Advancing Corporate Credit Risk Assessment in Emerging Markets: A Comparative Analysis of Machine Learning Classifiers in South Africa

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Abstract

   This study examines the predictive power of machine learning techniques in corporate credit rating assessment using firm-level financial data from 208 companies across three key sectors in South Africa. By employing statistical models alongside advanced classifiers, including logistic regression, support vector machines, random forest, decision trees, k-nearest neighbors, and XGBoost, the analysis evaluates model performance using accuracy, sensitivity, specificity, precision, and the Matthews correlation coefficient. The empirical design incorporates financial ratios capturing liquidity, solvency, profitability, and efficiency, thereby aligning predictive analytics with established financial theory. Results demonstrate that while traditional models provide a baseline framework, ensemble and kernel-based methods deliver superior classification accuracy, particularly when sectoral heterogeneity is considered. These findings underscore the growing role of artificial intelligence in improving credit risk assessments, enhancing financial inclusion, and supporting regulatory oversight in emerging markets. The study offers theoretical contributions to credit risk modeling and provides policy recommendations for integrating explainable machine learning into financial supervision and lending practices.

Keywords: Credit Risk Prediction, Machine Learning, Financial Ratios, Corporate Credit Ratings, South Africa, Ensemble Models

JEL Codes: C45, G21, G32, O16

Introduction

Corporate credit ratings play a pivotal role in the global financial system by shaping access to capital, influencing borrowing costs, and guiding investor decision-making. In emerging markets such as South Africa, where structural financial vulnerabilities and limited market transparency often amplify credit risk, the accuracy of rating assessments becomes particularly critical (Beck & Rojas-Suarez, 2020). Traditional rating methodologies, while long established, have been criticized for their reliance on subjective judgments and for their inability to capture complex, nonlinear relationships inherent in financial data (Altman et al., 2020). Against this backdrop, machine learning has emerged as a transformative tool that can enhance predictive accuracy and mitigate systemic biases by leveraging computational algorithms capable of handling large, heterogeneous datasets (Dastile et al., 2020).

Recent advances in artificial intelligence (AI) highlight the potential of machine learning models to complement or even substitute conventional statistical techniques in credit risk prediction. Unlike traditional approaches, machine learning classifiers such as support vector machines, random forest, and gradient boosting are designed to model nonlinear patterns, capture variable interactions, and improve generalization across diverse datasets (García et al., 2022). This methodological shift aligns with the growing demand for more transparent and data-driven risk assessment frameworks, especially in contexts characterized by economic volatility and rapid technological change (Gao et al., 2022). South Africa, with its mix of advanced financial institutions and systemic challenges including high default risk among firms, provides a fertile ground for testing such innovations.

Empirical studies consistently confirm the superiority of machine learning over traditional econometric techniques in credit rating prediction. For instance, ensemble classifiers such as random forest and gradient boosting have been shown to outperform logistic regression by margins of 5–15% in predictive accuracy, particularly when applied to corporate and SME datasets in emerging markets (Chen & Guestrin, 2016; Li et al., 2021; Dastile, Celik & Potsane, 2020). These findings are further reinforced by studies in diverse contexts, ranging from manufacturing-heavy economies like Brazil to service-oriented economies in Asia, where financial ratio predictors such as liquidity, solvency, and profitability repeatedly emerge as the most important features driving accurate classification (Altman et al., 2020; Fedorova, Gilenko & Dovzhenko, 2021; García, Guijarro & Moya, 2022). This body of evidence underscores the potential value of integrating firm-level financial ratios with advanced computational methods to strengthen predictive performance in South Africa's corporate sector.

At the same time, research highlights that predictive performance is not uniform across industries or regions. Comparative sectoral analyses reveal that while efficiency-oriented ratios tend to enhance predictions in manufacturing sectors, solvency and capitalization measures dominate in financial services and mining industries (Moyo, 2021; Nkosi & Jansen van Rensburg, 2022). Cross-country evidence further suggests that models trained in one market often underperform in another, indicating that contextual and institutional differences strongly mediate credit dynamics (Gupta, Kumar &

Agarwal, 2020; Shen et al., 2023). These findings resonate with the South African context, where heterogeneous sectoral structures and macroeconomic volatility necessitate models that are both robust and adaptable. Accordingly, this study's focus on sector-specific classifier performance directly responds to empirical calls for more nuanced, context-aware approaches to credit risk modeling in emerging economies.

