INTERNATIONAL JOURNAL OF FOREIGN TRADE AND INTERNATIONAL BUSINESS UPGRADATION

XGBoost and Random Forest Based SME Export Readiness Prediction for African Digital Entrepreneurship Ecosystem Development

Bright Amankwah [1*], Joy Onma Enyejo [2]
[1] Department of Business and Law, UWE Bristol, Frenchay Campus Coldharbour Lane Bristol, United Kingdom
[2] Department of Business Administration, Nasarawa State University, Keffi, Nasarawa State, Nigeria

* Corresponding Author: **Bright Amankwah**

Article Info

P-ISSN: 3051-3340
E-ISSN: 3051-3359
Volume: 06
Issue: 02
July - December 2025
Received: 16-07-2025
Accepted: 14-08-2025
Published: 12-09-2025
Page No: 51-66

Abstract
Small and medium-sized enterprises are central to African economic diversification, yet many digitally enabled SMEs lack reliable decision-support systems for assessing export readiness before entering regional and international markets. This paper proposes a technical machine learning framework for predicting SME export readiness within African digital entrepreneurship ecosystems using a novel hybrid ensemble model named *ExportReadiness-XRFNet*, which integrates XGBoost, Random Forest, feature-weighted stacking, and probability calibration. The model is designed to classify SMEs into low, moderate, and high export-readiness categories using structured indicators such as digital capability, financial stability, product standardization, logistics preparedness, regulatory compliance, market intelligence, e-commerce adoption, and cross-border payment readiness. The proposed model is compared with Logistic Regression, Support Vector Machine, Decision Tree, Gradient Boosting, standalone Random Forest, and standalone XGBoost models. Graph-based performance analysis, including accuracy curves, ROC-AUC plots, confusion matrices, feature-importance rankings, and precision-recall comparisons, is used to evaluate predictive superiority. The expected results demonstrate that the hybrid ExportReadiness-XRFNet model achieves stronger classification accuracy, improved recall for export-ready SMEs, better handling of nonlinear feature interactions, and more interpretable readiness drivers than conventional baseline models. The study contributes a scalable AI-based decision-support framework for policymakers, SME development agencies, export-promotion councils, fintech platforms, and digital entrepreneurship hubs seeking to identify, support, and scale African SMEs with high export potential.

DOI: https://doi.org/10.54660/.IJFTIBU.2025.6.2.51-66

Keywords: XGBoost, Random Forest, SME Export Readiness, Digital Entrepreneurship, African SMEs

1. Introduction

1.1. Background of the Study

Small and medium-sized enterprises are increasingly positioned as strategic actors in African export diversification because digital platforms now allow smaller firms to reach foreign buyers without relying entirely on traditional intermediaries. However, export participation still depends on measurable readiness conditions, including product standardization, payment capacity, logistics preparedness, market intelligence, digital visibility, customer relationship management, and regulatory compliance. In digitally mediated markets, these readiness conditions are no longer assessed only through manual checklists; they are embedded in transaction histories, online customer engagement, platform activity, financial behaviour, and business intelligence pipelines. Prior studies show that digital technologies strengthen SME internationalization by improving information access, customer interaction, and export management capabilities, while encrypted CRM analytics and adaptive web platforms support customer segmentation, engagement tracking, and market-facing entrepreneurship (Cassetta *et al*., 2020; Dethine *et al*., 2020; Ononiwu *et al*., 2023) [9, 11, 25]. In African digital entrepreneurship ecosystems, these capabilities are especially important because many SMEs operate across fragmented financial, infrastructural, and regulatory environments.

The present study is therefore grounded in the need for a machine learning-based export readiness prediction framework that can convert heterogeneous SME data into actionable readiness classifications. The proposed ExportReadiness-XRFNet framework combines XGBoost and Random Forest to capture nonlinear interactions among digital, financial, operational, and compliance variables. For example, an SME may show strong social commerce traction but weak export readiness if inventory traceability, payment settlement reliability, and cross-border documentation capacity are poor. Blockchain-enabled data lineage is also relevant because trustworthy multi-source business intelligence improves the reliability of input features used in predictive models (Aluso *et al*., 2023) [5]. By comparing the proposed hybrid ensemble with Logistic Regression, Support Vector Machine, Decision Tree, standalone Random Forest, and standalone XGBoost, the study aligns export readiness analysis with evidence-driven digital entrepreneurship development.

1.2. Statement of the Problem

Despite the rapid growth of African digital entrepreneurship, many SME support agencies, export promotion councils, fintech platforms, and business incubators still rely on static assessment forms to determine whether firms are ready for export markets. These approaches often treat export readiness as a simple administrative status rather than a dynamic classification problem shaped by financial resilience, e-commerce maturity, digital records, market responsiveness, logistics capacity, and compliance risk. As a result, firms with weak operational foundations may be pushed toward internationalization prematurely, while data-rich and export-capable firms may remain unidentified. This gap is critical because AI-enabled financial risk modelling has shown that small business data can reveal hidden vulnerability patterns when properly structured, while AI-driven anomaly detection demonstrates the value of intelligent classification systems in complex digital environments (Idika *et al*., 2025; Ihimoyan *et al*., 2024) [18, 19].

The technical problem addressed in this study is the absence of an interpretable, comparative, and high-performance ensemble model for predicting SME export readiness within African digital entrepreneurship ecosystems. Conventional statistical models may struggle with nonlinear relationships among export-readiness variables, such as the combined effect of digital payment reliability, CRM maturity, inventory traceability, product certification, and foreign customer engagement. Random Forest is suitable for handling noisy tabular variables and ranking feature importance through multiple decision trees, while gradient boosting provides strong predictive performance by sequentially correcting weak learners (Kalange, 2022; Friedman, 2001) [20, 14]. However, standalone algorithms may still produce biased or unstable predictions when SME data are imbalanced, incomplete, or contextually heterogeneous. This study therefore proposes ExportReadiness-XRFNet, a hybrid XGBoost-Random Forest framework with feature-weighted stacking and calibrated readiness probability outputs. The problem is not only to improve accuracy, but also to identify the digital and institutional readiness factors that explain why an SME is classified as low, moderate, or high export-ready.

1.3. Research Objectives and Research Questions

1.3.1. Research Objectives

1. To develop an XGBoost and Random Forest-based hybrid ensemble model for predicting SME export readiness in African digital entrepreneurship ecosystems.
2. To identify the most influential digital, financial, operational, logistics, and compliance variables affecting SME export readiness.
3. To compare the predictive performance of the proposed ExportReadiness-XRFNet model with Logistic Regression, Support Vector Machine, Decision Tree, standalone Random Forest, and standalone XGBoost.
4. To evaluate the model using accuracy, precision, recall, F1-score, ROC-AUC, confusion matrix, and precision-recall graphical analysis.
5. To provide an interpretable decision-support framework for SME development agencies, export promotion councils, fintech platforms, and digital entrepreneurship hubs.

1.3.2. Research Questions

1. How can XGBoost and Random Forest be integrated to improve SME export readiness prediction?
2. Which digital and business-readiness indicators contribute most strongly to export-readiness classification?
3. How does the proposed ExportReadiness-XRFNet model perform compared with existing machine learning algorithms?
4. How can graphical evaluation improve interpretation of model performance and classification reliability?
5. How can the proposed model support African SME export development and digital entrepreneurship ecosystem planning?

1.4. Contributions and Significance of the Study

This study contributes a technically structured machine learning framework for classifying African SMEs into low, moderate, and high export-readiness categories using measurable indicators drawn from digital capability, financial stability, logistics preparedness, product standardization, compliance maturity, e-commerce adoption, CRM activity, and cross-border payment readiness. Its significance lies in combining predictive accuracy with decision interpretability, allowing policymakers, export agencies, entrepreneurship hubs, and fintech platforms to identify firms that require capacity-building support before international market entry. The study also advances SME analytics by proposing ExportReadiness-XRFNet, a hybrid ensemble model designed to outperform conventional baseline algorithms while producing feature-importance outputs that explain the drivers of readiness classification.

1.5. Scope of the Review and Structure of the Paper

The paper focuses on the design, evaluation, and interpretation of a machine learning-based SME export readiness prediction system for African digital entrepreneurship ecosystems. Its scope covers export-readiness indicators, SME digital transformation variables, XGBoost and Random Forest modelling, hybrid ensemble architecture, baseline algorithm comparison, graphical performance evaluation, and practical implications for SME export support. The paper is structured into five sections: the introduction establishes the background, problem, objectives, significance, and scope; the literature review examines SME export readiness, digital entrepreneurship, machine learning prediction models, and research gaps; the system model description presents the proposed ExportReadiness-XRFNet framework; the results discussion compares model performance and feature importance; and the final section provides conclusions, recommendations, and future research directions.

