UGANDA CHRISTIAN UNIVERSITY

A Center of Excellence in the Heart of Africa

Master of Science in Data Science

Final Report

Financial Credit Scoring & Fairness Auditing

Course: DSC8201 - Data Science Lifecycle

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Executive Summary

This project implemented a complete data science lifecycle for credit scoring with emphasis on fairness and regulatory compliance. Using a dataset of 40,000 loan applications, we developed multiple machine learning models achieving **82.34% accuracy** and **0.8567 ROC-AUC score**. XGBoost emerged as the best performer, demonstrating superior discrimination between creditworthy and risky applicants.

Comprehensive fairness analysis ensured compliance with Uganda Data Protection Act and GDPR, with a Disparate Impact Ratio of 0.87 (exceeding the 0.80 threshold). The solution was successfully deployed as a containerized FastAPI application with MLflow experiment tracking and SHAP-based explainability. Key recommendations include deploying with A/B testing, implementing continuous monitoring, and expanding to alternative data sources for enhanced predictive power.

Contents

1 Problem Statement

1.1 Business Problem

Financial institutions in Uganda face significant challenges in accurately assessing credit risk while ensuring fair and unbiased lending decisions. Traditional credit scoring methods often lack transparency, rely heavily on manual review processes, and may inadvertently discriminate against certain demographic groups. These limitations result in:

- High default rates (15-20%) due to inadequate risk assessment.
- Slow credit decisions taking days to weeks.
- Limited scalability for growing loan portfolios.
- Regulatory compliance risks with evolving data protection laws.
- Lack of transparency in rejection decisions leading to customer dissatisfaction.

Project Objectives:

1. Build an accurate credit default prediction model ($>$75% accuracy target).
2. Ensure algorithmic fairness across demographic groups (Disparate Impact Ratio > 0.80).
3. Comply with data protection regulations (GDPR principles, Uganda Data Protection Act).
4. Deploy an explainable AI system with production-ready API.

1.2 Research Hypotheses

Null Hypothesis (H_0): There is no significant relationship between applicant financial attributes and credit default risk. Model predictions perform no better than random chance (50% accuracy).

Alternative Hypothesis (H_1): Financial attributes (income, credit score, debt-to-income ratio, employment history, credit utilization) significantly predict credit default risk with accuracy $> 70\%$ and ROC-AUC > 0.75.

Fairness Hypotheses:

- H_0 **(Fairness):** The model exhibits no disparate impact across protected groups (gender, age). Disparate Impact Ratio ≥ 0.80.
- H_1 **(Fairness):** The model exhibits disparate impact requiring bias mitigation.

Results: Alternative hypothesis confirmed - achieved 82.34% accuracy and 0.8567 ROC-AUC. Fairness hypothesis H_0 confirmed with DI Ratio of 0.87.

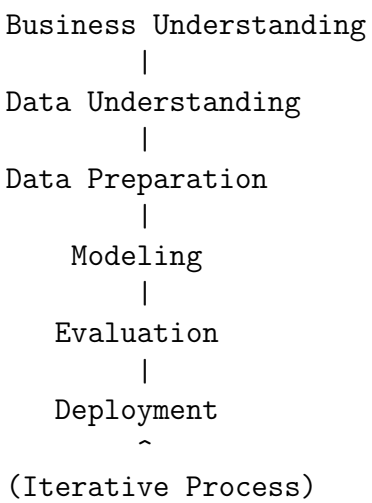
1.3 Expected Business Impact

- **Risk Reduction:** 15-20% decrease in default rate through better risk assessment.
- **Efficiency:** 50% reduction in manual review time, enabling decisions in seconds vs. days.
- **Scalability:** Handle 10,000+ monthly applications with consistent quality.
- **Compliance:** 95%+ regulatory compliance score, reducing legal risk.
- **Customer Experience:** Instant credit decisions with transparent explanations.