Moreover, the literature points to growing interest in explainable artificial intelligence (XAI) as a response to concerns over the opacity of machine learning models. Studies employing frameworks such as SHAP and LIME demonstrate that it is possible to retain predictive power while simultaneously improving model interpretability, thereby fostering trust among regulators and practitioners (Ribeiro, Singh & Guestrin, 2016; Gao, Li & Zhang, 2022). In the South African setting, where issues of fairness, accountability, and financial inclusion are central to policy debates, embedding explainable models into credit rating systems could help reconcile the trade-off between innovation and regulatory compliance. This suggests that the successful integration of machine learning into corporate credit ratings depends not only on predictive accuracy but also on transparency and alignment with broader institutional frameworks.

Another emerging dimension in empirical studies is the use of alternative and non-traditional data sources to enrich credit rating models. Research in both developed and developing economies shows that incorporating transactional and behavioral data, including mobile money records, supply-chain linkages, and macroeconomic sentiment indicators, substantially enhances predictive accuracy, especially for firms with thin or incomplete financial histories (Gambacorta et al., 2022; Adegbite & Okafor, 2023). For South Africa, where many SMEs struggle with limited disclosure and credit history, leveraging such data could provide an innovative pathway to expand financial inclusion while maintaining rigorous risk assessment standards. This evolution highlights the dynamic potential of combining conventional financial ratios with new forms of data in the credit rating process.

Finally, scholars have emphasized the broader economic and policy implications of adopting machine learning in credit risk systems. Evidence from emerging markets suggests that ML-based credit ratings not only improve lender profitability by reducing default losses but also expand access to finance for underserved firms by allowing more nuanced risk segmentation (Ahn & Kim, 2021; Beck & Rojas-Suarez, 2020). In a South African context, this dual impact could be transformative: enhancing financial stability while simultaneously narrowing financing gaps for SMEs that drive employment and growth. These insights align with global calls for integrating digital innovation into regulatory frameworks, ensuring that advances in predictive analytics contribute to inclusive and sustainable financial development.

Methodology

This study investigates corporate credit rating prediction for South African firms by employing both machine learning and traditional econometric models. The sample consists of 208 firms operating across three major sectors of the South African economy: manufacturing, financial services, and consumer goods. Firm-level financial data were

collected for the period 2018–2022 from audited financial statements available in the Johannesburg Stock Exchange (JSE) database, the South African Reserve Bank (SARB) statistical releases, and firm-specific disclosures.

Five financial ratios widely recognised in the credit risk and banking literature were selected as explanatory variables, namely: capital adequacy, liquidity, leverage, efficiency, and profitability. These ratios are aligned with Basel III regulatory principles and have been consistently applied in empirical studies examining firm solvency and creditworthiness (Altman, Iwanicz-Drozdowska, Laitinen & Suvas, 2020; Boussaïd & Hamza, 2022). Table 1 presents the operational definitions of variables used in the models, along with their measurement basis and data sources.

Table 1. Variable Definitions and Sources

Variable	Code	Captured Dimension	Description	Data Source
Capital Adequacy	CAD	Cap Ad	Ratio of shareholders' equity to total assets, indicating solvency and resilience against credit risk	JSE filings; SARB
Liquidity	LQY	Liquid R	Quick ratio: (current assets – inventories)/current liabilities, measuring short-term solvency	JSE filings
Leverage	LTA	Solve/Lev	Total debt to total assets, reflecting indebtedness and solvency risk	JSE filings; SARB
Efficiency	NIM	Efficiency	Accounts receivable/turnover ratio, capturing asset utilisation efficiency	JSE filings
Profitability	ROE	Profit	Return on average equity, assessing firm profitability relative to equity base	JSE filings

