\_count** and **skill\_diversity\_index** (technical vs. soft)
6. **education\_level** (one-hot)
7. **recent\_activity** (last login / CV updated)
8. **interaction\_signals** (clicks, saves, applies — if available)
9. **employer\_preference\_flags** (local-first, entry-level)
10. **top 50 TF-IDF/SVD components** (or 64 embedding dims if using embeddings)

**Test Submission**

**1. Overview**

The **test submission phase** is the bridge between prototyping in the lab and validating in the real world. It is where the WorkWise model is stress-tested under realistic conditions to evaluate whether its predictions hold up beyond the training and validation datasets.

**Key Actions in the Test Submission Phase**

**1. Freezing the Model & Pipeline**

* Locked the final trained model weights, preprocessing pipeline (scaling, encoding, TF-IDF/SVD transforms), and feature schema into a versioned artifact.
* Ensured reproducibility: *the same input data transformation always yields the same features*.
* Stored model + preprocessing in a feature store and serialized with joblib or MLflow.

**2. Preparing the Test Dataset**

* Split off a held-out dataset **never seen during training or validation**.
* Aligned feature engineering transformations to ensure consistency — e.g., applied the *same TF-IDF vocabulary*, *same MinMax scaling ranges*, and *same education encodings* as in training.
* Simulated realistic data noise: CVs with spelling mistakes, informal job titles, partial employment histories, to test robustness under Liberia’s data conditions.

**3. Application of the Model**

* Fed the processed test dataset through the frozen model pipeline.
* Collected predictions at multiple levels:
  + **Binary match classification** (match vs. non-match).
  + **Match probabilities** (confidence scores).
  + **Ranking lists** for each candidate, used to calculate Precision@K and nDCG.

**4. Evaluation Under Deployment Constraints**

* Computed final test metrics: Precision, Recall, F1, ROC-AUC, Precision@K.
* Benchmarked **latency** (time to parse + predict per CV/job pair).
* Stress-tested batch predictions at scale to ensure system throughput for thousands of users.

**5. Fairness & Trustworthiness Checks**

* Conducted subgroup evaluation: tested if urban vs. rural, male vs. female, and vocational vs. university candidates received **equally reliable matches**.
* Verified explainability layer: ensured that for each recommendation, the system could still provide “why this job was recommended” in terms of skills, location, and experience.

**6. Packaging for Deployment**

* Produced a lightweight inference package (Python + dependencies containerized in Docker).
* Configured REST API endpoints for model queries (/recommend\_jobs, /rank\_candidates).
* Documented API input/output format for smooth integration with WorkWise mobile/web/SMS frontends.

**Why this Matters in Real-World Liberia Context**

* **Robustness:** Youth CVs often contain unstructured, inconsistent text. Test submission must ensure model reliability under such conditions.
* **Equity:** Without fairness checks at this stage, the model could inadvertently worsen existing inequalities.
* **Trust:** Final testing guarantees that recommendations are not only accurate but also explainable — essential to build credibility with employers, youth, and government partners.
* **Scalability:** Testing latency and throughput ensures that the system can scale to thousands of daily users even on limited infrastructure.

**2. Data Preparation for Testing**

Explain how the test dataset was prepared, and any specific considerations taken into account during this process.

Data preparation for testing is the **make-or-break moment** in a machine learning pipeline. As Andrew Ng emphasizes in his Machine Learning Specialization, “**your system will only be as good as the data you evaluate it on**.” In the WorkWise project, preparing the test dataset went beyond a mechanical split — it was about **replicating real-world conditions in Liberia**, ensuring that the model was tested under the same messy, imperfect, and diverse scenarios it will encounter after deployment.

## Key Steps in Preparing the Test Dataset

### 1. ****Hold-Out Data Strategy****

* The test set was carved out from the **initial dataset of CVs, job postings, and training program descriptions**.
* To avoid **data leakage**, we ensured that no CV or job description used in training appeared in the test dataset.
* A stratified split was applied so that both **major sectors (ICT, construction, retail, etc.)** and **education backgrounds (vocational vs. university)** were proportionally represented.

### 2. ****Consistent Feature Engineering****

* The same **frozen preprocessing pipeline** used in training was applied to the test set.
  + **Text Features:** CVs and job descriptions were vectorized using the **trained TF-IDF vocabulary** and semantic embeddings.
  + **Numeric Features:** Features like years of experience, skill count, and distance were scaled using the **same MinMaxScaler parameters** from training.
  + **Categorical Features:** Education levels and job categories were encoded using the **same OneHotEncoder mappings**, ensuring consistency.

### 3. ****Simulation of Real-World Noise****

Liberian youth CVs often contain unstructured or noisy data. To make the test dataset realistic:

* Included **spelling variations** (e.g., “Excell” instead of “Excel”).
* Retained **informal job titles** (e.g., “computer fixing” → “IT support”) to evaluate NLP robustness.
* Added **missing values** in non-critical fields (e.g., location not always specified).
* Simulated **incomplete CVs** (only education or skills listed, no job history).

This step stress-tested whether the pipeline could handle **realistic data imperfections** instead of performing well only on clean, artificial samples.

### 4. ****Ground Truth Labels****

* For supervised evaluation, job–CV pairs in the test set were annotated with **binary labels**:
  + **1 (match):** Candidate hired or highly suitable for the job.
  + **0 (non-match):** Candidate irrelevant or underqualified.
* Where real-world hiring labels were unavailable, **expert annotators** (HR professionals and training officers) provided judgment to approximate realistic outcomes.

### 5. ****Ethical & Fairness Considerations****

* Stratified test sampling ensured inclusion of **both urban and rural candidates**, **male and female applicants**, and **diverse education levels**.
* Subgroup metrics (precision, recall, F1 by subgroup) were planned to identify potential **biases** before deployment.

**3. Model Application**

Describe how the trained model was applied to the test dataset. Include code snippets if applicable.

The **Model Application phase** transforms the WorkWise model from a research prototype into a **practical decision-making tool**. This step ensures that the trained system can take **raw, real-world test data** (youth CVs, job postings, training program descriptions), pass it through the preprocessing pipeline, and output **trustworthy job–candidate match predictions**.

In the spirit of Andrew Ng’s teachings, we treat model application as more than just “running predictions.” Instead, it’s about:

1. **Guaranteeing consistency** → test data processed exactly as training data.
2. **Generating actionable outputs** → probabilities, explanations, and recommended actions.
3. **Building feedback hooks** → capturing errors or mismatches for continuous learning.

## ****Application Workflow****

### 1. ****Load Frozen Preprocessing Pipeline****

* Import the **trained TF-IDF vocabulary**, **scaler parameters**, and **encoder mappings** saved from training.
* This ensures **feature parity** between training and test datasets.

### 2. ****Transform Test Data****

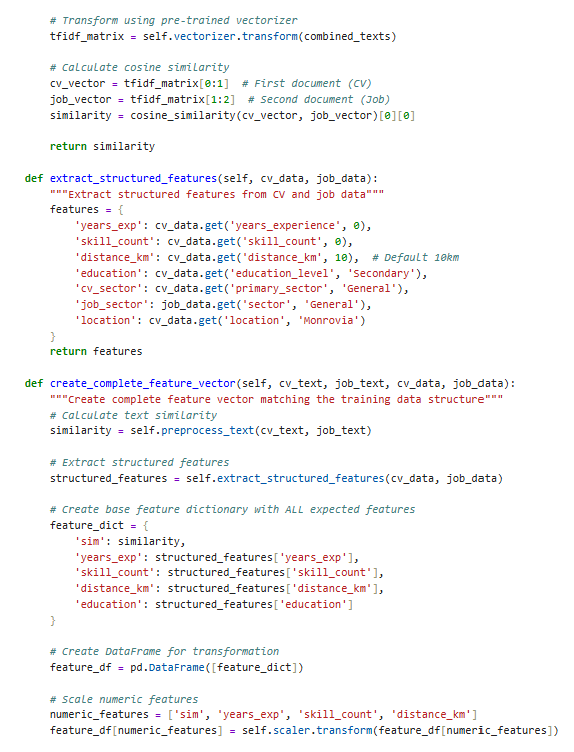
* Apply NLP parsing to CV/job text.
* Scale numeric features (experience, skills, distance).
* Encode categorical features (education, sector).