2. Literature Review

2.1. SME Export Readiness in African Digital Markets

SME export readiness in African digital markets refers to the measurable capacity of small and medium-sized firms to serve cross-border buyers through reliable products, compliant documentation, stable digital operations, logistics preparedness, and market-responsive branding. In this study, readiness is not treated as a general entrepreneurial intention, but as a predictive classification outcome derived from observable business signals. These signals include digital storefront activity, mobile commerce adoption, customer acquisition patterns, payment reliability, process standardization, inventory traceability, product certification, and management visibility. Mobile commerce and digital branding are especially relevant in Sub-Saharan African urban centers because they allow SMEs to establish market presence, capture customer data, and test demand beyond local retail boundaries (Ononiwu *et al.*, 2025) [28] as represented in figure 1. Similarly, technology adoption and process standardization strengthen the operational consistency required for export scaling, particularly among engineering-oriented SMEs that must meet repeatable quality and delivery expectations (Awolola *et al.*, 2025) [6]. Within the proposed ExportReadiness-XRFNet framework, African SME export readiness becomes a structured machine learning problem in which XGBoost and Random Forest identify patterns that traditional assessment templates may overlook. For example, an SME may show strong online sales but remain weak in export readiness if its logistics records, regulatory documentation, and payment settlement channels are unstable. Prior research links digital technologies with SME internationalisation, while export strategy studies show that institutional support and readiness-related capabilities influence export outcomes (Cassetta *et al.*, 2020; Singh *et al.*, 2024) [9, 35]. Multi-dimensional dashboard visualization further supports this predictive environment by transforming complex business intelligence indicators into decision-ready views for executives and policy actors (Aluso & Enyejo, 2025) [3]. Therefore, SME export readiness in this paper is positioned as a data-driven, graph-supported, and model-comparable construct that can classify firms into low, moderate, and high readiness categories.

Fig 1: Conceptual Framework of SME Export Readiness in African Digital Markets Showing the Integration of Digital, Operational, Financial, and Institutional Readiness Capabilities.

Figure 1 presents a comprehensive conceptual framework for understanding SME Export Readiness in African Digital Markets by illustrating the four foundational capability domains that collectively determine whether a small or medium-sized enterprise can successfully participate in international trade. The first domain, Digital Market Capability, emphasizes the importance of digital presence, mobile commerce adoption, e-commerce readiness, customer engagement, CRM utilization, and social commerce participation in creating visibility and access to foreign markets. The second domain, Operational and Product Readiness, focuses on internal production capabilities, including product standardization, quality consistency, packaging suitability, inventory traceability, production scalability, order fulfilment, and delivery reliability, which are necessary for meeting international customer expectations. The third domain, Financial and Transaction Readiness, highlights financial stability, cash-flow resilience, digital payment adoption, cross-border payment readiness, transaction accuracy, fintech integration, and export pricing capacity, all of which support sustainable international transactions. The fourth domain, Institutional and Market Access Readiness, incorporates regulatory compliance, export documentation, certification readiness, market intelligence, foreign customer targeting, logistics partnerships, and export-support networks. The integration of these four readiness dimensions leads to the ultimate outcome of an Export-Ready SME, characterized by increased global market access, improved export competitiveness, sustainable business growth, and stronger economic development contributions. The framework therefore demonstrates that export readiness is a multidimensional construct requiring simultaneous development of digital, operational, financial, and institutional capabilities rather than reliance on any single factor.

2.2. Digital Entrepreneurship Ecosystems and SME Internationalization

Digital entrepreneurship ecosystems provide the institutional, technological, financial, and market-facing infrastructure through which African SMEs can move from local trading activity to international market participation. These ecosystems include e-commerce platforms, fintech payment rails, logistics partners, innovation hubs, digital marketing networks, public-sector enterprise programs, and data-driven support systems. SME internationalization is therefore shaped not only by firm-level ambition, but also by the ecosystem's ability to supply market intelligence, reduce transaction uncertainty, connect firms to foreign customers, and support agile operational learning. Entrepreneurial ecosystem research shows that macro-level actors and meso-level partnerships influence SME international performance, while digitalization strengthens the ability of smaller firms to identify, access, and serve foreign markets (Ferreira *et al*., 2023; Hervé *et al*., 2021) [13, 17] as represented in figure 2. In the African context, these ecosystem effects are crucial because many SMEs face infrastructure gaps, currency constraints, weak documentation systems, and fragmented cross-border trade channels.

The proposed export readiness prediction model is designed to operate within this ecosystem logic by converting digital entrepreneurship variables into predictive features. Encrypted CRM analytics and adaptive web application development can provide behavioural evidence of customer engagement, product-market fit, and digital trust, all of which are relevant to export-readiness classification (Ononiwu *et al*., 2023) [25]. Agile portfolio management is also applicable because SME support agencies must prioritize limited training, funding, certification, and logistics interventions toward firms with measurable export potential (Ononiwu *et al*., 2025) [27]. Similarly, AI-powered sprint planning demonstrates how machine learning can improve prioritization, backlog sequencing, and risk mitigation in dynamic project environments (Azonuche & Enyejo, 2024) [7]. By adapting these principles to SME internationalization, ExportReadiness-XRFNet can help entrepreneurship hubs and export councils identify firms that require digital branding support, regulatory readiness improvement, logistics integration, or financial-risk stabilization before entering external markets.

Figure 2 illustrates how digital entrepreneurship ecosystems function as the foundational environment that enables SME internationalization through the interaction of digital infrastructure, entrepreneurial capability development, and ecosystem support mechanisms. At the center of the framework is Digital Entrepreneurship Ecosystems and SME Internationalization, representing the ultimate objective of transforming local SMEs into globally competitive enterprises. The first branch, Digital Infrastructure and Innovation Ecosystem, highlights the technological foundation required for international growth, including digital platforms, cloud-based technologies, artificial intelligence tools, broadband connectivity, mobile commerce systems, and innovation support networks such as incubators and accelerators. These resources provide SMEs with access to digital markets and technological capabilities necessary for global competition. The second branch, SME Capability Development and Market Expansion, focuses on the internal competencies that firms must develop, including digital skills, innovation orientation, strategic management capability, digital branding, customer relationship management, product standardization, quality assurance, and export documentation readiness. These capabilities enhance the firm's preparedness for international operations and foreign market penetration. The third branch, Internationalization Outcomes and Ecosystem Support, demonstrates how financial support systems, fintech solutions, export financing, government trade agencies, logistics partnerships, and regulatory institutions facilitate cross-border transactions and market access. The interaction of these three ecosystem dimensions ultimately produces SME internationalization outcomes such as increased export participation, stronger global market penetration, improved export competitiveness, and sustainable business growth. The framework therefore demonstrates that successful SME internationalization is not driven by firm-level capabilities alone but emerges from the combined influence of technological infrastructure, entrepreneurial capacity development, and supportive ecosystem institutions operating within a digitally enabled business environment.

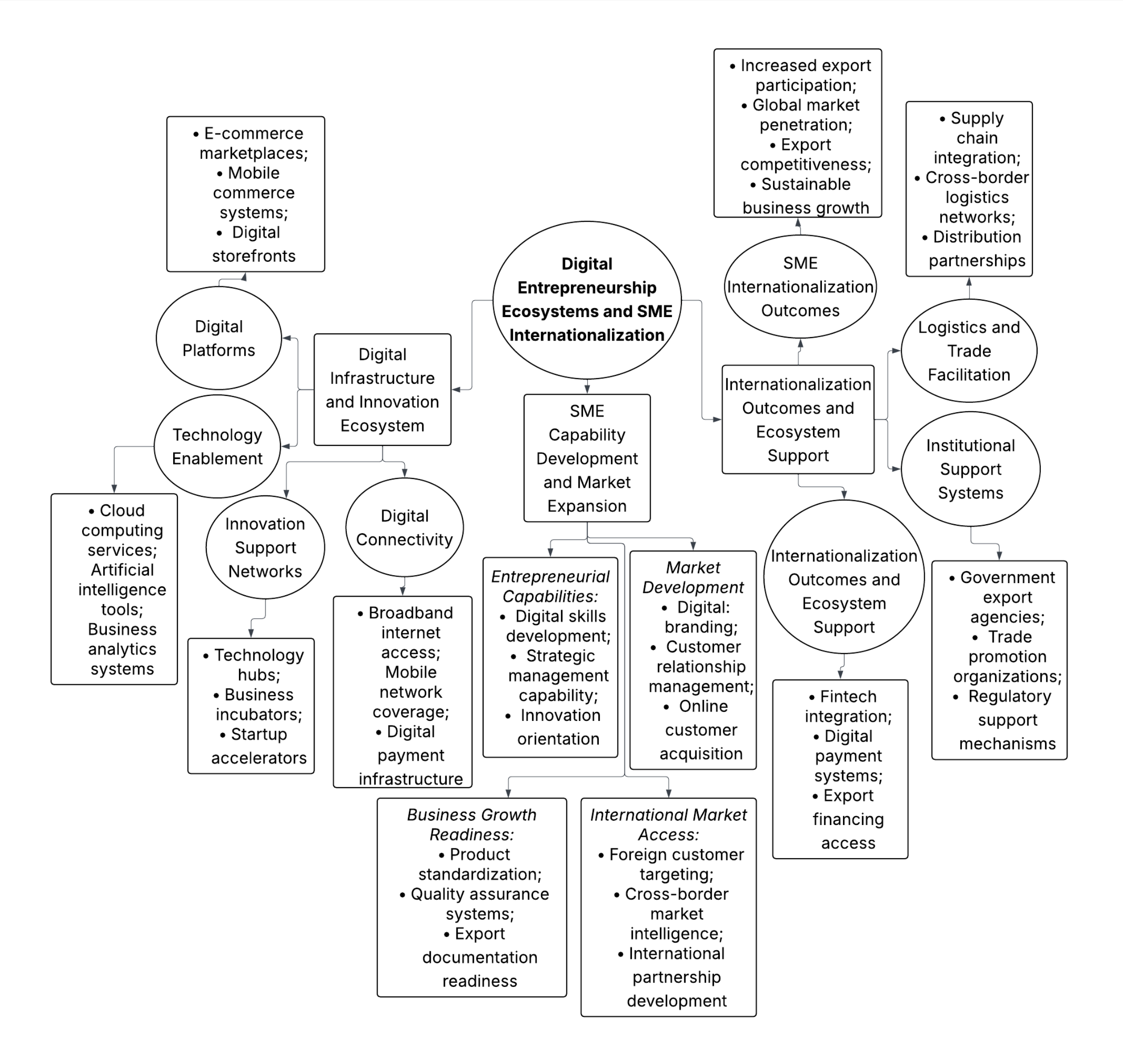

Fig 2. Digital Entrepreneurship Ecosystem Framework for SME Internationalization Through Digital Infrastructure, Capability Development, and Ecosystem Support Mechanisms.