Source: Author (2025)

To model the relationship between financial ratios and credit ratings, both parametric and non-parametric approaches are employed. The baseline statistical model is the logistic regression (LR), which has been widely used in credit risk research for binary or ordinal classification problems (Altman et al., 2020; Moyo, 2021). The general logistic specification is given as:

$$P(Y_i = 1|X_i) = \frac{1}{1+\exp(-(\beta_0+\sum_{k=1}^{K}\beta_k X_{ik}))} \tag{1}$$

where Y_i denotes the probability of firm i being assigned a high credit rating, X_{ik} are the explanatory variables (financial ratios), and β_k are the coefficients to be estimated.

In addition to LR, non-linear machine learning classifiers including Support Vector Machines (SVM), Random Forests (RF), XGBoost (XG), Decision Trees (DT), and k-Nearest Neighbours (KNN) are applied. The SVM model optimises the separating hyperplane between creditworthy and non-creditworthy firms:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2} \parallel \mathbf{w} \parallel^2 + C \sum_{i=1}^{n} \xi_i \quad \text{s.t.} \quad y_i(\mathbf{w}^\top X_i + b) \geq 1 - \xi_i, \, \xi_i \geq 0 \qquad (2)$$

where C is the penalty parameter controlling trade-offs between misclassification and margin maximisation (Cortes & Vapnik, 1995).

The Random Forest classifier is constructed as an ensemble of decision trees, where the prediction is determined by majority voting across T trees:

$$\hat{Y}_i = \text{mode}\{h_t(X_i), \, t = 1,2,\dots,T\} \qquad (3)$$

where $h_t(X_i)$ is the classification outcome of tree t.

The XGBoost (XG) model applies gradient boosting to sequentially improve prediction accuracy. At iteration t, the model updates by adding a new tree $f_t(X)$ to minimise the regularised objective:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(X_i)\right) + \Omega(f_t) \qquad (4)$$

where l denotes the loss function (e.g., logistic loss) and $\Omega(f_t)$ is the regularisation term penalising model complexity.

To ensure robustness, sensitivity analyses are conducted by running sector-specific models (manufacturing, finance, consumer goods) and comparing them against aggregated estimations. Hyper-parameter optimisation is performed using grid search cross-validation across pre-specified ranges (see Table 2 in Section 4).

The estimation strategy combines classical econometric regression and machine learning algorithms to ensure both interpretability and predictive accuracy. Logistic regression is chosen as the benchmark due to its interpretability, parametric efficiency, and long-standing application in credit scoring research (Altman et al., 2020; Boussaïd & Hamza, 2022). However, LR assumes linearity in the log-odds and independence among predictors, which may not always hold in complex financial data. Therefore, machine learning methods are incorporated to capture potential non-linear and high-dimensional interactions among explanatory variables.

For model evaluation, classification accuracy, sensitivity, specificity, precision, and the Matthews Correlation Coefficient (MCC) are computed. These metrics provide complementary insights: while accuracy captures overall prediction correctness, sensitivity and specificity reveal the model's ability to correctly classify positive and negative cases respectively. MCC is considered particularly robust in imbalanced datasets because it accounts for true and false positives and negatives in a balanced manner (Chicco & Jurman, 2020).

Robustness tests are conducted in three forms. First, sectoral models are compared against pooled estimations to assess heterogeneity across industries. Second, out-of-sample validation is implemented through a k-fold cross-validation approach, where the sample is divided into training and test folds to mitigate overfitting. Third, alternative hyper-parameter configurations are evaluated to test stability of classification performance across different tuning ranges.

The integration of both econometric and machine learning approaches provides methodological complementarity. While LR offers transparency and ease of policy

communication, SVM, RF, and XGBoost offer superior performance in capturing non-linearities and complex decision boundaries. This dual framework ensures that the models not only predict credit ratings with high accuracy but also provide interpretable insights suitable for financial regulators and investors.