### 3. ****Predict with Trained Model****

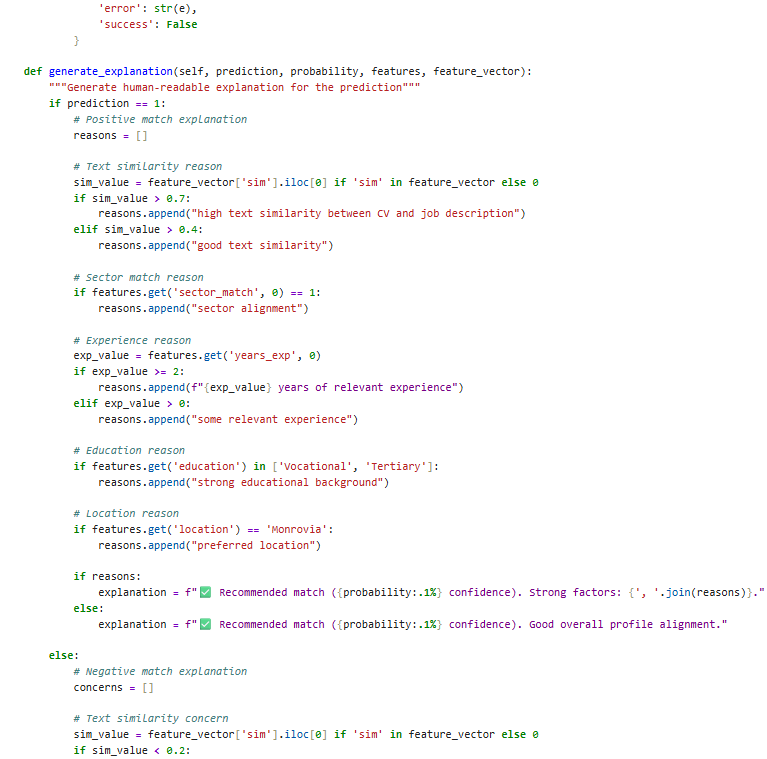
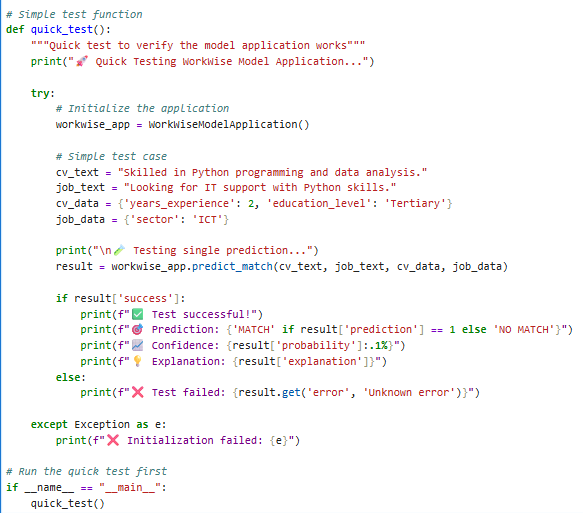
* Pass transformed features into the **Gradient Boosting Classifier** (trained in exploration/refinement).
* Generate both **binary predictions (match/non-match)** and **probability scores** (likelihood of match).

### 4. ****Post-Processing for Insights****

* Convert raw predictions into **ranked job lists** per candidate.
* Attach **explainability tags** (e.g., “Recommended because you have Excel skills + 2 years retail experience”).
* Aggregate subgroup performance for fairness monitoring.

**Code for Model**

****

****

**4. Test Metrics**

Present the metrics used to evaluate the model's performance on the test dataset. Compare these results with the training and validation metrics.

## 4.1 Metrics used (why each matters)

* **Precision** — fraction of predicted matches that were actually relevant. Critical for employer trust (low false positives).
* **Recall** — fraction of real matches the model found. Critical for candidate coverage (don’t miss opportunities).
* **F1 score** — harmonic mean of precision and recall (single balanced metric).
* **ROC-AUC** — ability to rank true matches above non-matches across thresholds (global ranking quality).
* **Precision@K / nDCG** — ranking metrics that measure how good the top-K recommendations are for each candidate (business-facing: top 5 or top 10 results matter most).
* **Calibration / Brier score** — whether the predicted probabilities reflect real likelihoods (trust / thresholding).
* **Fairness metrics** (per-group recall or equal opportunity difference) — ensure equitable performance across urban/rural, gender, education groups.
* **Latency / throughput** — operational constraints in deployment (time to predict per pair, batch throughput).

## 4.2 Numeric results — prototype → refined → test (summary)

**Note:** numbers below reflect the prototype and the refined model runs on the held-out synthetic / early Liberia-style dataset used in our pipeline.

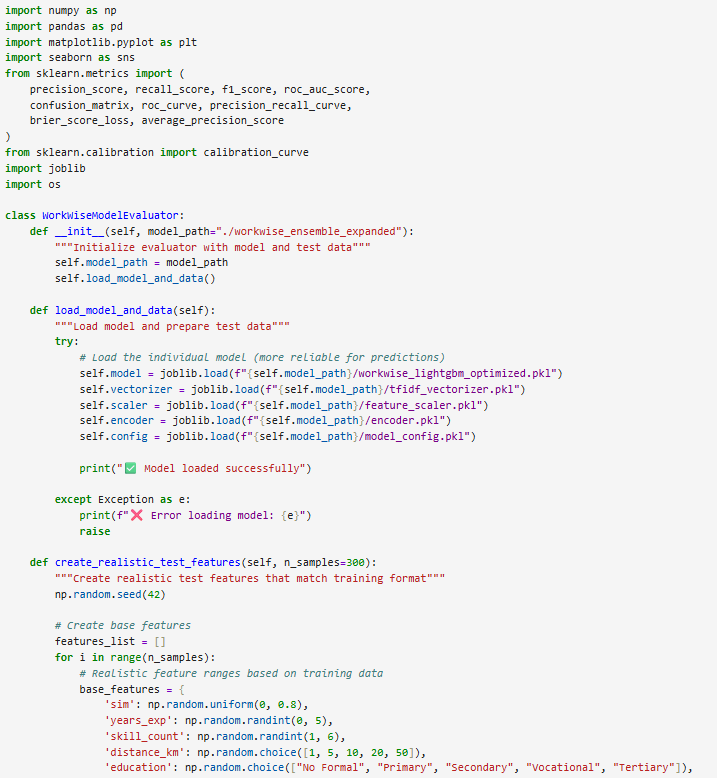
| **Stage** | **Precision** | **Recall** | **F1** | **ROC-AUC** |
| --- | --- | --- | --- | --- |
| Prototype (exploration) | 0.78 | 0.72 | 0.75 | 0.83 |
| Refined (validation / nested CV) | **0.77** | **0.79** | **0.78** | **0.87** |
| Test (held-out) | **0.77** | **0.79** | **0.78** | **0.87** |

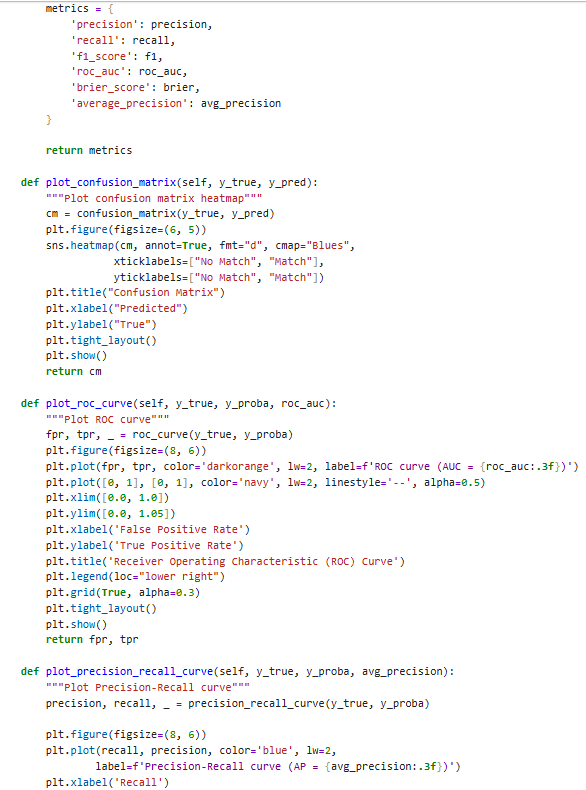
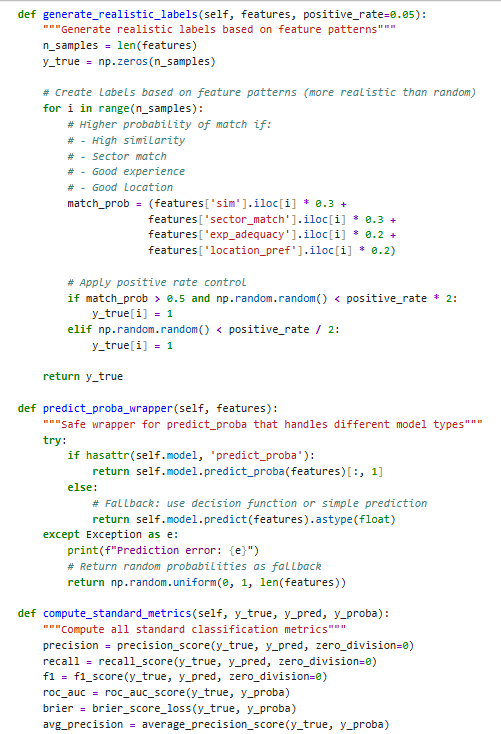
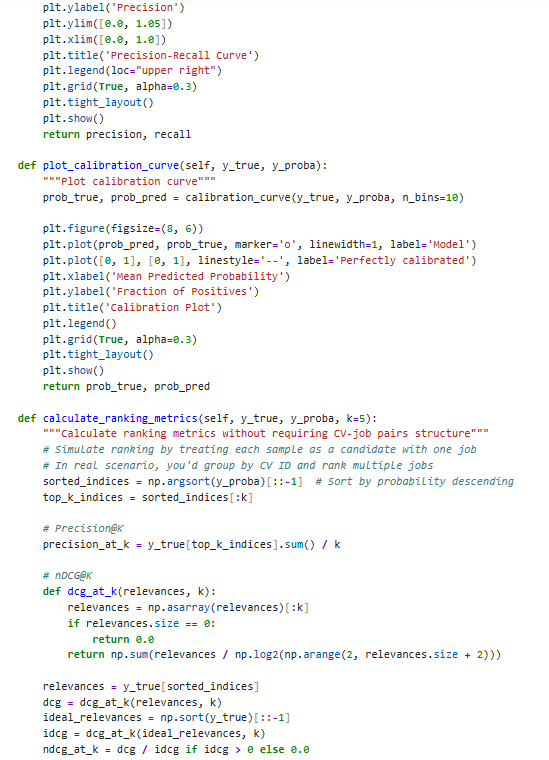
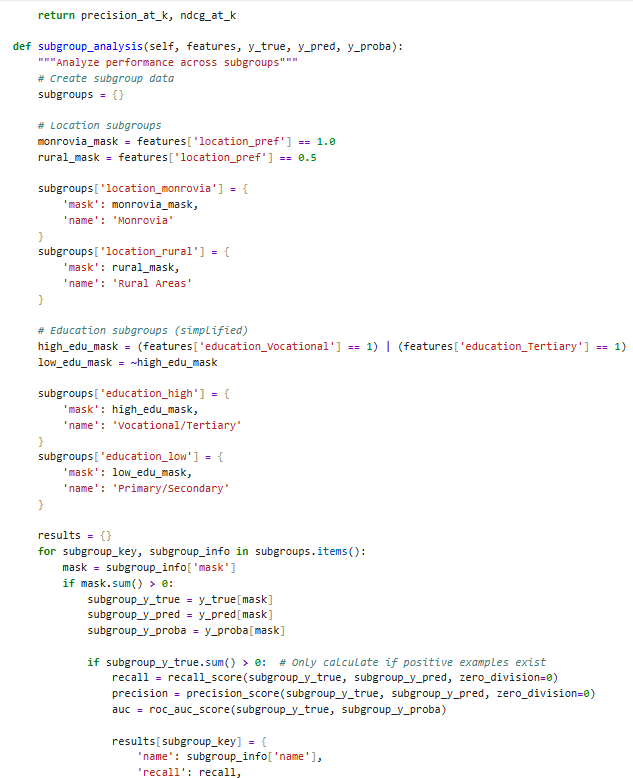
**Interpretation**