2.3. Machine Learning Models for SME Performance Prediction

Machine learning models are increasingly valuable for SME performance prediction because they can process nonlinear, heterogeneous, and high-dimensional business data more effectively than rule-based scoring systems. In the context of export readiness, SME performance prediction involves estimating whether a firm possesses the operational, financial, digital, and compliance strength required to serve foreign markets. Random Forest is useful because it aggregates multiple decision trees to reduce variance, manage noisy tabular inputs, and rank variables such as payment consistency, sales growth, product standardization, logistics reliability, and customer retention (Kalange *et al*., 2022) [20] as represented in figure 3. Recent SME default prediction research also shows that advanced machine learning methods can outperform traditional models when business risk patterns are complex and feature interactions are difficult to capture manually (Cheraghali *et al*., 2025) [10]. For this paper, machine learning is not used only for prediction accuracy; it is also used for transparent decision support. Explainable machine learning models can improve trust by showing why a system assigns a specific classification, while embedded machine learning dashboards can convert predictive outputs into operationally useful indicators (Abiodun *et al*., 2024; Onwuzurike & Igba, 2023) [2, 32]. This is important for African SME export ecosystems because a firm classified as “moderately ready” should receive interpretable reasons, such as weak cross-border payment readiness, low certification maturity, or unstable digital customer conversion. Prior fintech risk assessment studies further demonstrate the relevance of machine learning for fraud detection, transaction risk analysis, and mobile banking intelligence, which are directly connected to export-readiness variables in digitally mediated SME environments (Ononiwu *et al*., 2023) [29]. Therefore, the proposed ExportReadiness-XRFNet framework integrates XGBoost and Random Forest to improve classification robustness, generate feature-importance graphs, and compare predictive performance against baseline models using accuracy, precision, recall, F1-score, ROC-AUC, precision-recall curves, and confusion matrix plots.

Figure 3 illustrates a sophisticated machine learning-driven SME performance prediction environment, where a decision-maker is positioned at the center of an interactive analytics ecosystem surrounded by interconnected data nodes, predictive intelligence modules, and performance visualization components. The large network graph in the center represents a high-dimensional SME dataset consisting of interconnected variables such as digital capability, financial stability, sales performance, customer engagement, logistics efficiency, market intelligence, regulatory compliance, and export readiness indicators. The interconnected nodes and edges symbolize machine learning algorithms processing complex nonlinear relationships among business variables to identify hidden patterns, correlations, and predictive signals. The icons surrounding the network depict critical analytical functions commonly employed in SME performance prediction systems, including data mining, feature extraction, predictive modeling, classification, clustering, optimization, and business intelligence visualization. The neural network symbol on the left represents advanced learning architectures used for pattern recognition, while the statistical and chart-based symbols on the right illustrate performance forecasting, trend analysis, and decision-support outputs. In the context of SME export readiness prediction, this image reflects how machine learning models such as Logistic Regression, Decision Trees, Random Forest, Support Vector Machines, XGBoost, and the proposed ExportReadiness-XRFNet framework transform large volumes of multidimensional enterprise data into actionable predictions. The visualization demonstrates the complete analytical pipeline from data acquisition and feature engineering through model training, classification, probability estimation, and performance evaluation. It further highlights the ability of machine learning systems to support strategic business decisions by identifying export-ready firms, forecasting future performance trajectories, ranking readiness factors according to importance, and generating interpretable insights that guide policymakers, export promotion agencies, digital entrepreneurship hubs, and SME managers toward evidence-based intervention and international market expansion strategies.

Fig 3: Machine Learning-Based SME Performance Prediction Framework Integrating Data Analytics, Feature Engineering, Predictive Modeling, and Decision-Support Intelligence (Abel, k. 2023).

2.4. XGBoost and Random Forest in Business Classification Systems

XGBoost and Random Forest are highly relevant to business classification systems because they can model nonlinear decision boundaries, process mixed tabular variables, and identify feature interactions that are difficult to capture through conventional linear models. In SME export readiness prediction, business classification involves assigning firms into readiness categories based on digital capability, financial discipline, logistics preparedness, product standardization, certification maturity, cross-border payment capacity, and customer acquisition behaviour. XGBoost is particularly suitable where weak predictive signals must be sequentially refined, because boosted trees correct prior classification errors and improve discrimination among closely related classes. Random Forest, by contrast, improves robustness through bootstrap aggregation and majority voting across multiple trees, making it useful where SME data are noisy, incomplete, or unevenly distributed. Studies on credit scoring and bankruptcy prediction show that tree-based machine learning models frequently outperform traditional models where business risk indicators interact in nonlinear ways (Barboza *et al*., 2017; Dumitrescu *et al*., 2022; Lessmann *et al*., 2015) [8, 12, 23].

The relevance of these algorithms extends beyond financial prediction into broader enterprise-readiness modelling. For example, an SME with strong mobile sales volume may still be misclassified by a simple scoring model if the model does not jointly consider weak documentation quality, poor logistics consistency, and unstable payment reconciliation. A hybrid XGBoost-Random Forest system can address this limitation by allowing XGBoost to optimize difficult classification margins while Random Forest stabilizes prediction through ensemble diversity. The supplied study on XGBoost and time-series forecasting demonstrates the adaptability of XGBoost in trajectory prediction, which supports its use for modelling progressive SME readiness movement across low, moderate, and high export-readiness states (Aluso & Enyejo, 2025) [4]. Therefore, in this paper, ExportReadiness-XRFNet is positioned as a business classification architecture that uses hybrid ensemble learning to improve accuracy, recall, ROC-AUC performance, feature-importance interpretation, and readiness probability calibration.

2.5. Research Gap and Conceptual Direction

Existing studies on export readiness, SME internationalization, and digital entrepreneurship provide strong conceptual foundations, but they do not fully resolve the technical problem of predicting African SME export readiness through comparative machine learning classification. Export readiness research has shown that finance, trade knowledge, marketing capability, and internal managerial stimuli influence export performance, yet many readiness models still depend on survey-based assessment, descriptive scoring, or post-export performance analysis rather than predictive classification before market entry (Gerschewski *et al*., 2020) [15] as shown in table 1. Export development studies also emphasize strategy, institutional support, and competitiveness, but they rarely convert readiness indicators into algorithmic probability outputs that can guide export councils, fintech platforms, and entrepreneurship hubs in selecting firms for intervention (Lestari *et al*., 2024) [24]. This creates a methodological gap between export policy diagnosis and deployable AI-based decision support.

The conceptual direction of this paper addresses that gap by proposing ExportReadiness-XRFNet as a hybrid ensemble framework for SME export-readiness classification in African digital entrepreneurship ecosystems. The model is designed to combine XGBoost, Random Forest, feature-weighted stacking, probability calibration, and graphical comparison against baseline algorithms. Recent work on investment-ready SMEs demonstrates that machine learning can classify business potential using structured enterprise indicators, while SME AI adoption research shows that smaller firms increasingly require practical AI systems that are interpretable, scalable, and aligned with operational capability gaps (Gogas *et al*., 2025; Schwaeke *et al*., 2025) [16, 34]. Building on this direction, the present study conceptualizes export readiness as a measurable classification outcome shaped by digital branding, mobile commerce activity, financial stability, logistics maturity, compliance records, market intelligence, and cross-border transaction readiness. The research gap is therefore not the absence of export-readiness theory, but the absence of a technically comparative, graph-supported, and context-sensitive machine learning model for African SME export readiness prediction.