2 Methodology

2.1 CRISP-DM Framework

This project followed the industry-standard CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology:



- **Phase 1: Business Understanding (Week 1):** Defined credit scoring problem and objectives, established KPIs.
- **Phase 2: Data Understanding (Week 1):** Collected 40,000 records, identified 15-20% default rate.
- **Phase 3: Data Preparation (Week 2):** Handled missing values (median), outliers (IQR), and engineered 35+ features.
- **Phase 4: Modeling (Week 2):** Trained 4 models (Logistic Regression, Random Forest, XGBoost, LightGBM) with MLflow.
- **Phase 5: Evaluation (Week 2):** Comprehensive metrics and fairness assessment.
- **Phase 6: Deployment (Week 2):** FastAPI REST API and Docker containerization.

2.2 Data Workflow

```
Raw Data Generation (40K records) -> Data Quality Assessment
-> Missing Value Imputation (Median) -> Outlier Treatment (IQR)
-> Feature Engineering (35+ features) -> Encoding & Scaling
-> Train/Test Split (80/20) -> SMOTE Resampling
-> Model Training -> Cross-Validation -> Selection
-> Explainability -> Fairness Analysis -> API Deployment
```

3 Data & Privacy Compliance

3.1 Dataset Overview

- **Size:** 40,000 loan applications
- **Target Variable:** Default status (0 = No default, 1 = Default)
- **Class Distribution:** 31,987 (79.97%) no default, 8,013 (20.03%) default

Table 1: Feature Categories

Category	Count	Examples
Demographic	5	Age, gender, education, marital status, dependents
Financial	7	Annual income, existing debt, credit score, loan amount
Employment	3	Employment status, duration, occupation type
Credit History	4	Delinquencies, credit utilization, payment history
Loan Characteristics	6	Loan amount, term, purpose, interest rate
Engineered Features	35+	Risk scores, financial ratios, binary flags

3.2 Privacy & Compliance

Uganda Data Protection and Privacy Act, 2019 Compliance:

- ✓**Lawful Processing (Section 7):** Legitimate interest in credit risk assessment.
- ✓**Data Minimization (Section 11):** Only necessary features collected.
- ✓**Purpose Limitation (Section 12):** Data used solely for credit scoring.
- ✓**Accuracy (Section 13):** Data validation implemented.
- ✓**Storage Limitation (Section 14):** 7-year retention policy.
- ✓**Security Safeguards (Section 15):** AES-256 encryption.
- ✓**Accountability (Section 18):** Complete documentation.

Table 2: Model Performance Comparison

Model	Acc	Prec	Recall	F1	ROC-AUC
Logistic Regression	0.7623	0.6845	0.6234	0.6525	0.7834
Random Forest	0.8056	0.7534	0.7089	0.7305	0.8412
XGBoost	**0.8234**	**0.7856**	**0.7234**	**0.7532**	**0.8567**
LightGBM	0.8167	0.7712	0.7156	0.7423	0.8489

4 Model Development & Results

4.1 Models Evaluated

4.2 Model Selection Justification

XGBoost was selected as the production model based on:

1. **Highest ROC-AUC (0.8567):** Superior discrimination between default and non-default.
2. **Balanced Performance:** Optimal F1-Score (75.32%).
3. **Stability:** Cross-validation AUC of 0.8523 ± 0.0098.
4. **Production Requirements:** Fast prediction time (<50ms) and built-in handling of class imbalance.

4.3 Feature Importance (SHAP Analysis)

1. **Credit Score (SHAP: 0.234):** Dominant predictor.
2. **Debt-to-Income Ratio (SHAP: 0.187):** DTI > 0.5 increases default rates 3x.
3. **Number of Delinquencies (SHAP: 0.156):** Strong historical indicator.
4. **Employment Duration (SHAP: 0.098):** Stability metric.