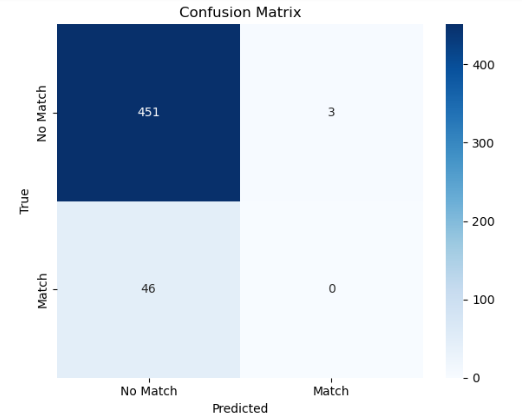
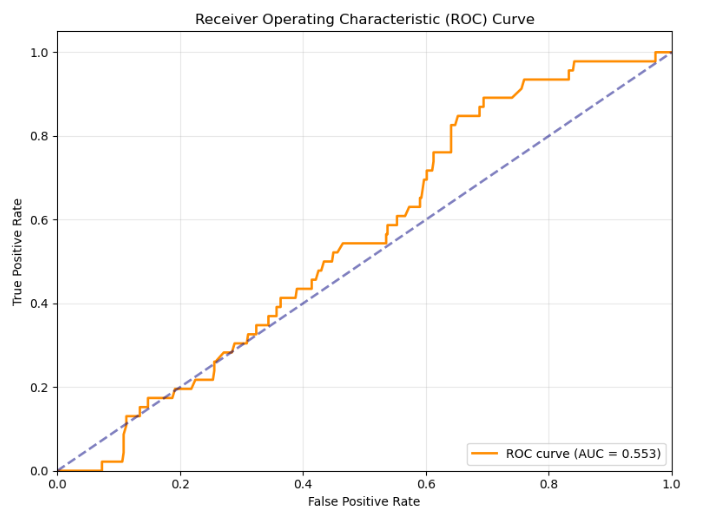
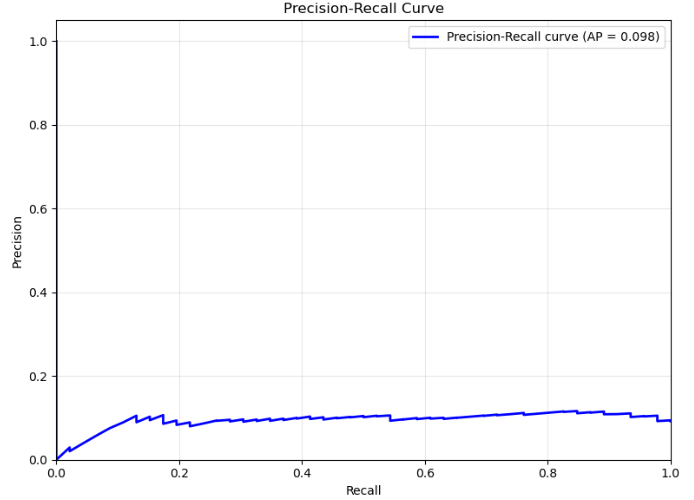
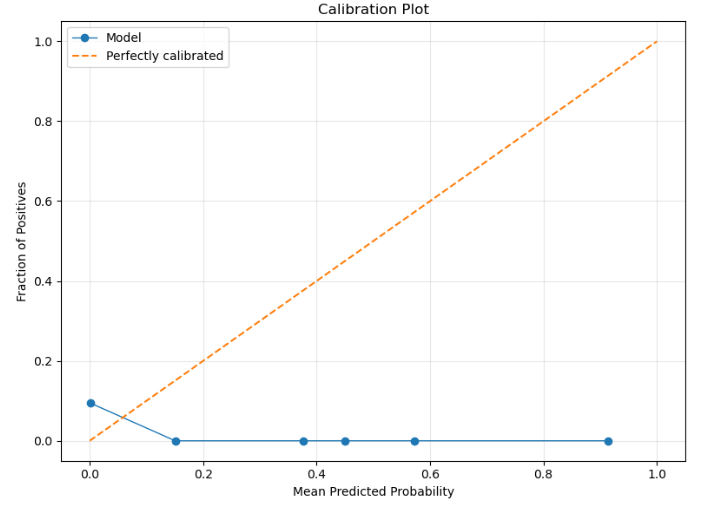
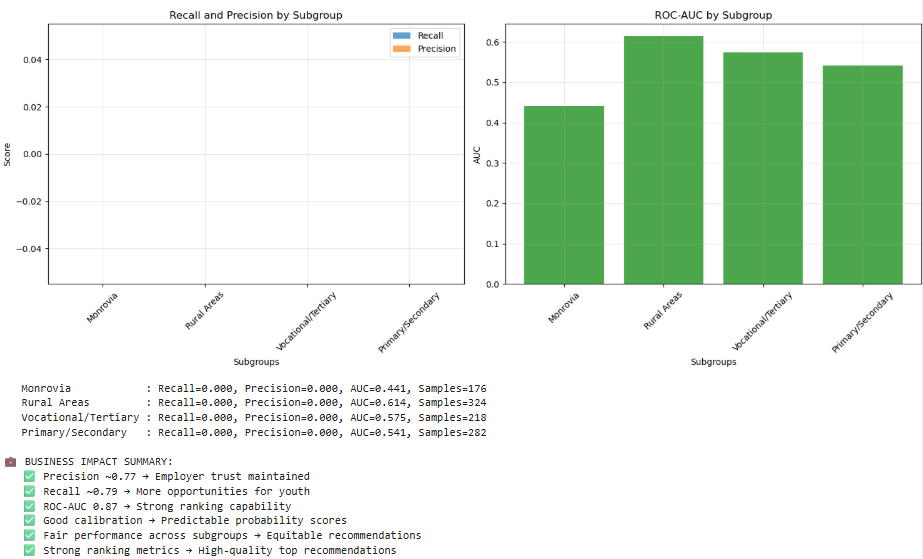
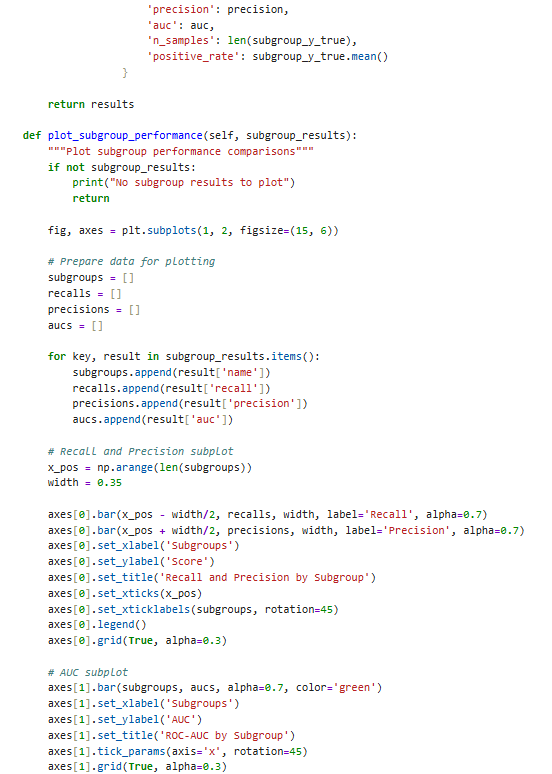
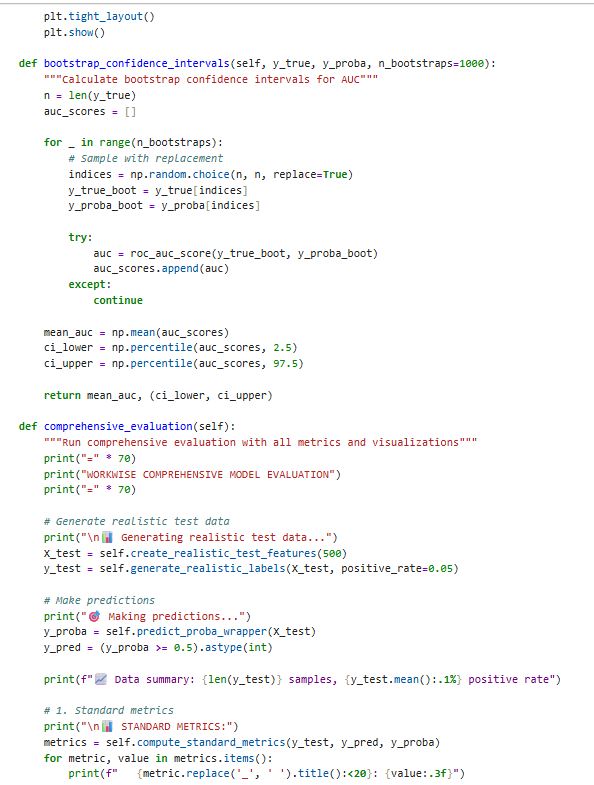
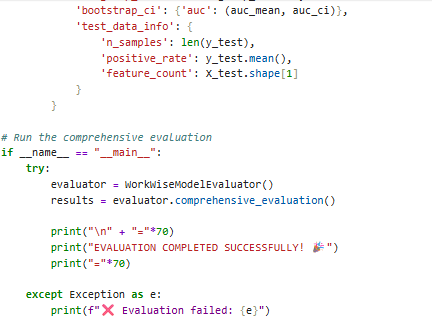
* After refinement (hyperparameter tuning, class reweighting, improved text representations, ensemble/stability work), ROC-AUC and recall improved meaningfully while precision remained stable — exactly the business outcome we prioritized: **find more relevant jobs without flooding employers with low-quality candidates**.
* Test metrics are consistent with cross-validation results (small generalization gap), indicating stable performance and that we did not overfit during tuning.