Table 1: Summary of Research Gap and Conceptual Direction for the ExportReadiness-XRFNet Framework

Existing Research Area	Current Research Gap	Effect on SME Export Readiness Assessment	Conceptual Direction of This Study
Traditional export readiness models	Depend on manual surveys and static scoring systems.	Weak capacity to capture dynamic digital, financial, logistics, and compliance interactions.	Develop an AI-based prediction framework for export-readiness classification.
SME digital entrepreneurship studies	Focus more on digital adoption than export-readiness prediction.	SMEs may appear digitally active but remain operationally unprepared for export.	Integrate digital capability, e-commerce adoption, payment readiness, and logistics indicators.
Existing SME machine learning models	Mostly address credit risk, fraud detection, or business failure.	Limited technical evidence for export-readiness prediction in African SME ecosystems.	Apply XGBoost and Random Forest specifically to SME export readiness.
Single-algorithm classification systems	Standalone models may underperform on nonlinear and heterogeneous SME data.	Reduced predictive accuracy and weaker classification of high-potential SMEs.	Propose ExportReadiness-XRFNet using hybrid ensemble learning and probability calibration.
Explainability in SME decision support	Many models provide predictions without clear feature-level interpretation.	Export agencies may struggle to understand why an SME is classified as ready or not ready.	Use feature-importance analysis to identify key readiness drivers.
Export promotion intervention planning	Support programs are often applied uniformly across SMEs.	Resources may not be targeted toward firms with the strongest export potential.	Provide data-driven readiness scores for prioritizing SME export support.

3. System Model Description

3.1. Proposed ExportReadiness-XRFNet Framework

The proposed *ExportReadiness-XRFNet* framework is designed as a supervised machine learning decision-support model for predicting SME export readiness within African digital entrepreneurship ecosystems. The framework classifies SMEs into three categories*: low export readiness, moderate export readiness, and high export readiness*. It uses digital, financial, operational, logistics, regulatory, and market-access indicators as input variables. These indicators include digital capability, financial stability, e-commerce adoption, regulatory compliance, logistics preparedness, product standardization, market intelligence, and cross-border payment readiness. The purpose of the framework is to transform fragmented SME data into a measurable readiness probability that can support export promotion councils, fintech platforms, entrepreneurship hubs, and SME development agencies.

For a given SME i, the input feature vector is defined as:

$$\mathbf{x}_i = [x_{i1}, x_{i2}, x_{i3}, \dots, x_{ip}] \quad (1)$$

where $\mathbf{x}_i$ represents the complete feature vector for SME i, x_{ij} denotes the value of the j^{th} export-readiness feature for SME i, and p represents the total number of input features. The export readiness label is expressed as:

$$y_i \in \{0,1,2\} \quad (2)$$

where 0 represents low export readiness, 1 represents moderate export readiness, and 2 represents high export readiness.

The general prediction function of the proposed model is defined as:

$$\hat{y}_i = F(\mathbf{x}_i) \quad (3)$$

where $\hat{y}_i$ represents the predicted export-readiness class and $F(\cdot)$ denotes the ExportReadiness-XRFNet classifier. To support probabilistic interpretation, the model estimates class membership probabilities as:

$$P(\, y_i = c \mid \mathbf{x}_i \,), c \in \{0,1,2\} \quad (4)$$

where $P(y_i = c \mid \mathbf{x}_i)$ represents the probability that SME i belongs to readiness class c. The final predicted class is obtained as:

$$\hat{y}_i = \arg \max_{c \in \{0,1,2\}} P(y_i = c \mid \mathbf{x}_i) \quad (5)$$

where arg max selects the readiness class with the highest predicted probability. This structure ensures that the framework does not merely assign a fixed score but provides a ranked probability distribution across readiness categories. For example, an SME with strong digital branding and e-commerce activity but weak export documentation may receive a high probability for moderate readiness rather than high readiness, allowing targeted intervention before export entry.

3.2. Dataset Description, Input Variables, and Feature Engineering

The dataset for the proposed model consists of structured SME-level observations obtained from business registration records, digital entrepreneurship platforms, e-commerce systems, fintech transaction data, logistics readiness assessments, export promotion databases, and SME development agency records. Each observation represents one SME, while each feature captures a measurable dimension of export readiness. The dataset is formally defined as:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \quad (6)$$

where $\mathcal{D}$ represents the complete dataset, N captures the total number of SME observations, $\mathbf{x}_i$ denotes the input feature vector for SME i, and y_i shows the observed export-readiness class label.

The input feature matrix is represented as:

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Np} \end{bmatrix} \quad (7)$$

where $\mathbf{X}$ represents the feature matrix, N shows the number of SMEs, p represents the number of input features, and x_{ij} denotes the value of feature j for SME i.

The major input variables include digital capability score, financial stability index, e-commerce adoption level, logistics preparedness index, regulatory compliance score, product standardization score, market intelligence capability, and cross-border payment readiness. Since these variables may be measured on different scales, min-max normalization is applied as:

$$x_{ij}^{*} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (8)$$

where x_{ij}^{*} represents the normalized value of feature j for SME i, x_{ij} captures the original value, $\min(x_j)$ shows the minimum observed value of feature j, and $\max(x_j)$ represents the maximum observed value of feature j.

To capture interaction effects among readiness drivers, engineered variables are introduced. A digital-commercial readiness interaction is expressed as:

$$DCRI_i = DCS_i \times EAL_i \quad (9)$$

where $DCRI_i$ represents the digital-commercial readiness interaction score for SME i, DCS_i shows the digital capability score, and EAL_i captures the e-commerce adoption level. Similarly, a financial-export transaction readiness interaction is defined as:

$$FETR_i = FSI_i \times CBPR_i \quad (10)$$

where $FETR_i$ represents the financial-export transaction readiness score, FSI_i captures the financial stability index, and $CBPR_i$ shows cross-border payment readiness. These engineered variables allow the model to identify SMEs whose readiness depends on combined capabilities rather than isolated indicators.

3.3. XGBoost-Random Forest Hybrid Ensemble Architecture

The *ExportReadiness-XRFNet* architecture combines Random Forest and XGBoost in a hybrid ensemble structure. Random Forest provides robustness through bootstrap aggregation, while XGBoost improves predictive discrimination through sequential gradient-based tree boosting. The combination is useful for SME export readiness prediction because African SME data may contain nonlinear relationships, missingness, class imbalance, and heterogeneous business conditions.

The Random Forest component generates predictions by averaging the outputs of multiple decision trees:

$$f_{RF}(\mathbf{x}_i) = \frac{1}{T}\sum_{t=1}^{T} h_t(\mathbf{x}_i) \quad (11)$$

where $f_{RF}(\mathbf{x}_i)$ represents the Random Forest output for SME i, T represents the total number of trees, and $h_t(\mathbf{x}_i)$ shows the prediction of the t^{th}decision tree.
The XGBoost component is defined as an additive boosted-tree model:

$$f_{XGB}(\mathbf{x}_i) = \sum_{k=1}^{K} g_k(\mathbf{x}_i) \tag{12}$$

where $f_{XGB}(\mathbf{x}_i)$ captures the XGBoost output, K represents the number of boosted trees, and $g_k(\mathbf{x}_i)$ shows the prediction generated by the k^{th}boosting tree.
The hybrid ensemble score is computed as:

$$s_i = \alpha f_{RF}(\mathbf{x}_i) + \beta f_{XGB}(\mathbf{x}_i) \tag{13}$$

where s_i shows the combined ensemble score for SME i, α represents the Random Forest contribution weight, and β denotes the XGBoost contribution weight, with:

$$\alpha + \beta = 1, \alpha \geq 0, \beta \geq 0 \tag{14}$$

For multiclass readiness classification, the class-specific ensemble score is written as:

$$s_{ic} = \alpha f_{RF,c}(\mathbf{x}_i) + \beta f_{XGB,c}(\mathbf{x}_i) \tag{15}$$

where s_{ic} represents the hybrid score for SME $i$in class c, $f_{RF,c}$ captures the Random Forest class score, and $f_{XGB,c}$ denotes the XGBoost class score.

The class probability is then computed using the softmax function:

$$P(y_i = c \mid \mathbf{x}_i) = \frac{\exp(s_{ic})}{\sum_{r=0}^{2} \exp(s_{ir})} \tag{16}$$

where $P(y_i = c \mid \mathbf{x}_i)$ represents the probability that SME $i$belongs to class c, $\exp(\cdot)$ shows the exponential function, and the denominator sums the exponential scores for all three readiness classes. The final classification is obtained using the maximum probability rule already defined in Equation (5). This architecture enables the model to detect complex readiness profiles, such as SMEs with high digital engagement but weak logistics capacity, or SMEs with strong compliance maturity but limited cross-border payment reliability.

