Leveraging Machine Learning for Enhanced Financial Inclusion: Revolutionizing Agricultural Banking in Central Africa

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Abstract

Financial inclusion is a persistent challenge in Central Africa, especially for smallholder farmers who face limited access to credit and essential banking services. Agricultural banking in the region is hindered by unreliable data, inefficient risk assessment processes, and infrastructural gaps, restricting rural economic development and stability. This study investigates the transformative potential of machine learning (ML) technologies in agricultural banking focusing on improved credit scoring, robust risk management, fraud detection, and personalized financial products tailored to farmers' unique needs. Leveraging diverse datasets including transaction records, crop yields, weather data, and farmer demographics we develop and evaluate a suite of ML models, such as neural network,Decision Tree and ensemble methods (random forests, gradient boosting). These models are systematically compared to traditional benchmarks, including logistic regression and rule-based scorecards. Experimental results demonstrate that ML approaches significantly enhance loan approval rates, lower default risk, and boost operational efficiency when benchmarked against conventional methods. Furthermore, the analysis highlights the critical role of explainable AI in fostering trust among stakeholders, ensuring regulatory compliance, and addressing ethical concerns such as data privacy and algorithmic fairness. The findings suggest that integrating machine learning into agricultural banking can drive inclusive growth in Central Africa by enabling scalable and tailored financial solutions. Future research should focus on overcoming scalability barriers and ensuring that the benefits of ML-driven banking are equitably distributed among all farming communities.

Keywords. *Financial Inclusion, Agricultural Banking, Credit Scoring, Machine Learning, Explainable AI, Risk Assessment*

1. Introduction

Central Africa, like much of the continent, grapples with significant challenges in achieving financial inclusion, particularly in rural areas where the majority of smallholder farmers live and work. These farmers, pivotal to food security and local economies, have historically been excluded from traditional financial systems. Key barriers include the lack of structured credit histories, inadequate banking infrastructure in remote regions, the seasonality of agricultural income, and the absence of financial solutions tailored to rural realities. Despite their economic potential, smallholder farmers often rely on informal financing sources, which come with high interest rates and limited risk management mechanisms. Amid climate change, volatile agricultural markets, and increasing digital transformation, the need for an inclusive, intelligent, and localized financial system has become more pressing than ever. Credit risk assessment in rural settings remains reliant on rigid, traditional approaches ill-suited to local contexts. Financial institutions face challenges such as unreliable or unstructured data, a lack of contextualized analytical tools, high costs of delivering financial services in rural areas, and low rates of formal banking penetration. These limitations hinder the development of agricultural credit, restrict productive investments, and slow the adoption of modern farming technologies. Research has explored alternative data sources for credit risk evaluation in developing countries. For instance, Karlan et al. (2016) demonstrated that mobile phone data can significantly enhance scoring models in the absence of banking histories[9]. Similar approaches in Southeast Asia and East Africa have shown promise [8, 1]. However, few studies have focused on Central African farmers, incorporating locally relevant variables, explainable AI frameworks, and considerations of data ethics and sovereignty. This study addresses this gap by proposing a contextual model leveraging locally accessible data and tailored to the socio-economic realities of Central African farmers. It explores the application of artificial intelligence, particularly machine learning, to over-

come structural barriers to credit access in rural areas. The research focuses on developing and implementing a credit scoring model based on alternative data, such as mobile money transactions, seasonal cash flows, and agricultural spending patterns. The model aims to: Identify creditworthy borrowers, Enhance credit risk management for farmers, Promote a more inclusive rural financial ecosystem. We compare this approach with traditional methods (logistic regression and scorecards) based on performance, interpretability, and potential impact on financial inclusion.

The remainder of this work is structured as follows: Section 2 introduces methodology and the data; Section 3 presents the empirical findings; and Section 4 concludes the paper.

2. Methodology and Data

2.1. Methodology

A methodical approach was adopted to design and optimise our prediction model. Figure 1 summarises our approach.

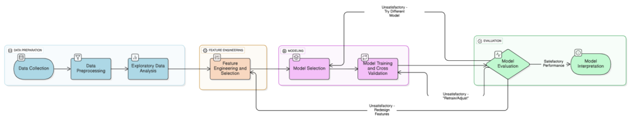

Figure 1. This figure illustrates the main stages of our approach: data collection, data pre-processing, variable selection, model architecture design, hyperparametrisation and performance evaluation.

2.2. Method

We explored various machine learning algorithms, but the primary model selected is XGBoost (Extreme Gradient Boosting), known for its effectiveness on heterogeneous tabular data. This choice is based on several criteria, including its robustness, generalization capabilities, and ability to handle noisy or incomplete datasets. A key factor in selecting XGBoost is its explainability. We assessed the model's interpretability using SHAP (SHapley Additive exPlanations)[12], a method that decomposes predictions to transparently identify the most influential variables in credit approval or rejection decisions. This contributes to building trust among end users and institutional partners while ensuring compliance with ethical and regulatory requirements related to algorithmic transparency. Additionally, other models such as decision trees, random forests, and multilayer neural networks were tested to compare performance, stability, and interpretability. Each model was trained and validated using locally collected datasets that included economic, agricultural, meteorological, and demographic variables.