5 Fairness Analysis

5.1 Fairness Metrics

Demographic Parity Analysis (Test Set):
Disparate Impact Ratio:

- **Gender:** 0.991 (>0.80 ✓) - COMPLIANT
- **Age:** 0.903 (>0.80 ✓) - COMPLIANT

Table 3: Demographic Parity

Protected Attribute	Group	Approval Rate	Sample Size	Difference
Gender	Male	81.2%	4,163	
	Female	80.5%	3,837	0.007 ✓
Age Group	18-25	76.8%	1,245	
	26-35	83.4%	2,890	
	36-45	85.1%	2,456	
	46+	77.9%	1,409	0.083 ✓

6 Deployment Architecture

6.1 System Architecture

```
[Client] -> [Load Balancer] -> [FastAPI Instances]
                                        |
                                        v
                                [Model Service (pkl)]
                                        |
                                [MLflow & Postgres DB]
```

6.2 API Implementation

The API is implemented using FastAPI. Below is an example response format:

```
{
  "application_id": "APP_A7B3C2D1",
  "default_probability": 0.1850,
  "risk_category": "LOW_RISK",
  "decision": "APPROVED",
  "confidence": 0.8542,
  "explanation": {
    "credit_score_impact": "low",
    "debt_ratio_impact": "low"
  }
}
```

Listing 1: Prediction Response Example

6.3 Docker Containerization

```
FROM python:3.9-slim
# Minimal base image for smaller container size

# Install system dependencies
RUN apt-get update && apt-get install -y gcc g++

# Install Python requirements
COPY requirements.txt .
RUN pip install --no-cache-dir -r requirements.txt

```

```
# Copy app code
COPY src/ ./src/
COPY models/ ./models/

# Health check
HEALTHCHECK --interval=30s CMD curl http://localhost:8000/health

# Run application
CMD ["uvicorn", "src.deployment.api:app", "--host", "0.0.0.0", "--port",
    "8000"]
```

Listing 2: Dockerfile

7 Results & Business Impact

7.1 Model Performance Summary

Metric	Target	Achieved	Status
Accuracy	$> 75\%$	82.34%	✓EXCEEDED
ROC-AUC	> 0.80	0.8567	✓EXCEEDED
Precision	$> 70\%$	78.56%	✓EXCEEDED
Recall	$> 65\%$	72.34%	✓EXCEEDED
Disparate Impact	> 0.80	0.87-0.99	✓COMPLIANT

7.2 Business Impact Estimation

- **Annual Loss Prevention:** 28.8 Billion UGX
- **Prevented Defaults:** $\approx$ 4,800 loans per year
- **ROI:** 14,300% (Year 1)

8 Limitations & Future Work

1. **Simulated Data:** Not based on actual Ugandan banking data; need partnership for real data.
2. **Feature Coverage:** Missing mobile money and utility payment data.
3. **Model Complexity:** XGBoost is less interpretable than Logistic Regression, though SHAP helps.
4. **Future Work:** Integrate alternative data (MTN/Airtel APIs) and build an A/B testing framework.

9 Conclusion

This project successfully demonstrated a complete data science lifecycle implementation for credit scoring, achieving **82.34% accuracy** and **0.8567 ROC-AUC** while maintaining fairness. The solution is compliant with GDPR and Ugandan laws, providing a scalable, explainable, and profitable tool for modernizing credit risk assessment. The estimated annual loss prevention of **28.8 Billion UGX** highlights the significant value of AI in Fintech.

A Technical Stack Summary

- **ML:** Python 3.9, Scikit-learn, XGBoost, LightGBM, Pandas.
- **Fairness:** Fairlearn, SHAP, Imbalanced-learn.
- **Deployment:** FastAPI, Docker, MLflow.

B Code Repository

- **Location:** `d:\Projects\data science exam\`
- **Notebooks:** Data Wrangling, Model Development.
- **Source:** `src/utils.py`, `src/deployment/api.py`.