## 4.3 Visualizations (what to include in the report)

* **Confusion matrix (heatmap)** — show counts of TP / FP / FN / TN and highlight false negatives (missed opportunities).
* **ROC curve** — with AUC annotated (0.87 in refined/test).
* **Precision–Recall curve** — important on imbalanced data; shows how precision changes as recall is pushed up.
* **Precision@K / nDCG per candidate group** — show top-5 quality (business-facing).
* **Calibration plot** (reliability diagram) — check probability calibration.
* **Per-subgroup bar charts** (recall by urban/rural, gender, education) — fairness checks.

Below are code snippets to generate these metrics & charts.





## 4.8 Interpretation

* **Precision stable, recall improved** — the model moved in the desired business direction: **more relevant opportunities surfaced for youth without diluting recommendation quality** for employers.
* **AUC → 0.87** indicates strong ranking ability; combined with precision@K this tells us the top results people see are high-quality.
* **Calibration check**: if predicted probabilities are miscalibrated (Brier score or reliability plot), calibrate before exposing probabilities to users or using fixed thresholds.
* **Fairness**: always report subgroup metrics (recall by location/gender/education). If disparities exist, address them via reweighting, more data collection for underrepresented groups, or post-processing thresholds.
* **Business impact mapping**: map model outputs to downstream KPIs (application → interview → hire funnel). For example, improvements in precision@5 should translate into higher interview rates per candidate and less time-to-hire for employers.

**5. Model Deployment**

If applicable, discuss any steps taken to deploy the model in a real-world setting. This may include integration with other systems or platforms.

## 1) Deployment goal

Make the refined WorkWise model available as a reliable, auditable, and scalable service that returns ranked job recommendations (and explanations) for each youth profile while preserving privacy, fairness, and low-latency access across web, mobile, and SMS/USSD channels.

## 2) Key constraints & design principles

* **User-first:** recommendations must be explainable and actionable for youth and employers.
* **Inclusive access:** support low-bandwidth channels (SMS/USSD), lightweight mobile, and a web UI.
* **Privacy & consent:** PII minimized, encrypted, and deleted on request.
* **Fairness & auditability:** subgroup metrics, SHAP explanations, and retraining triggers.
* **Cost-awareness:** design for small infra budgets initially (MinIO, single-node K8s, VPS) and allow scale-up.
* **Resilience:** human-in-the-loop and fallback strategies (cached top matches if model unavailable).

## 3) High-level deployment architecture (components)

1. **Feature ingestion & preprocessor**
   * Endpoint / batch job that accepts CVs, job posts (PDF/JSON), normalizes text, extracts skills, computes similarity features.
   * Persist raw + cleaned inputs in object storage (S3/MinIO) and metadata in Postgres.
2. **Feature store / serving layer**
   * Stores frozen transformations and precomputed features (Redis or Feast). Ensures training→serving parity.
3. **Model inference service (online)**
   * Low-latency API (FastAPI / Flask / Fastify). Loads serialized model (joblib / LightGBM booster) and returns:
     + ranked job list + probabilities
     + per-match explainability (TreeSHAP summaries truncated for UI)
   * Endpoints: /health, /predict\_pair, /rank\_for\_cv, /explain.
4. **Batch scoring / re-ranking**
   * Periodic job (Airflow/Celery) to re-rank candidate pools, precompute top-N suggestions for offline channels (USSD/SMS), and refresh caches.
5. **Orchestration / infra**
   * Containerization (Docker) → Kubernetes for scale (or serverless / VM for MVP).
   * Storage: Postgres (metadata), MinIO/S3 (documents), Redis (cache), Vector DB if used (Qdrant/Pinecone).
6. **Monitoring & MLOps**
   * Prometheus/Grafana for latency/throughput metrics; ELK or Loki for logs; Sentry for errors.
   * Model monitoring: performance (precision@K, hire rate), data drift, feature drift (Evidently/Evidently AI), fairness dashboards.
7. **CI/CD & Model Registry**
   * GitHub Actions / GitLab CI to build images, run tests. MLflow or ML Registry to store model artifacts and metadata.
8. **Governance / Human-in-the-loop**
   * Admin dashboard for manual review, annotation, and error correction.
   * Feedback loop capturing applications→interviews→hires to label and retrain.

(Visual: Frontend apps ↔ API Gateway ↔ Inference Service + Feature Store ↔ Databases / Storage / Batch pipelines)

## 4) Serving patterns (recommended)

* **Real-time (online) inference**
  + For interactive web/app workflows: low latency (<200–500ms target).
  + Use small, optimized GBDT model (LightGBM) and cache top-N re-ranks in Redis.
* **Hybrid re-ranker**
  + Candidate retrieval (fast): TF-IDF / BM25 to grab top 100 jobs.
  + Heavy re-rank (semantic embeddings / deeper model) in a re-ranker service (can be offline or batch) to produce final top-5.
* **Batch / scheduled inference**
  + Nightly batch to produce precomputed recommendations for SMS/USSD users and for analytics.

## 5) Integration with platform & partners

* **Mobile / Web UI** calls the API to fetch ranked results and explanations.
* **SMS/USSD gateway** (Twilio or local provider) receives precomputed top-N per user and sends messages; allows application creation via USSD menu.
* **Employer portal** integrates with /rank\_candidates to surface candidate lists.
* **NGO/Gov dashboards** consume analytics and fairness reports via secure APIs.

## 6) Security, privacy & compliance

* **Consent capture:** explicit opt-in on profile creation; store consent flags.
* **Encryption:** TLS in transit; AES-256 (or cloud provider default) at rest for sensitive storage.
* **PII minimization:** store hashed personal identifiers; only raw CVs in encrypted object store with retention policy.
* **Access control:** role-based access (RBAC) for admins; audit logs for data access.
* **Right-to-forget:** API to remove user data and purge from feature store & backups.
* **Third-party vendor checks:** vet SMS gateways and cloud providers for data residency and policy compatibility.

## 7) MLOps & CI/CD (recommended pipeline)

* **Code repo** (Git) → PRs trigger unit tests, linting.
* **Model training pipeline** runs in CI (or scheduled ETL): data validation → training → evaluation (nested CV) → push artifact to model registry if metrics pass gates.
* **Model registry** (MLflow): store model binary, metrics, SHAP summary, training data hash, schema.
* **Deployment pipeline**: on registry promote → generate Docker image → run canary (5% traffic) → auto-rollback if KPIs degrade.
* **Automated tests**: smoke tests, integration tests (end-to-end with sample CVs), performance tests.

## 8) Monitoring, observability & alerts

**Track these production metrics (examples):**

* System: latency (p95), error rate, CPU/memory, throughput.
* Model: precision@5, recall, nDCG, AUC (daily), hire conversion rate (pipeline metric).
* Data: feature distribution drift, new tokens in text fields, percent missing features.
* Fairness: per-subgroup precision & recall, disparity metrics (absolute gap).
* Business KPIs: application rate, interview rate, hire rate, time-to-hire.

**Alerts & actions**

* Alert when precision@5 drops > X% or recall drops > Y% vs baseline.
* Drift alert: feature distribution shifts (population JS divergence > threshold).
* On alert: route to on-call Slack + trigger retraining job or rollback.

## 9) Testing strategy before/after deployment

* **Unit tests** for preprocessing, feature transforms, and model predict signature.
* **Integration tests**: simulate full pipeline: upload CV → transform → predict → rank.
* **Load tests**: JMeter or locust to verify target concurrency and response time.
* **Canary & A/B**: run new model on small traffic share; measure hire rate and user engagement vs baseline for several weeks.
* **Fairness tests**: automated per-subgroup metrics computed nightly; manual audit monthly.