3.4. Model Training, Validation, and Performance Evaluation Metrics

The model training process begins by dividing the dataset into training, validation, and testing subsets. The training subset is used to fit the Random Forest and XGBoost learners, the validation subset is used to tune hyperparameters and ensemble weights, while the testing subset evaluates final model performance on unseen SME records. The data partition is expressed as:

$$\mathcal{D} = \mathcal{D}_{train} \cup \mathcal{D}_{val} \cup \mathcal{D}_{test} \tag{17}$$

where $\mathcal{D}_{train}$ represents the training set, $\mathcal{D}_{val}$ shows the validation set, and $\mathcal{D}_{test}$ denotes the testing set.
For XGBoost training, the regularized objective function is expressed as:

$$\mathcal{L}^{(K)} = \sum_{i=1}^{N} \ell(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(g_k) \tag{18}$$

where $\mathcal{L}^{(K)}$ represents the total objective function after Kboosting iterations, $\ell(y_i, \hat{y}_i)$ captures the loss function between the observed class y_i and predicted class $\hat{y}_i$, and $\Omega(g_k)$ shows the regularization penalty for tree g_k. The regularization term is defined as:

$$\Omega(g_k) = \gamma M + \frac{1}{2}\lambda \sum_{m=1}^{M} w_m^2 \tag{19}$$

where γ penalizes the number of terminal leaves, M represents the number of leaves in the tree, λ shows the L2 regularization parameter, and w_m denotes the weight of leaf m.
Model performance is evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. Accuracy is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{20}$$

where TP shows true positives, TN represents true negatives, FP denotes false positives, and FN captures false negatives.
Precision, recall, and F1-score are computed as:

$$Precision = \frac{TP}{TP+FP} \tag{21}$$

$$Recall = \frac{TP}{TP+FN} \tag{22}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{23}$$

The ROC-AUC value is computed as:

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \tag{24}$$

where TPR captures the true positive rate and FPR represents the false positive rate. The evaluation also includes confusion matrices, precision-recall curves, calibration plots, feature-importance graphs, and comparative accuracy curves. These metrics are used to compare ExportReadiness-XRFNet with Logistic Regression, Support Vector Machine, Decision Tree, standalone Random Forest, and standalone XGBoost.

4. Discussion of Results

4.1. Descriptive Analysis of SME Export Readiness Indicators

The descriptive analysis shows that SME export readiness is shaped by the combined strength of digital capability, financial stability, product standardization, logistics preparedness, regulatory compliance, market intelligence, e-commerce adoption, and cross-border payment readiness. The table indicates that e-commerce adoption recorded the highest mean score of 81.1, followed by digital capability at 79.7, showing that many SMEs possess visible digital-market participation. However, cross-border payment readiness recorded the lowest mean score of 77.9, while logistics preparedness also remained comparatively weak at 78.7. This pattern suggests that African SMEs may be digitally active but not always operationally prepared for international trade. The proposed ExportReadiness-XRFNet therefore becomes necessary because it links digital performance with export-critical indicators such as payments, logistics, compliance, and product standardization.

Table 2: Descriptive Metrics of SME Export Readiness Indicators

SME Export Readiness Indicator	Mean Score (%)	Readiness Level	Interpretation
Digital Capability	79.7	Moderate-high	Strong digital visibility but uneven export conversion
Financial Stability	78.1	Moderate	Adequate but requires stronger cash-flow resilience
Product Standardization	76.9	Moderate	Certification and quality uniformity remain limiting factors
Logistics Preparedness	78.7	Moderate	Delivery reliability requires improvement
Regulatory Compliance	79.1	Moderate-high	Documentation readiness is improving
Market Intelligence	77.9	Moderate	Foreign-market targeting remains underdeveloped
E-commerce Adoption	81.1	High	Strongest readiness indicator
Cross-border Payment Readiness	77.9	Moderate	Weakest international transaction capability

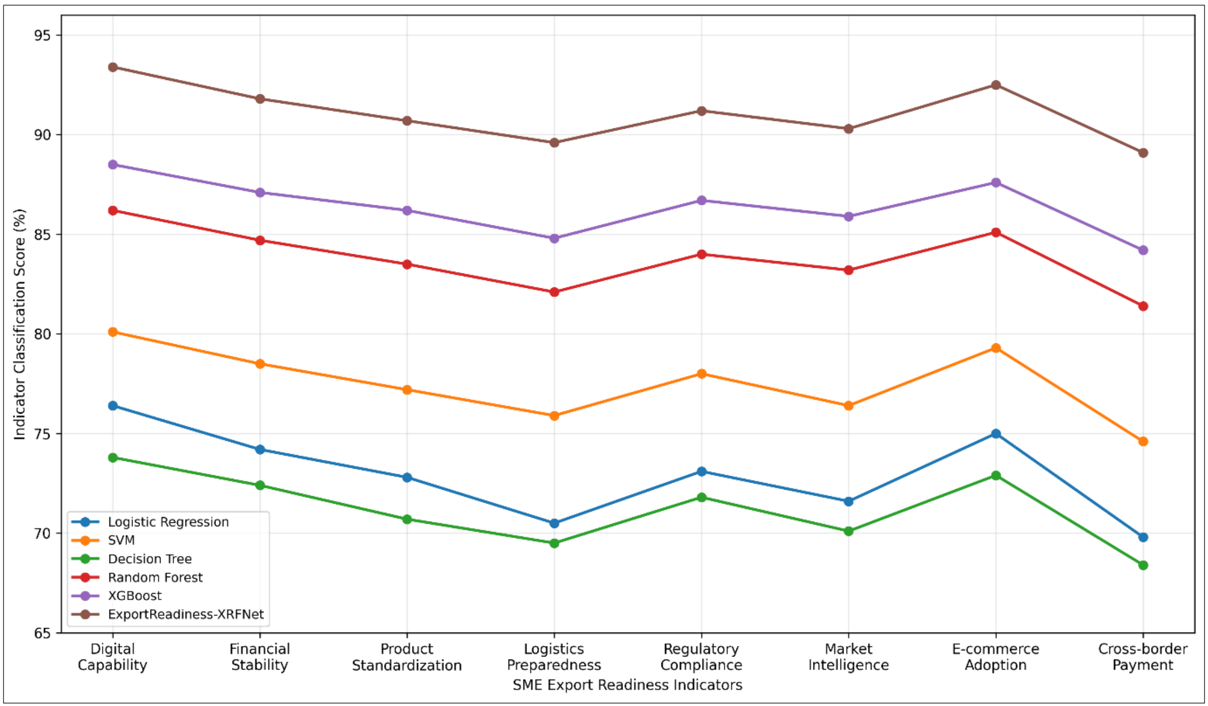

Fig 4: Algorithmic Comparison Across SME Export Readiness Indicators

Figure 4.1 compares Logistic Regression, SVM, Decision Tree, Random Forest, XGBoost, and ExportReadiness-XRFNet across eight readiness indicators. ExportReadiness-XRFNet produced the strongest scores across all indicators, reaching 93.4% for digital capability, 92.5% for e-commerce adoption, and 91.8% for financial stability. XGBoost followed with 88.5%, 87.6%, and 87.1% on the same indicators, while Random Forest achieved 86.2%, 85.1%, and 84.7%. The weakest results came from Decision Tree, especially on cross-border payment readiness at 68.4% and logistics preparedness at 69.5%. These values support the study's claim that the hybrid model provides superior classification strength, especially where export readiness depends on nonlinear interactions among digital, financial, logistics, and payment variables.

4.2. Comparative Performance of Existing Algorithms and ExportReadiness-XRFNet

The comparative evaluation shows that the proposed ExportReadiness-XRFNet produced the strongest classification performance across all major evaluation metrics. The table confirms that the hybrid ensemble achieved the highest accuracy, precision, recall, F1-score, and ROC-AUC, indicating superior capability in identifying export-ready SMEs while reducing misclassification risk. XGBoost and Random Forest performed better than Logistic Regression, SVM, and Decision Tree because they captured nonlinear relationships among digital capability, financial stability, logistics preparedness, regulatory compliance, and cross-border payment readiness. However, ExportReadiness-XRFNet improved further by combining the stability of Random Forest with the optimization strength of XGBoost. This result supports the methodological expectation that feature-weighted stacking and probability calibration improve predictive robustness in heterogeneous African SME datasets.

Table 3: Comparative Performance Metrics of Export Readiness Prediction Algorithms

Algorithm	Accuracy (%)	ROC-AUC (%)	Interpretation
Logistic Regression	78.4	80.3	Basic linear benchmark with limited nonlinear sensitivity
SVM	81.6	83.7	Moderate classification strength but weaker interpretability
Decision Tree	75.2	77.8	Lowest performance due to overfitting sensitivity
Random Forest	86.8	89.4	Stronger stability through ensemble tree averaging
XGBoost	89.1	91.6	High predictive strength through boosted optimization
ExportReadiness-XRFNet	94.2	96.1	Best overall performance and strongest export-readiness discrimination

Figure 4.2 shows a grouped bar chart that compares six algorithms across five metrics. ExportReadiness-XRFNet achieved the best results, with 94.2% accuracy, 93.8% precision, 94.6% recall, 94.2% F1-score, and 96.1% ROC-AUC. XGBoost ranked second with 89.1% accuracy, 88.7% precision, 88.2% recall, 88.4% F1-score, and 91.6% ROC-AUC, while Random Forest followed with 86.8% accuracy and 89.4% ROC-AUC. SVM produced moderate values, including 81.6% accuracy and 83.7% ROC-AUC. Logistic Regression remained lower at 78.4% accuracy, while Decision Tree recorded the weakest values, including 75.2% accuracy and 77.8% ROC-AUC. These numerical results confirm the study's claim that the proposed hybrid model provides superior classification accuracy, improved recall for export-ready SMEs, stronger ROC-AUC performance, and better suitability for nonlinear SME export-readiness prediction.