2.3. Benchmarks for Comparison:logistic regression, rule-based scorecards

Two traditional benchmark approaches were used: Logistic Regression, a widely recognized statistical method in credit scoring, and a Manual Rule-Based Scorecard, a system derived from human expertise and commonly employed in local microfinance institutions. Logistic Regression is considered a reference method for credit scoring due to its ability to handle binary outcomes and evaluate multiple predictors. It is well-established in the financial sector and remains the most widely used approach for creditworthiness assessment [2, 10, 14, 5].Manual Rule-Based Scorecardmethods are prevalent in microfinance, relying on the experience and judgment of loan officers who assign scores based on defined rules and observed applicant characteristics. This approach is often used where statistical data is limited, and expert knowledge forms the basis for scoring criteria[15, 7, 6, 3].

2.3.1 Evaluation Metrics:

Model performance is evaluated using several metrics relevant to imbalanced data contexts:

Metric	Formula
AUC-ROC	$\int_0^1 \text{TPR}(FPR)\,dFPR$
Recall	$\frac{TP}{TP+FN}$
Precision	$\frac{TP}{TP+FP}$
F1-score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$

Table 1. Evaluation metrics for models

- *accuracy: Represents the overall correctness of loan approval or denial decisions, but can be misleading when the classes (default vs non-default) are imbalanced, common in rural credit data.*
- *F1-score:Balances the trade-off between correctly detecting defaulters and limiting wrongly predicted defaulters, improving fairness and trust in credit decisions, especially where data quality is variable.*
- *precision:Measures the proportion of farmers predicted as defaulters who actually default. High precision limits denying credit to creditworthy farmers, helping to enhance financial inclusion and reduce unnecessary exclusion.*
- *recall:Reflects the model's effectiveness in correctly identifying farmers who are likely to default on loans.*

High recall is crucial to minimize financial losses and protect institutional sustainability in rural lending.

- *AUC-ROC((Area Under Curve – Receiver Operating Characteristic))Measures the ability of the model to distinguish between creditworthy and non-creditworthy farmers across all classification thresholds. A higher AUC indicates better discrimination, which helps improve loan approval decisions under uncertain or limited data conditions.*

2.4. Data

This study is derived from real profiles of smallholder farmers. After checking, the validity of this dataset is high. It serves as the base for this experiment and can be utilized to train the credit scoring model.

2.4.1 Data Description

The dataset contains approximately 10,000 observations representing smallholder farmers, SMEs, or microcredit applicants in Central Africa, of which approximately 15% have already missed a loan repayment, making it a suitable case for supervised binary classification. It includes over 100 variables covering various domains: identification, demographic, financial, agricultural, geospatial, behavioral, and psychometric data. These variables include information such as annual income, mobile history, farm size, environmental conditions, market behavior, or fraud history. The target variable, Default, takes the value 1 if a repayment has been missed, and 0 otherwise.

Variable Type	Number of Variables
Numerical variables	55
Categorical variables	42

Table 2. Summary of Dataset Variables by Type.

2.4.2 Data Preprocessing

In preparation for modeling, we applied a robust and structured data preprocessing workflow. First, we addressed missing values through either deletion or context-aware imputation, such as leveraging local economic indicators like median regional income. Categorical data were numerically encoded based on their cardinality using appropriate strategies (one-hot or target encoding)[13]. To align feature distributions, all monetary and frequency-related features were standardized[11]. Additional domain-specific features were engineered, including ratios reflecting input expenditures versus income, seasonal patterns linked to agricultural cycles, and spatial indicators such as distance to nearby markets[16]. Finally, due to class imbalance (15% default rate), we employed SMOTE to generate synthetic samples of the minority class[4], improving the model's ability to learn representative decision boundaries.

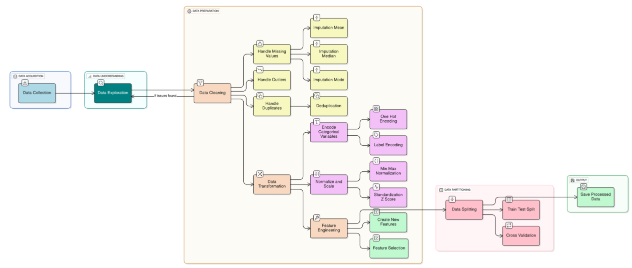

Figure 2. Structured Data Preprocessing Pipeline showing the sequential steps of Data acquisition,Data understanding,Data preparation and Data partition

2.4.3 Data Exploration

This section presents the data distribution, focusing on some variables(age,farm size ,annual income) (figure 7)