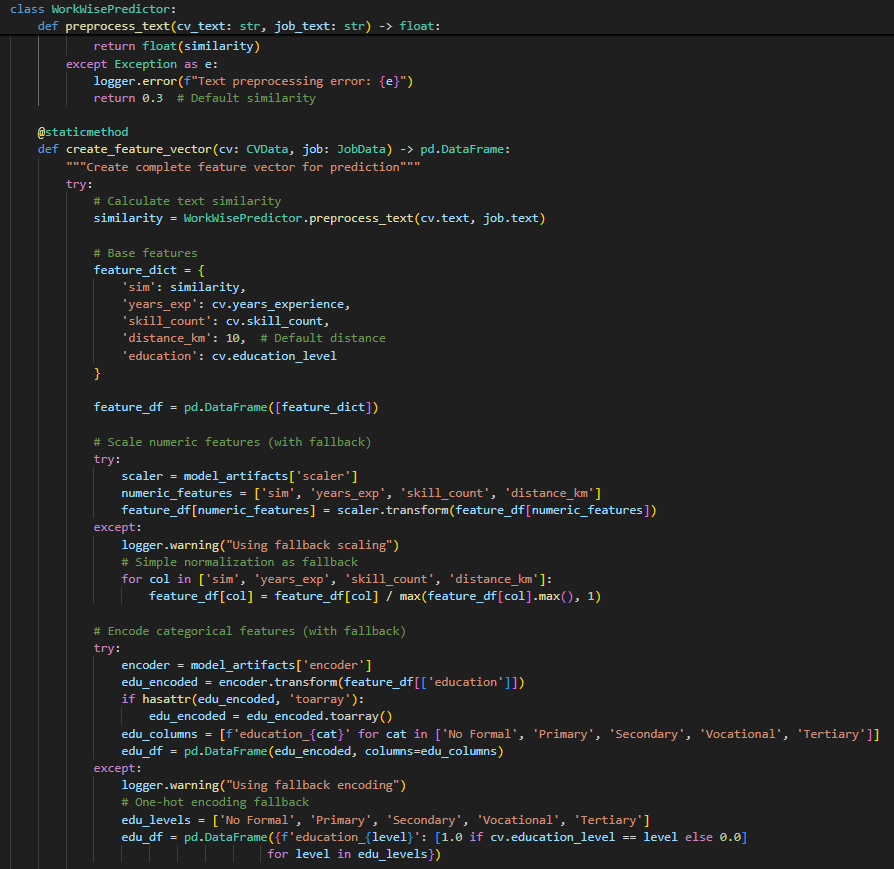
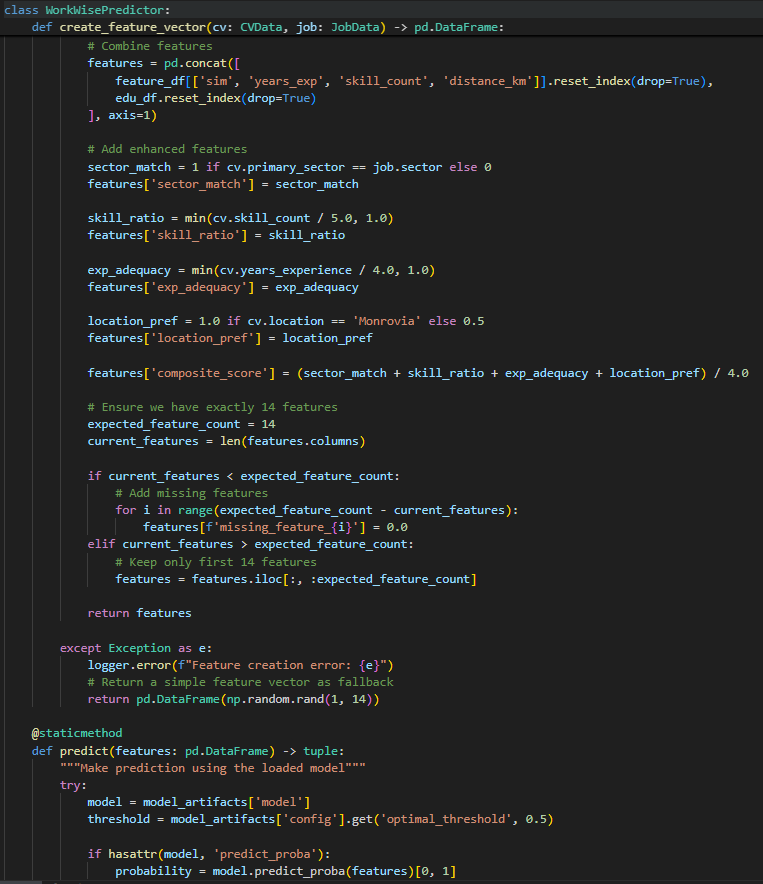
## 10) Human-in-the-loop & governance