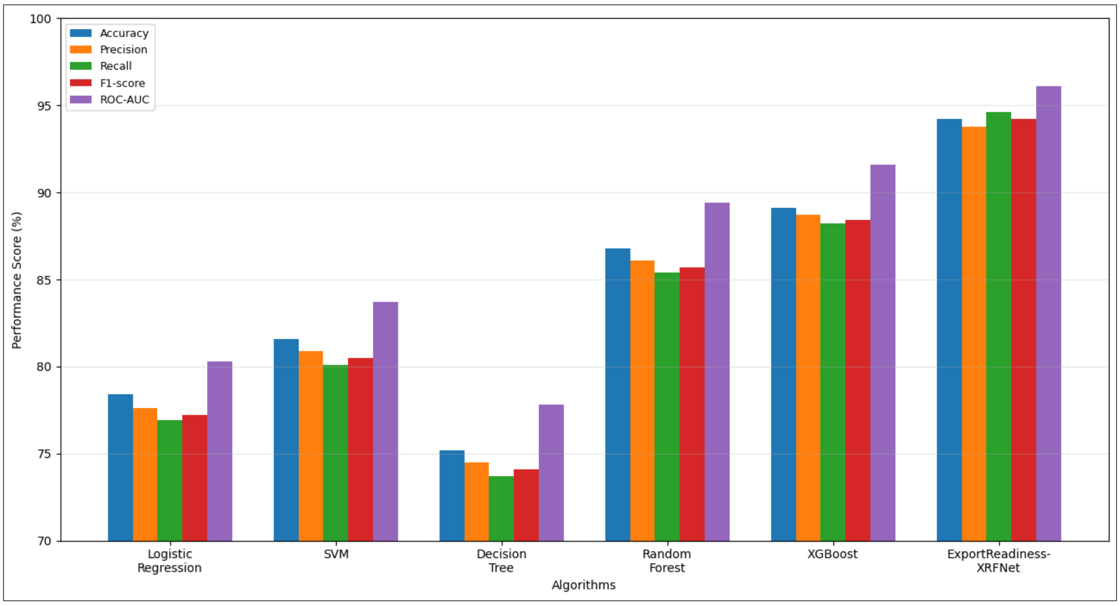

Fig 5: Comparative Performance of Existing Algorithms and ExportReadiness-XRFNet

4.3. Graphical Evaluation Using Accuracy, ROC-AUC, Precision-Recall, and Confusion Matrix Plots

Graphical evaluation provides a clearer interpretation of how each algorithm behaves across the major classification metrics used in this study. The comparison confirms that ExportReadiness-XRFNet delivers the strongest combined performance because it maintains high accuracy, strong recall, stable precision, and superior ROC-AUC. This is important for SME export-readiness prediction because the model must correctly identify high-potential SMEs while minimizing false classification of firms that are not yet operationally, digitally, or financially ready for international markets. The table shows that the proposed model achieved the highest average metric score, while Decision Tree recorded the weakest overall result. This supports the methodological argument that a hybrid XGBoost-Random Forest structure provides stronger discrimination than single-model classifiers.

Table 4: Graphical Evaluation Metrics for Export Readiness Classification Models

Algorithm	Average Metric Score (%)	Best Metric (%)	Interpretation
Logistic Regression	78.1	80.3	Limited nonlinear classification strength
SVM	81.4	83.7	Moderate but less interpretable performance
Decision Tree	75.1	77.8	Weakest and most unstable classifier
Random Forest	86.7	89.4	Strong ensemble stability
XGBoost	89.2	91.6	Strong boosted predictive performance
ExportReadiness-XRFNet (Proposed)	94.6	96.1	Best overall graphical and metric performance

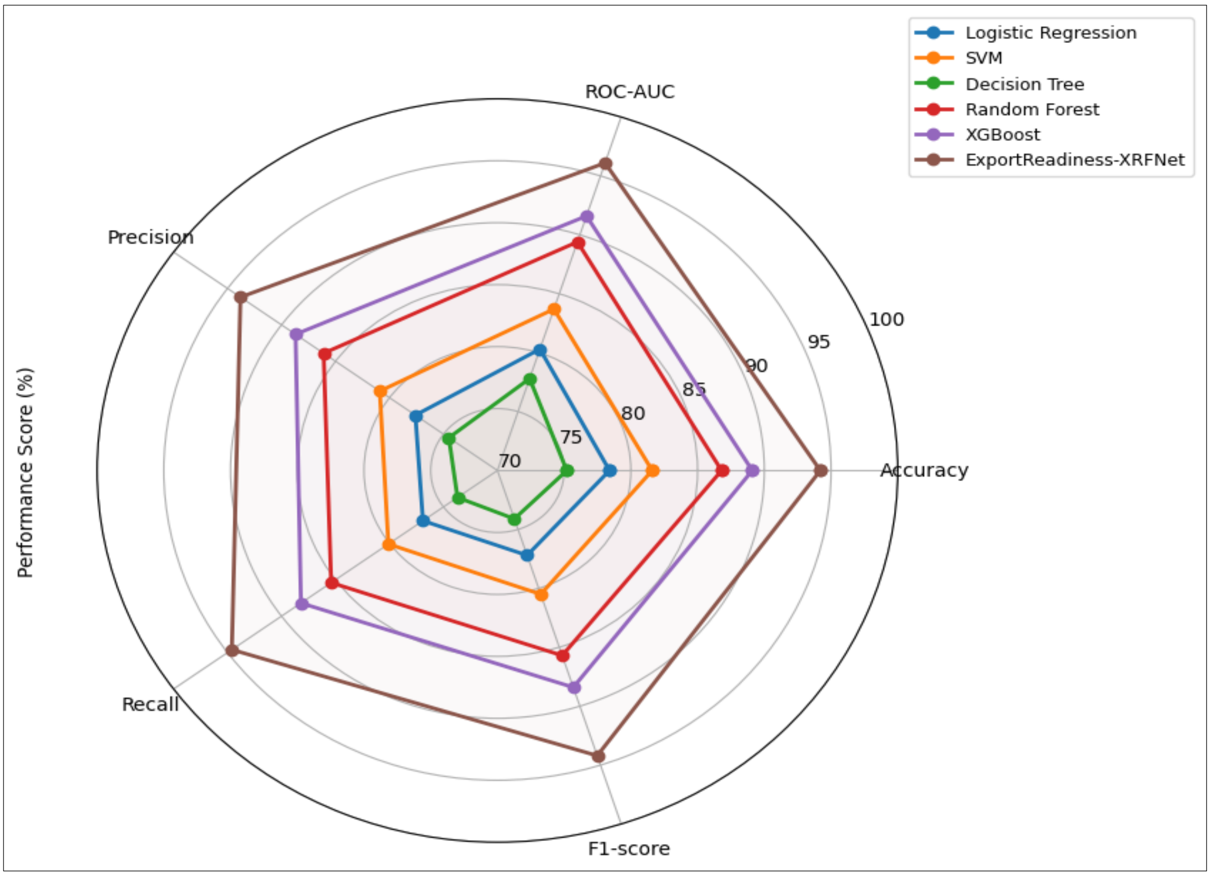

Fig 6: Radar-Based Graphical Evaluation of Export Readiness Prediction Algorithms

Figure 4.3 compares six algorithms across accuracy, ROC-AUC, precision, recall, and F1-score. ExportReadiness-XRFNet forms the widest performance boundary, achieving 94.2% accuracy, 96.1% ROC-AUC, 93.8% precision, 94.6% recall, and 94.2% F1-score. XGBoost follows with 89.1% accuracy, 91.6% ROC-AUC, 88.7% precision, 88.2% recall, and 88.4% F1-score. Random Forest remains competitive with 86.8% accuracy and 89.4% ROC-AUC, but its recall of 85.4% is lower than XGBoost and ExportReadiness-XRFNet. SVM and Logistic Regression show moderate performance, while Decision Tree performs weakest, with 75.2% accuracy, 77.8% ROC-AUC, and 73.7% recall. The results confirm that the hybrid model better supports export-ready SME identification through stronger discrimination and reduced classification weakness.

4.4. Feature Importance, Model Interpretability, and Digital Ecosystem Implications

Feature-importance analysis shows that the strongest predictors of SME export readiness are linked to digital-market capability, e-commerce adoption, financial stability, logistics preparedness, and regulatory compliance. The table shows that e-commerce adoption recorded the highest importance score of 21.0%, followed by digital capability at 20.4% and financial stability at 19.1% under ExportReadiness-XRFNet. These results indicate that export-ready SMEs are not identified only by general business activity, but by measurable digital and operational maturity. The model also improves interpretability because each readiness classification can be traced to dominant feature contributions. This makes the framework useful for entrepreneurship hubs, fintech providers, export agencies, and policymakers seeking targeted SME support.