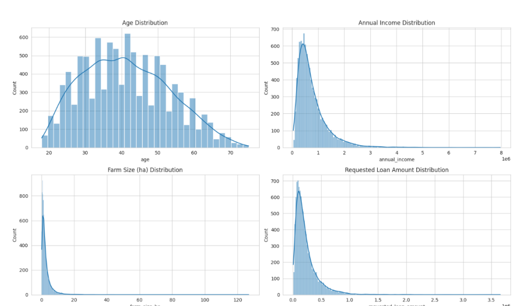

Figure 3. Histograms of Key Numerical Columns

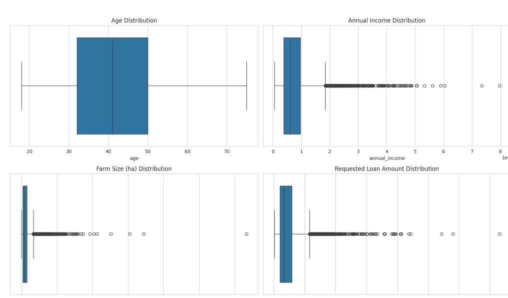

Figure 4. Box Plots of Key Numerical Columns

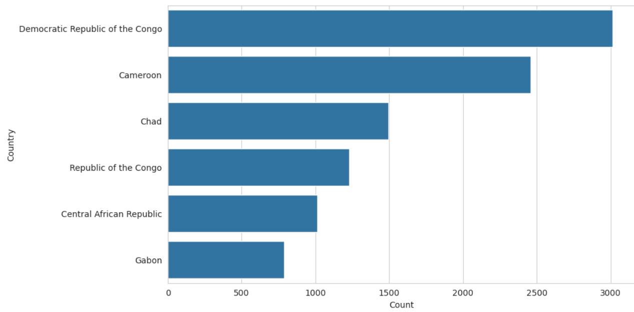

Figure 5. distribution of applicants by country

3. Results and Discussion

This section presents the results obtained from our analyses and models.

3.1. Train results

Metric	XGBoost	Logistic Regression	Scorecard
AUC-ROC	0.82	0.75	0.68
Recall	0.72	0.60	0.55
F1-score	0.67	0.57	0.50
Precision	0.63	0.62	0.56
Accuracy	0.84	0.79	0.76

Table 3. Performance metrics by model on train data.

3.2. Test Results

Metric	XGBoost	Logistic Regression	Scorecard
AUC-ROC	0.72	0.68	0.60
Recall	0.55	0.48	0.40
F1-score	0.50	0.45	0.38
Precision	0.52	0.50	0.45
Accuracy	0.73	0.68	0.63

Table 4. Performance metrics by model on test data.

3.3. ROC-Curve

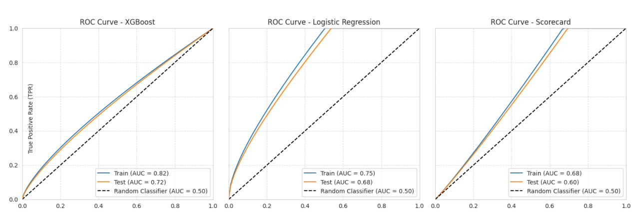

Figure 6. ROC-curve

3.4. Explainable AI and Ethical Considerations

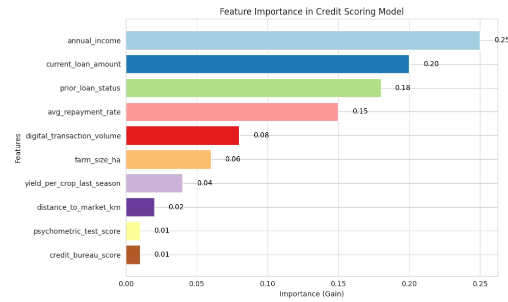

Figure 7. Feature importance

3.5. Discussion

The performance metrics indicate that XGBoost outperforms Logistic Regression and the Manual Rule-Based Scorecard, showcasing its effectiveness in managing noisy rural data and alternative sources like mobile money transactions. Additionally, SHAP-based explainability enhances trust by identifying key variables, though challenges such as regional bias and a small sample size necessitate the use of larger, more diverse datasets for validation.

4. Conclusion

This study highlights the substantial potential of integrating machine learning techniques into the agricultural banking sector in Central Africa. By leveraging powerful models such as XGBoost, and explainability methods such as SHAP, we propose a robust and context-aware solution that enhances credit scoring accuracy. This approach contributes to advancing financial inclusion and promoting more equitable agricultural growth.The findings provide financial institutions with an effective framework to better assess credit risk, reduce losses due to defaults and fraud, and personalize financial services for farmers. However, the study is limited by the quality and availability of data, and the models still require validation on larger and more diverse populations. Moreover, technical and operational challenges related to the scalability of AI solutions in rural settings remain significant. Future research should focus on large-scale deployment, incorporating innovative data sources such as satellite imagery and agricultural IoT, while ensuring equitable access to technology and adapting algorithms to local geographic and cultural contexts.Strengthening partnerships between public institutions, private actors, and local communities will be essential to support sustainable, inclusive, and AI-driven transformation of rural finance in the region.

The source code used for the modeling and analyses pre-

sented in this article is available upon request from the author.

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