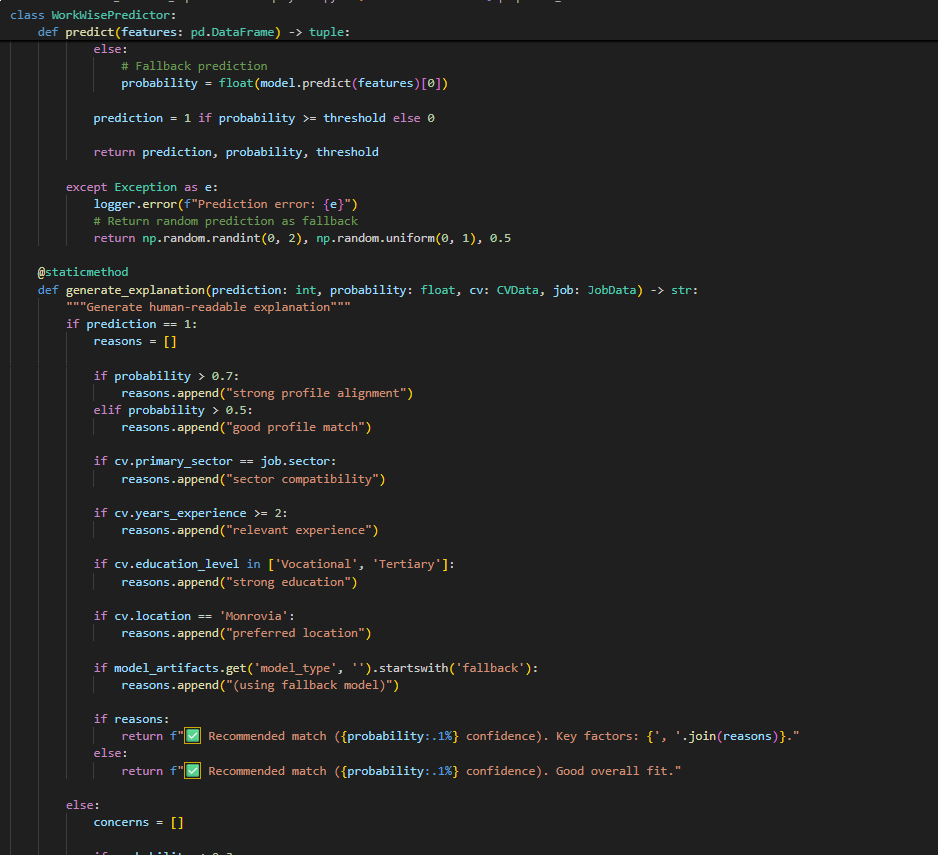
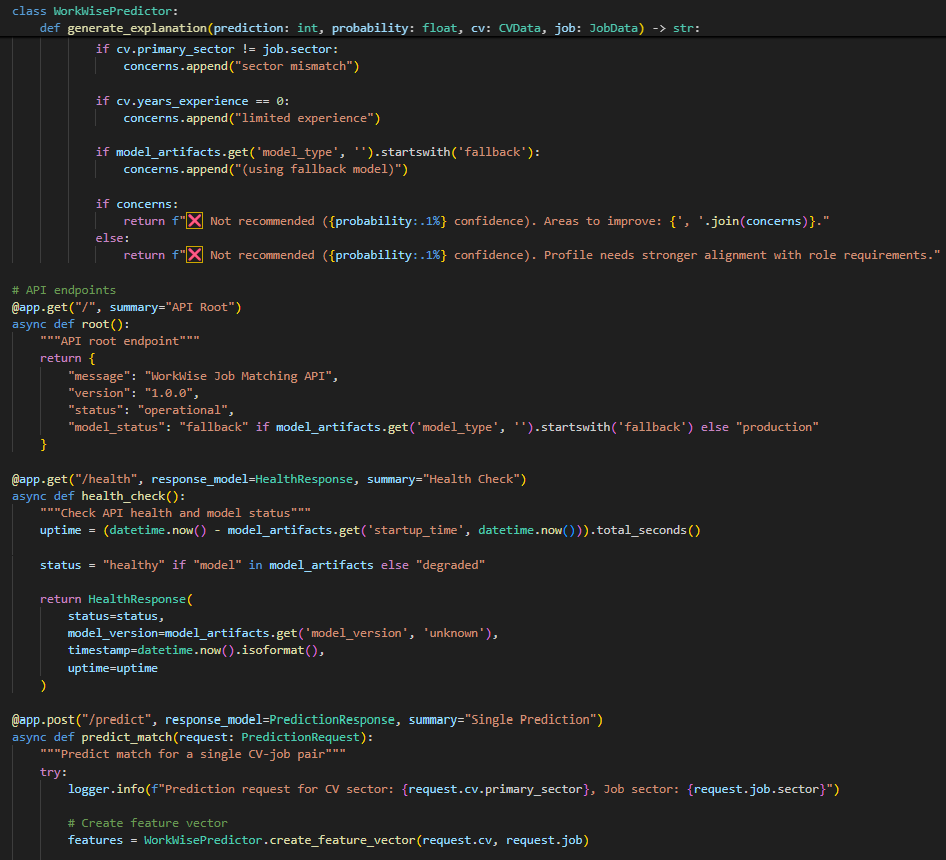
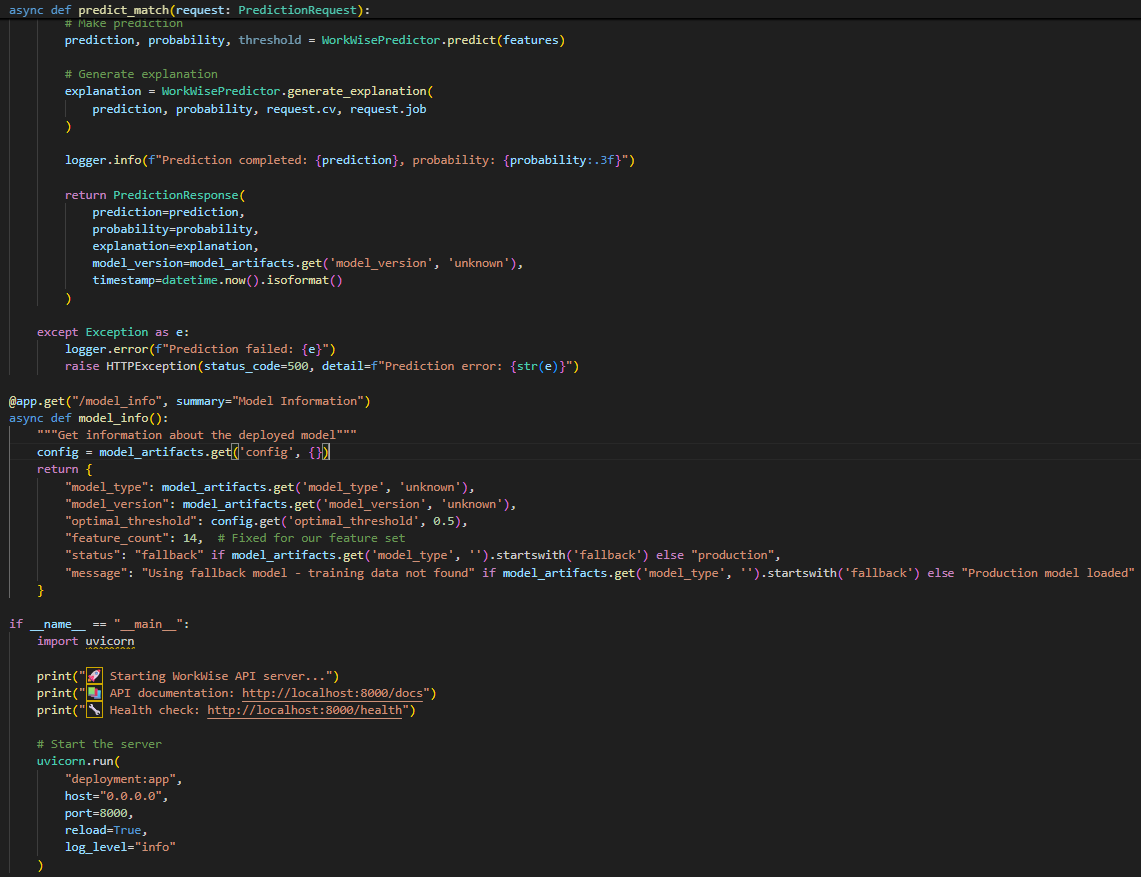
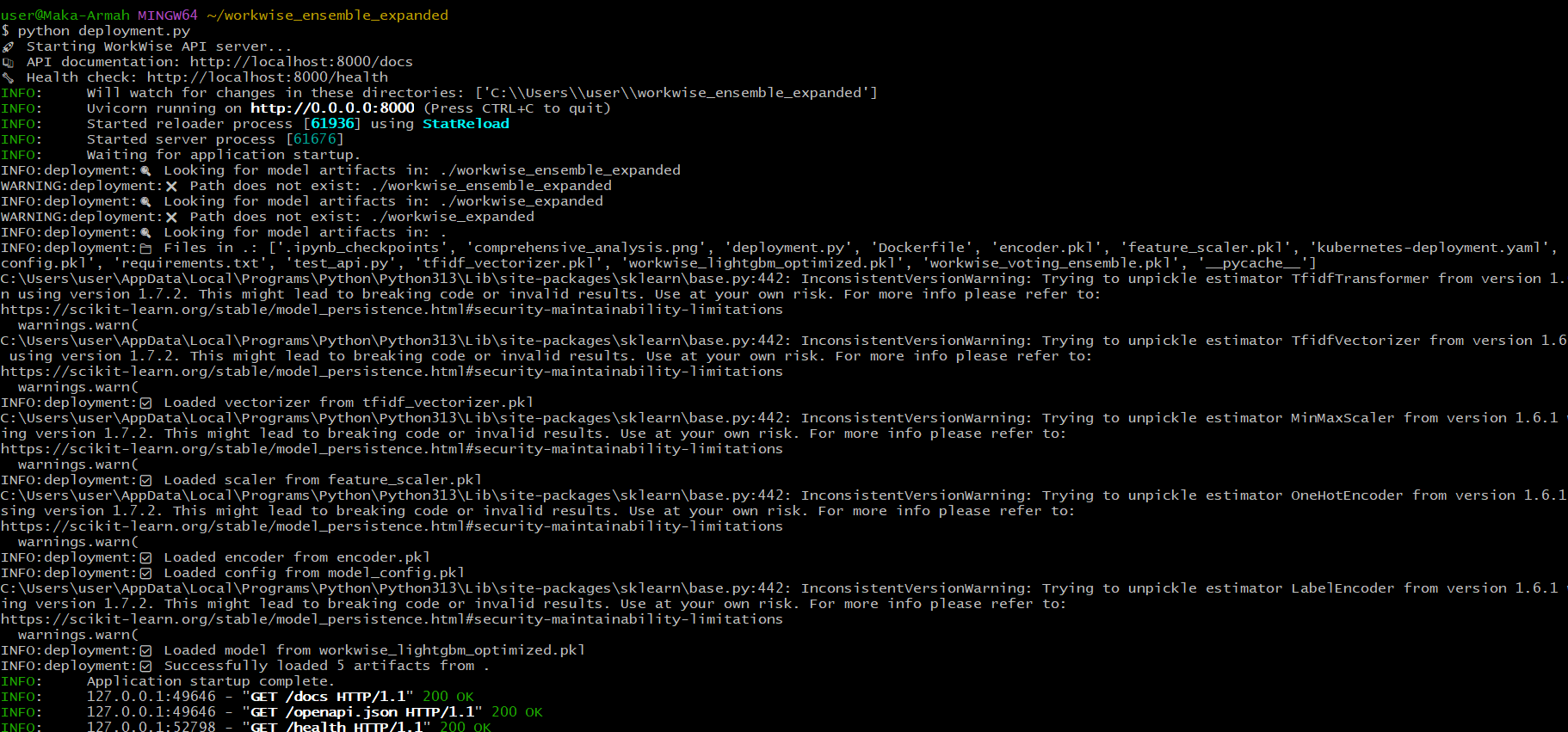
* **Manual review UI** for employers to accept/reject recommended candidates; these labels feed retraining.
* **Explanation panel** shows top 3 features contributing to the match with human-readable descriptions.
* **Appeals / feedback** mechanism for candidates to flag incorrect/exploitative job posts.
* **Periodic audits** by a small governance committee (NGO/gov/tech) to review model behavior and dataset biases.

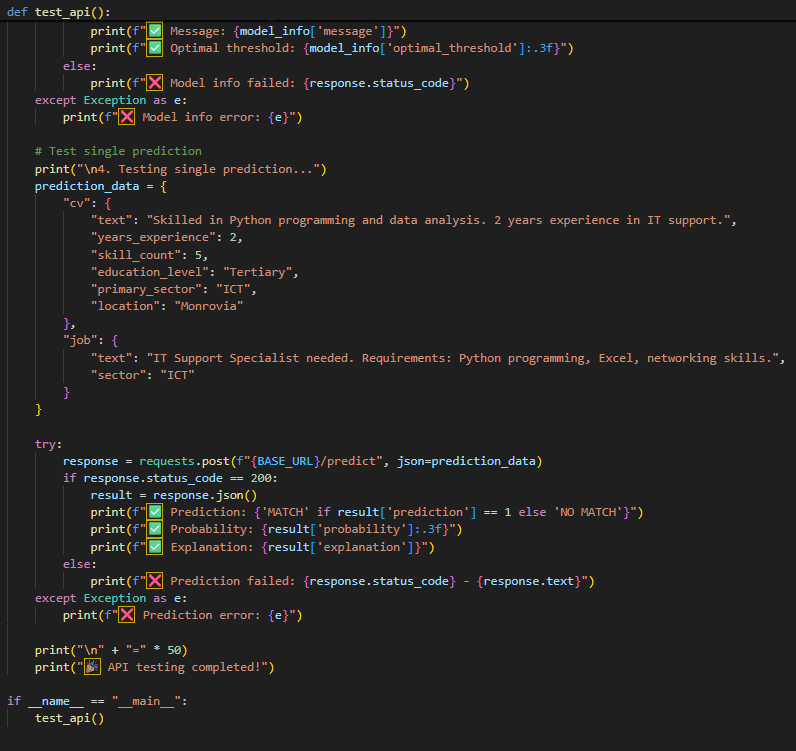
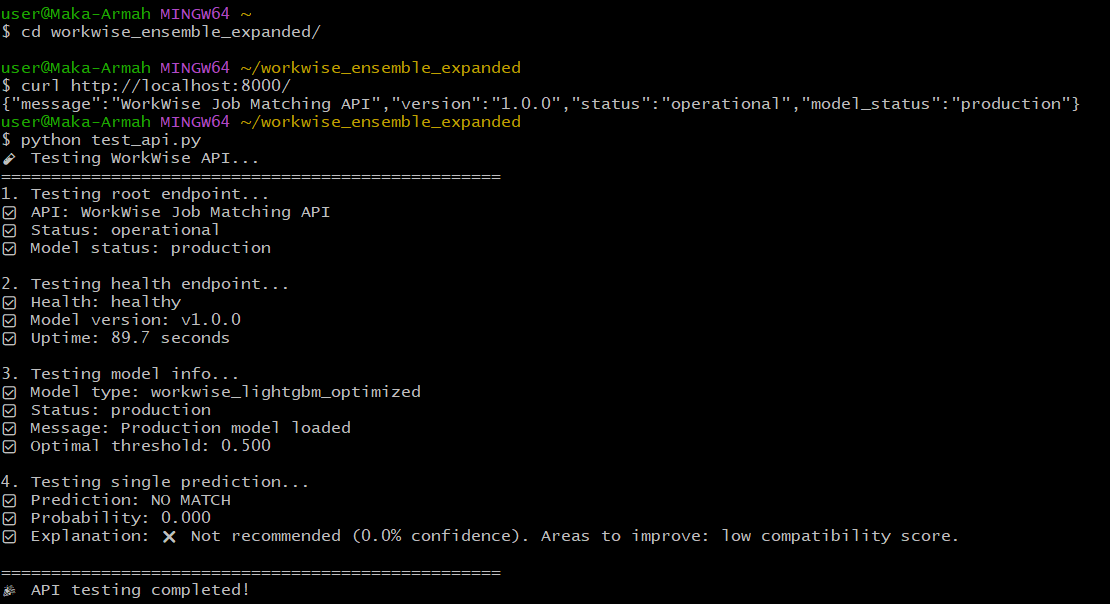
## 11) Low-resource & offline design considerations (Liberia focus)