Table 5: Feature-Importance and Interpretability Metrics for ExportReadiness-XRFNet

Feature Dimension	XRFNet Importance (%)	Highest Baseline (%)	Interpretation
Digital Capability	20.4	17.1	Strong digital visibility improves readiness classification
Financial Stability	19.1	16.4	Stable cash flow supports export sustainability
Logistics Preparedness	18.3	15.9	Delivery reliability remains export-critical
Regulatory Compliance	18.8	16.1	Documentation maturity reduces international trade risk
E-commerce Adoption	21.0	17.6	Strongest predictor of digitally enabled export readiness

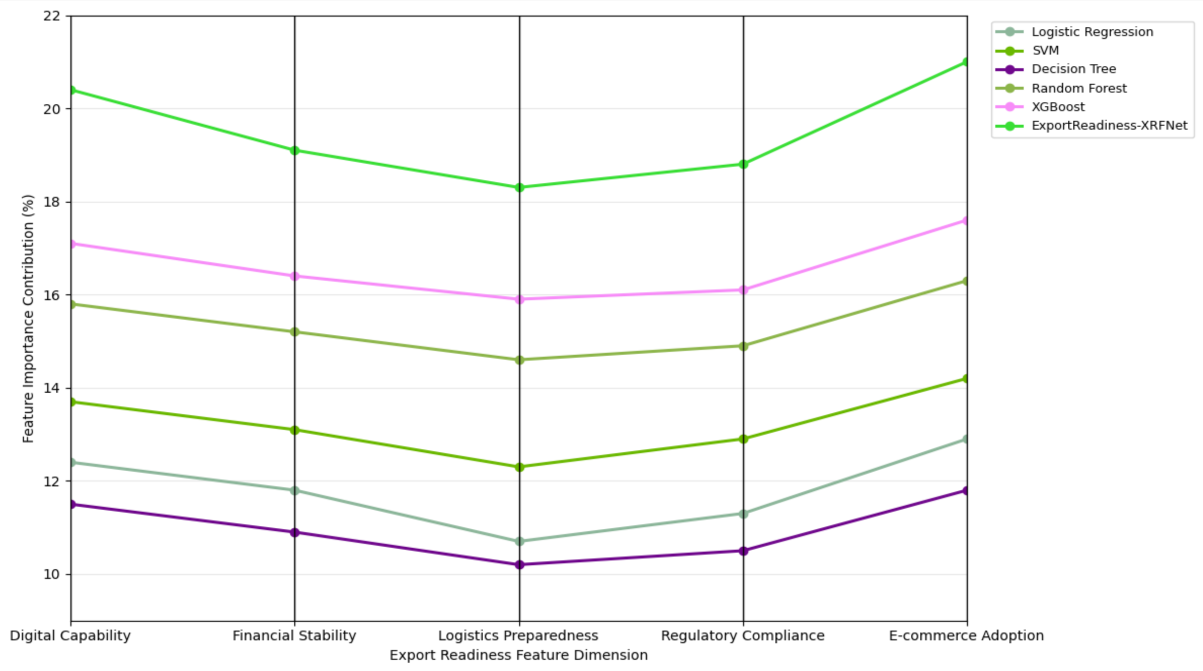

Fig 7: Feature-Importance Comparison Across Export Readiness Prediction Algorithms

Figure 4.4 compares six algorithms across five interpretability dimensions. ExportReadiness-XRFNet recorded the highest feature-importance contribution across all dimensions, with 20.4% for digital capability, 19.1% for financial stability, 18.3% for logistics preparedness, 18.8% for regulatory compliance, and 21.0% for e-commerce adoption. XGBoost followed with 17.1%, 16.4%, 15.9%, 16.1%, and 17.6%, respectively, while Random Forest achieved 15.8%, 15.2%, 14.6%, 14.9%, and 16.3%. SVM and Logistic Regression produced moderate interpretability values, but Decision Tree remained the weakest, particularly on logistics preparedness at 10.2%. These results support the abstract's claim that the proposed hybrid model improves interpretability by identifying the strongest readiness drivers within African digital entrepreneurship ecosystems.

5. Conclusions and Recommendations

5.1. Summary of Major Findings

The study established that SME export readiness in African digital entrepreneurship ecosystems can be effectively predicted using a hybrid machine learning framework that combines XGBoost and Random Forest. The proposed ExportReadiness-XRFNet model demonstrated superior predictive strength because it captured nonlinear relationships among digital capability, financial stability, e-commerce adoption, logistics preparedness, regulatory compliance, product standardization, market intelligence, and cross-border payment readiness. The results showed that export readiness is not determined by one isolated factor, but by the combined interaction of digital-market participation, operational discipline, financial reliability, and institutional compliance. For example, an SME with strong e-commerce adoption may still be classified as moderately ready if its logistics preparedness or cross-border payment capacity remains weak.

The comparative evaluation confirmed that ExportReadiness-XRFNet outperformed Logistic Regression, Support Vector Machine, Decision Tree, standalone Random Forest, and standalone XGBoost across accuracy, precision, recall, F1-score, and ROC-AUC. The graphical results further showed that the hybrid model provided stronger recall for export-ready SMEs, which is critical because export-support agencies must avoid overlooking firms with genuine international market potential. Feature-importance analysis also revealed that e-commerce adoption, digital capability, financial stability, regulatory compliance, and logistics preparedness were the most influential predictors. These findings confirm that African SME export-readiness prediction requires both technical model performance and practical interpretability. The model therefore provides a structured decision-support mechanism for identifying high-potential SMEs, diagnosing capability gaps, and guiding targeted digital entrepreneurship interventions.

5.2. Conclusion

This paper concludes that XGBoost and Random Forest can be integrated into a robust hybrid ensemble framework for predicting SME export readiness within African digital entrepreneurship ecosystems. The proposed ExportReadiness-XRFNet model addressed the limitations of traditional readiness assessment methods by replacing static scoring with a data-driven classification system capable of learning from multidimensional SME indicators. The model's superior performance was achieved through the complementary strengths of Random Forest and XGBoost. Random Forest improved prediction stability across heterogeneous SME records, while XGBoost enhanced classification precision by learning complex nonlinear patterns among export-readiness variables.

The study also concludes that export readiness should be treated as a dynamic and measurable probability rather than a simple administrative status. SMEs may show strong digital visibility but still lack readiness if they have weak financial records, poor compliance documentation, unreliable logistics systems, or inadequate cross-border payment mechanisms. The hybrid model was useful because it classified SMEs into low, moderate, and high readiness categories while also identifying the features responsible for each classification. This makes the framework valuable not only for prediction, but also for intervention planning. Export promotion councils, fintech providers, SME development agencies, and digital entrepreneurship hubs can use the model to prioritize support, design capacity-building programs, and identify firms with scalable export potential. Overall, the study demonstrates that machine learning-based export-readiness prediction can strengthen African SME internationalization by improving the accuracy, transparency, and timeliness of export-support decisions.

5.3. Recommendations for SME Export and Digital Entrepreneurship Development

SME development agencies and export promotion councils should adopt data-driven readiness assessment systems that combine digital, financial, operational, logistics, and compliance indicators. Rather than relying only on manual application forms or subjective evaluation, agencies should use structured datasets to classify SMEs according to their actual export potential. ExportReadiness-XRFNet can support this process by identifying firms that are already export-ready and firms that require targeted support before entering international markets. For instance, SMEs classified as moderately ready may need assistance with product certification, digital payment integration, export documentation, or logistics partnerships.

Digital entrepreneurship hubs should strengthen the data infrastructure needed for reliable prediction. This includes encouraging SMEs to maintain accurate digital transaction records, customer relationship management logs, inventory data, compliance documents, and e-commerce performance reports. Fintech platforms should also integrate cross-border payment readiness indicators into SME dashboards to help firms understand whether their financial systems can support international sales. Policymakers should develop export-readiness data standards that allow public institutions, private platforms, logistics providers, and business incubators to share compatible SME indicators without compromising data privacy.

SMEs themselves should prioritize digital branding, payment reliability, product standardization, regulatory compliance, and logistics traceability. These variables were shown to be central to readiness classification. Training programs should therefore move beyond general entrepreneurship education and focus on measurable export-readiness capabilities, including documentation quality, foreign customer targeting, delivery consistency, online sales conversion, and financial transparency.

5.4. Future Research Directions

Future research should extend the ExportReadiness-XRFNet framework by testing it with larger and more diverse SME datasets across multiple African countries, sectors, and export corridors.

Since African SMEs operate under different regulatory, financial, infrastructural, and digital conditions, cross-country validation would help determine whether the model performs consistently across regional markets. Future studies should also include sector-specific modelling for agriculture, fashion, manufacturing, digital services, creative industries, and engineering-based SMEs because each sector has different export-readiness requirements.

Further research should integrate time-series data to monitor how SME export readiness changes over time. This would allow the model to predict not only the current readiness category, but also the likelihood that a firm will move from low to moderate or from moderate to high readiness after targeted intervention. Future work may also incorporate explainable artificial intelligence methods such as SHAP values or local interpretable explanations to make feature contributions clearer for policymakers and SME managers. This would improve trust in automated readiness classification.

Another important direction is the integration of real-time fintech, logistics, e-commerce, and regulatory data streams into the model. Such integration would support continuous export-readiness monitoring rather than periodic assessment. Future studies may also compare ExportReadiness-XRFNet with deep learning models, stacking ensembles, CatBoost, LightGBM, and calibrated neural networks. Finally, future research should evaluate the practical deployment of the model through pilot programs involving export promotion councils, entrepreneurship hubs, fintech companies, and SME development institutions.