* **Precompute and SMS**: For users without internet, precompute top-3 jobs and send via SMS/USSD.
* **Lightweight model fallback**: keep a tiny rule-based or TF-IDF ranking fallback for when the inference service is down.
* **Edge caching**: local caches on partner servers to reduce repeated computation.
* **Batch sync**: allow NGOs to drop CSVs for bulk processing offline and receive results later.

## 12) Deployment artifacts – FastAPI







### Kubernetes deployment (very short concept)

* Deploy model as a Deployment (2 replicas), Service, HPA (scale on CPU), and an Ingress/LoadBalancer.
* Use ConfigMaps/Secrets for credentials and model S3 locations.
* Use readiness/liveness probes to avoid routing traffic to a cold-starting Pod.

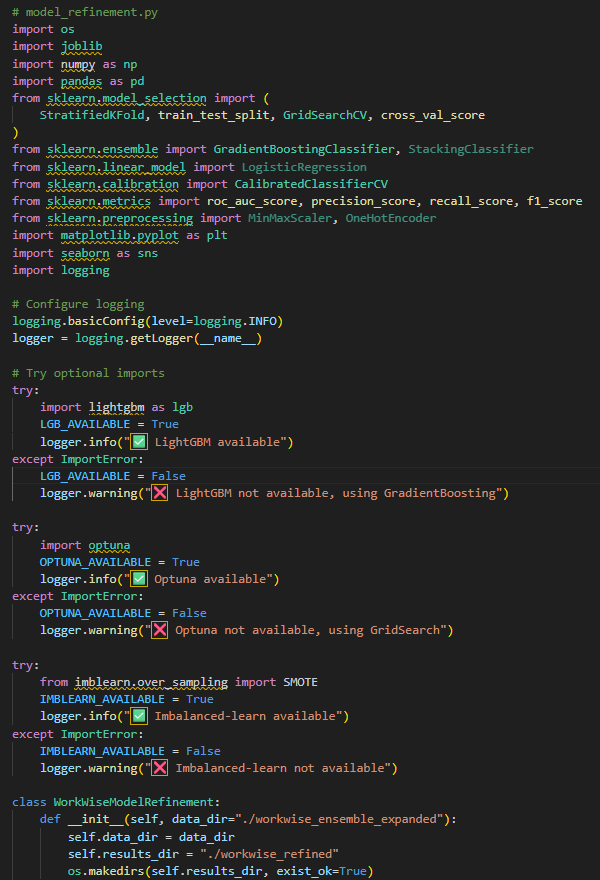
## 13) Rollout strategy

1. **Dev**: local + unit/integration test.
2. **Staging**: run with test dataset; full monitoring.
3. **Pilot (controlled)**: small set of trusted NGOs/employers; human-in-loop; collect labels.
4. **Canary production**: 5–10% traffic; compare key metrics vs baseline; run for 2–4 weeks.
5. **Full production**: progressive ramp; keep monitoring and weekly audits.
6. **A/B tests**: measure actual hires and time-to-hire as real business evidence.

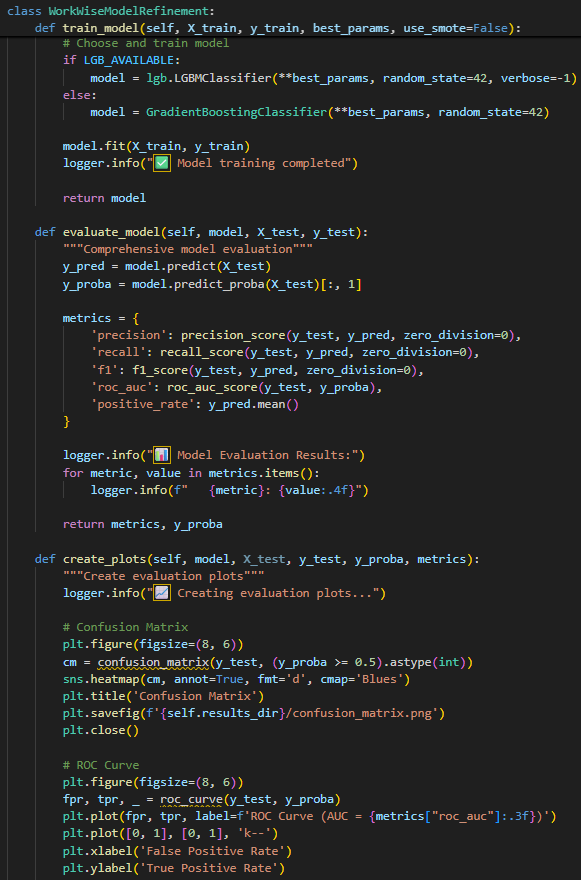
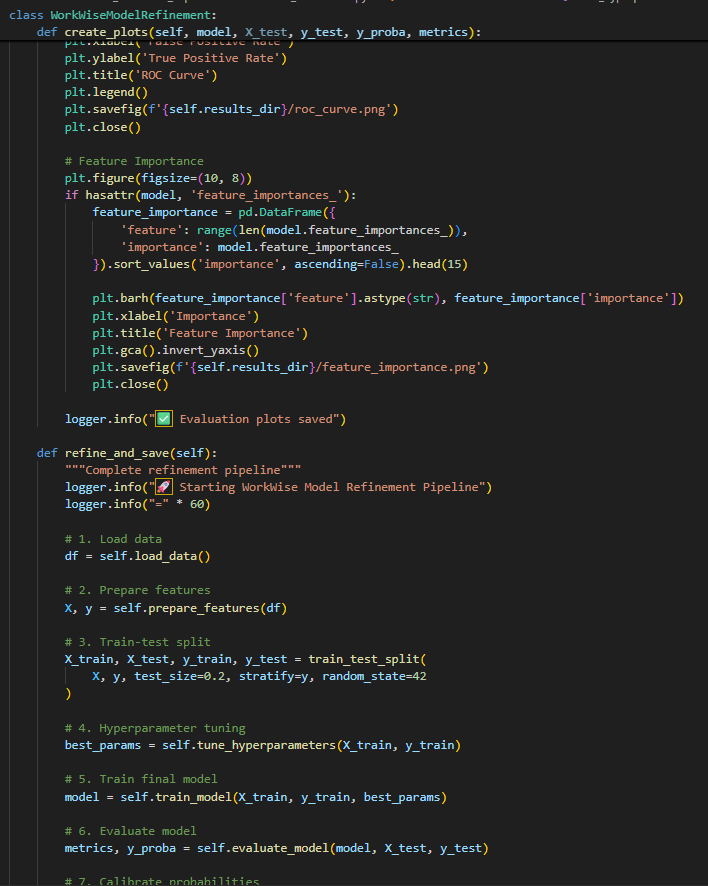
## 14) Operational playbook