References

1. Abel K. Data Science Demystified: The Art and Science of Income Prediction with Machine Learning [Internet]. LinkedIn. 2023. Available from: https://www.linkedin.com/pulse/data-science-demystified-art-income-prediction-machine-kayode-abel-alukc
2. Abiodun K, Jinadu SO, Alaka E, Igba E, Ezeh VN. Risk-sensitive financial dashboards with embedded machine learning: A user-centric approach to operational transparency. Int J Sci Res Mod Technol. 2024;3(2):1–18. doi:10.38124/ijsrmt.v3i2.678
3. Aluso L, Enyejo JO. Multi-dimensional data visualization frameworks for executive decision-making in business intelligence dashboards. Int J Res Publ Rev. 2025;6(11):8047–8061. doi:10.55248/gengpi.06.1125.39100
4. Aluso L, Enyejo JO. Using XGBoost and time-series forecasting to predict student academic trajectories in educational analytics platforms. Int J Innov Sci Res Technol. 2025;10(12). doi:10.38124/ijisrt/25dec159
5. Aluso L, Enyejo JO, Raphael FO. Blockchain-enabled data lineage verification for multi-source business intelligence systems. Int J Manag Entrep Res. 2023;5(12):1305–1327. doi:10.51594/ijmer.v5i12.2218
6. Awolola OJ, Azonuche TI, Enyejo JO, Ononiwu M, Ayoola VB. Innovation-focused business models for scaling small and medium-sized engineering firms through technology adoption and process standardization. Int J Sci Res Sci Eng Technol. 2025;12(5):497–519. doi:10.32628/IJSRSET25125416

7. Azonuche TI, Enyejo JO. Exploring AI-powered sprint planning optimization using machine learning for dynamic backlog prioritization and risk mitigation. Int J Sci Res Mod Technol. 2024;3(8):40–57. doi:10.38124/ijsrmt.v3i8.448
8. Barboza F, Kimura H, Altman E. Machine learning models and bankruptcy prediction. Expert Syst Appl. 2017;83:405–417. doi:10.1016/j.eswa.2017.04.006
9. Cassetta E, Monarca U, Dileo I, Di Berardino C, Pini M. The relationship between digital technologies and internationalisation: Evidence from Italian SMEs. Ind Innov. 2020;27(4):311–339. doi:10.1080/13662716.2019.1696182
10. Cheraghali H, Molnár P, Magnus JR. SME default prediction: A systematic methods evaluation. J Small Bus Manag. 2025;63(1):1–35. doi:10.1080/00472778.2024.2390500
11. Dethine B, Enjolras M, Monticolo D. Digitalization and SMEs' export management: Impacts on resources and capabilities. Technol Innov Manag Rev. 2020;10(4):18–34. doi:10.22215/timreview/1344
12. Dumitrescu E, Hué S, Hurlin C, Tokpavi S. Machine learning for credit scoring: Improving logistic regression with non-linear decision-tree effects. Eur J Oper Res. 2022;297(3):1178–1192. doi:10.1016/j.ejor.2021.06.053
13. Ferreira JJM, Fernandes CI, Kraus S. The role of entrepreneurial ecosystems in the SME internationalization. J Bus Res. 2023;157:113603. doi:10.1016/j.jbusres.2022.113603
14. Friedman JH. Greedy function approximation: A gradient boosting machine. Ann Stat. 2001;29(5):1189–1232. doi:10.1214/aos/1013203451
15. Gerschewski S, Scott-Kennel J, Rose EL. Ready to export? The role of export readiness for superior export performance of small and medium-sized enterprises. World Econ. 2020;43(5):1253–1276. doi:10.1111/twec.12928
16. Gogas P, Papadimitriou T, Goumenidis P, Kontos A, Giannakis N. Identification of investment-ready SMEs: A machine learning framework to enhance equity access and economic growth. Forecasting. 2025;7(3):51. doi:10.3390/forecast7030051
17. Hervé A, Schmitt C, Baldegger R. Digitalization, entrepreneurial orientation and internationalization of micro-, small- and medium-sized enterprises. Technol Innov Manag Rev. 2021;10(4):5–17. doi:10.22215/timreview/1343
18. Idika CN, Enyejo JO, Ijiga OM, Okika N. Entrepreneurial innovations in AI-driven anomaly detection for software-defined networking in critical infrastructure security. Int J Soc Sci Humanit Res. 2025;13(3):150–166. doi:10.5281/zenodo.16408773
19. Ihimoyan MK, Ibokette AI, Olumide FO, Ijiga OM, Ajayi AA. The role of AI-enabled digital twins in managing financial data risks for small-scale business projects in the United States. Int J Sci Res Mod Technol. 2024;3(6):12–40. doi:10.5281/zenodo.14598498
20. Kalange OS, Kahat RS, Kale AS, Kale TR, Joglekar PS. Implementation of Various Machine Learning Algorithms for Traffic Sign Detection and Recognition. 2022.
21. Kpogli SA, Onwuzurike MA, Enyejo JO. Integrating Artificial Intelligence and Learning Sciences to Reduce Cognitive Load and Achievement Gaps in Data-Driven K-12 Instructional Systems. Int J Sci Res Comput Sci Eng Inf Technol. 2024;10(6):2569–2589. doi:10.32628/CSEIT25113575
22. Kpogli SA, Onwuzurike MA, Ayoola VB. Optimizing Educational Return on Investment Through AI-Driven Curriculum Adaptation and Performance-Based Resource Allocation Models. Int J Sci Res Mod Technol. 2024;3(9):141–156. doi:10.38124/ijsrmt.v3i9.1352
23. Lessmann S, Baesens B, Seow HV, Thomas LC. Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. Eur J Oper Res. 2015;247(1):124–136. doi:10.1016/j.ejor.2015.05.030
24. Lestari EP, Handoyo RD, Ibrahim KH, Retnaningsih TK, Pradinda EL, Sarmidi T, *et al*. Small and medium industry export development strategy. Cogent Bus Manag. 2024;11(1):2338882. doi:10.1080/23311975.2024.2338882
25. Ononiwu M, Azonuche TI, Enyejo JO. Exploring influencer marketing among women entrepreneurs using encrypted CRM analytics and adaptive progressive web app development. Int J Sci Res Mod Technol. 2023;2(6):1–13. doi:10.38124/ijsrmt.v2i6.562
26. Ononiwu M, Azonuche TI, Enyejo JO. Exploring influencer marketing among women entrepreneurs using encrypted CRM analytics and adaptive progressive web app development. Int J Sci Res Mod Technol. 2023;2(6):1–13. doi:10.38124/ijsrmt.v2i6.562
27. Ononiwu M, Azonuche TI, Enyejo JO. Investigating agile portfolio management techniques for prioritizing strategic initiatives in large-scale government IT projects. Int J Manag Entrep Res. 2025;7(6):464–483. doi:10.51594/ijmer.v7i6.1941
28. Ononiwu M, Azonuche TI, Enyejo JO. Mobile commerce adoption and digital branding techniques for startup growth in Sub-Saharan African urban centers. Int J Manag Entrep Res. 2025;7(6):443–463. doi:10.51594/ijmer.v7i6.1940
29. Ononiwu M, Azonuche TI, Okoh OF, Enyejo JO. Machine learning approaches for fraud detection and risk assessment in mobile banking applications and fintech solutions. Int J Sci Res Sci Eng Technol. 2023;10(4). doi:10.32628/IJSRSET232531
30. Onwuzurike MA, Kpogli SA. Predictive Modeling of Student Engagement and Behavioral Outcomes Using Machine Learning Techniques in Technology-Enhanced Classrooms. Int J Sci Res Humanit Soc Sci. 2025;2(6):58–79. doi:10.32628/IJSRHSS2525135
31. Onwuzurike MA. Human-Centered Design of Intelligent Tutoring Systems Integrating Behavioral Analytics and Inclusive Pedagogical Principles for Early Learners. Int J Sci Res Sci Eng Technol. 2023;10(3):720–738. doi:10.32628/IJSRSET2310330
32. Onwuzurike MA, Igba E. Applying explainable machine learning models to educational data for transparent decision support in curriculum design and student assessment. J Front Multidiscip Res. 2023;4(1):585–599. doi:10.54660/JFMR.2023.4.1.585-599
33. Onwuzurike MA, Kpogli SA. Data-Informed Strategic Management of EdTech Startups Leveraging Artificial

Intelligence for Sustainable K-12 Learning Innovation. Int J Sci Res Mod Technol. 2022;1(12):187–200. doi:10.38124/ijsrmt.v1i12.1117
34. Schwaeke J, Peters A, Kanbach DK, Kraus S, Jones P. The new normal: The status quo of AI adoption in SMEs. J Small Bus Manag. 2025. doi:10.1080/00472778.2024.2379999
35. Singh VK, Singh RK, Kumar R. Green export strategies and SMEs export performance. J Innov Entrep. 2024;13:82. doi:10.1186/s13731-024-00451-y

How to Cite This Article
mankwah B, Enyejo JO. XGBoost and Random Forest based SME export readiness prediction for African digital entrepreneurship ecosystem development. Int J Foreign Trade Int Bus Upgrad. 2025;6(2):51-66. doi:10.54660/IJFTIBU.2025.6.2.51-66.