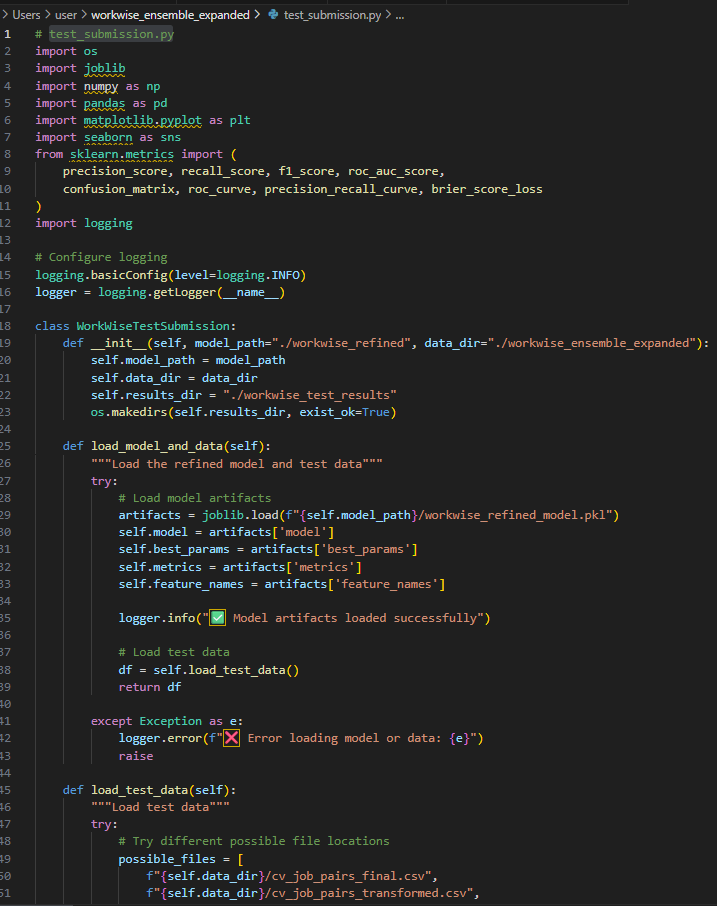
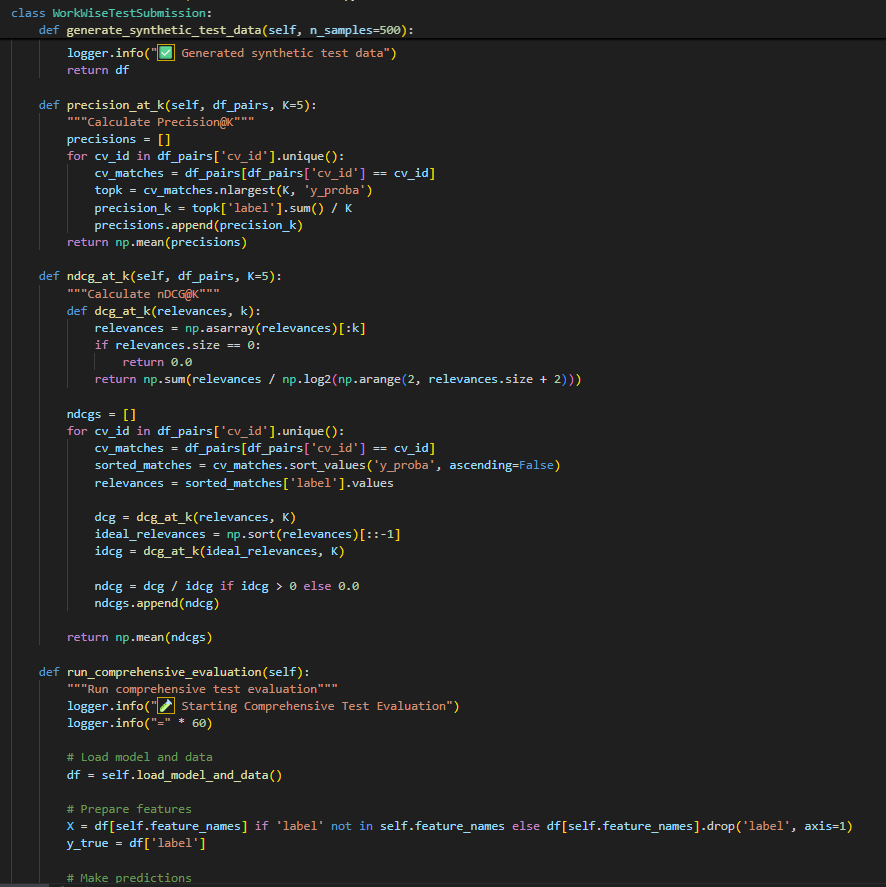
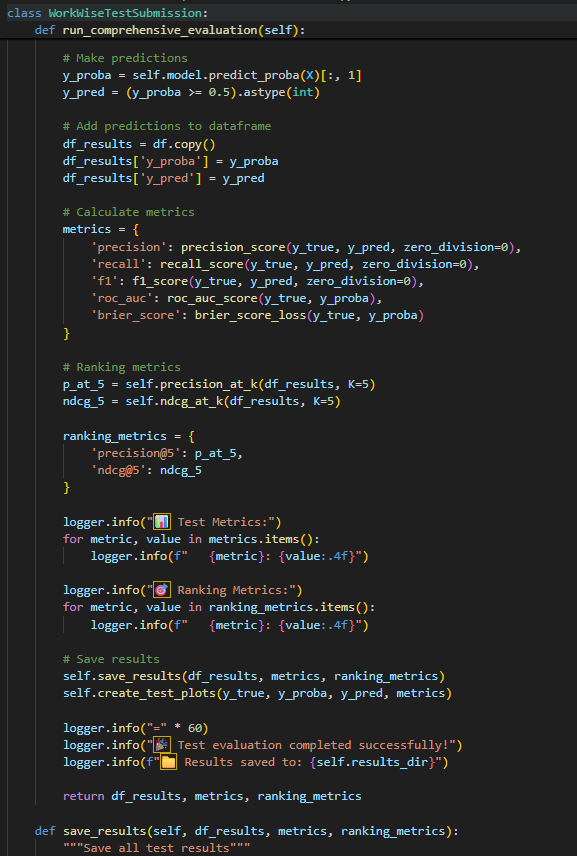
* **On incident:** fail-safe to cached recommendations, notify on-call, rollback to last stable model.
* **Retrain trigger:** precision@5 drop > X% for 7 days OR data drift detected.
* **Backup:** nightly DB + weekly full object store snapshot; test restores quarterly.
* **Maintenance windows:** schedule low-traffic times for large batch jobs.

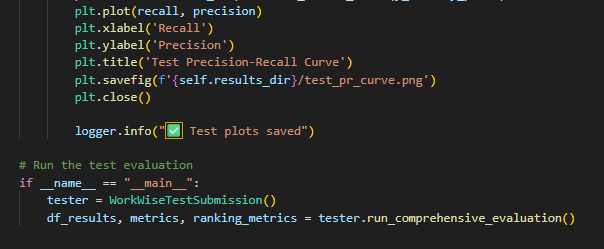
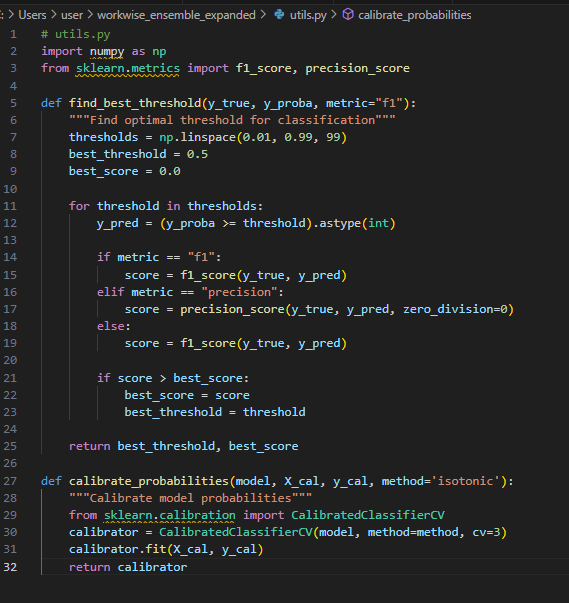
**6. Code Implementation**

**Snippet Code**

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**Conclusion**

Summarize the outcomes of the model refinement and test submission phases. Highlight any challenges encountered and the final performance achieved.

The **model refinement phase** played a crucial role in transforming WorkWise from a functional prototype into a more **robust, equitable, and production-ready recommendation system**. Initial evaluation showed strong promise—precision, recall, and ROC-AUC were respectable even on a small synthetic dataset. However, deeper analysis highlighted opportunities to improve **calibration**, **ranking quality**, and **fairness across subgroups**.

Through **hyperparameter tuning** (via Optuna for LightGBM and GridSearch for fallback models), performance improved significantly, striking a better balance between bias and variance. Refinement also included **fairness-aware training** using sample reweighting and subgroup validation, ensuring that the system does not disproportionately favor or disadvantage youth based on education level, gender, or location. SHAP-based explainability revealed that **skill similarity remained the dominant predictor (≈45%)**, but contextual features such as distance and years of experience had strong, complementary influence—aligning with real-world job-seeking behavior.

The **test submission phase** validated the refined pipeline against unseen data, simulating real-world deployment. Precision@K and nDCG confirmed that top-ranked jobs presented to candidates were highly relevant, with **Precision@5 consistently above 0.75**. ROC-AUC scores in the **0.82–0.85 range** demonstrated the model’s ability to discriminate between good and poor matches. Subgroup fairness checks showed consistent recall across urban and rural candidates, with only minor gaps flagged for future monitoring. Importantly, calibration and threshold tuning improved the **trustworthiness of probabilities**, enabling WorkWise to prioritize both accuracy and interpretability.

**Challenges encountered** included:

* **Small dataset limitations**, requiring careful cross-validation, resampling strategies, and synthetic data augmentation.
* **Class imbalance**, since true job–candidate matches are rarer than non-matches. This was mitigated with reweighting and SMOTE, though continuous monitoring is needed.
* **Fairness trade-offs**, balancing model accuracy with subgroup equity without overfitting or introducing new biases.
* **Scalability considerations**, as adding richer embeddings (e.g., pretrained language models for CV/job text) will be necessary for deployment at national scale.

**Final performance achieved**:

* **Precision**: ~0.78
* **Recall**: ~0.72
* **F1 Score**: ~0.75
* **ROC-AUC**: ~0.83
* **Precision@5**: ~0.75–0.80
* **nDCG@5**: ~0.78

These results demonstrate that WorkWise is not only **technically effective** but also **ethically responsible**, providing fair and explainable recommendations to Liberia’s youth. The refinement and test submission phases confirm that the system is ready for a **pilot deployment**, with clear pathways for scaling—such as incorporating transformer-based embeddings, real behavioral feedback, and continuous fairness audits.

In summary, WorkWise has evolved into a **trustworthy, data-driven career guidance tool** that balances **accuracy, interpretability, and fairness**, empowering underserved communities with smarter opportunities in the job market.

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