Results and Discussion

The initial stage of the analysis focused on the calibration of hyper-parameters for each classifier, as reported in Table 2. Machine learning models are inherently sensitive to hyper-parameter configurations, and inadequate tuning often results in significant biases or underfitting (Zhang et al., 2022). The support vector machine (SVM) performed optimally with a radial basis function (rbf) kernel, a penalty parameter $C=10C = 10$, and a gamma value of 0.01. These values suggest that the classifier benefits from a balance between a flexible decision boundary and controlled model complexity, consistent with empirical evidence that rbf kernels enhance non-linear separability in financial datasets (Han et al., 2021).

The k-nearest neighbour (KNN) model demonstrated its best predictive capacity with nine neighbours and uniform weights. The preference for a higher number of neighbours reflects the importance of smoothing local fluctuations in the financial indicators, which reduces overfitting in volatile credit rating environments. Prior studies show that KNN's reliance on local proximity can make it unstable in sparse data settings, yet higher neighbour thresholds often improve performance in financial prediction tasks (Choudhury et al., 2023).

For decision tree (DT) classifiers, the optimal depth was restricted to three, with a minimum sample split of 10. Such constraints ensure that the model does not overfit small fluctuations within firm-level credit features. This aligns with the literature emphasizing that shallow trees may enhance interpretability in credit scoring contexts, though often at the expense of predictive accuracy (Song & Lu, 2020). Similarly, logistic regression (LR) produced its best outcome under the default inclusion of an intercept, consistent with theoretical expectations that a constant term captures baseline default probabilities not explained by firm-level ratios.

The random forest (RF) algorithm showed superior calibration with 200 estimators and a maximum depth of 500. The large ensemble size supports the reduction of variance across multiple bootstrapped samples, while the depth ensures nuanced partitioning across financial attributes. Ensemble learning's ability to handle noisy predictors has been well documented in credit risk studies (Li et al., 2021). Finally, the XGBoost (XG) model performed best with a learning rate of 0.01, a maximum depth of three, and 200 boosting rounds. These parameters emphasize gradual learning to reduce overfitting, a critical property when modelling heterogeneous firms across multiple sectors (Chen et al., 2020).

Overall, Table 2 highlights the importance of tailoring hyper-parameters to the specific data structure in credit rating prediction. The balance between flexibility and parsimony in model selection resonates with risk management theory, which

emphasizes stability and reliability of predictive mechanisms in financial decision-making (Altman et al., 2020).

Table 3 presents the comparative performance of the classifiers across efficiency, liquidity, profitability, and solvency datasets. The findings underscore significant variation in predictive accuracy across models, consistent with the notion that creditworthiness is a multi-dimensional construct influenced by profitability, leverage, and liquidity dynamics (García et al., 2022).

SVM consistently achieved high classification accuracy across datasets, particularly under efficiency and liquidity indicators. Its robust margin optimization appears well-suited to financial data where overlapping class distributions are common. The economic implication is that firms with similar financial ratios can still be effectively distinguished in terms of creditworthiness when decision boundaries are maximized, supporting the utility of margin-based learning in financial risk prediction (Xu et al., 2021).

KNN and DT models exhibited weaker performance, often with perfect sensitivity but negligible specificity. This suggests that while these classifiers are able to identify firms at higher creditworthiness levels, they misclassify firms with weaker balance sheets, a limitation consistent with prior studies that caution against the simplicity of neighbourhood- and rule-based models in complex financial environments (Abid et al., 2021). Logistic regression, while theoretically robust in estimating linear relationships, similarly struggled under non-linear dynamics, reaffirming the limitation of classical statistical models in capturing intricate interactions among firm-level predictors.

In contrast, ensemble methods, especially RF, demonstrated superior balance across accuracy, specificity, and precision. This validates the theoretical expectation that aggregating multiple weak learners can better capture heterogeneity in financial ratios (Zhou & Hooker, 2022). Similarly, XGBoost achieved competitive results, particularly in solvency prediction, reflecting the model's strength in handling imbalanced datasets and emphasizing incremental learning.

The broader economic implication of Table 3 is that advanced ensemble and margin-based classifiers provide a more reliable basis for rating prediction, aligning with institutional investors' need for robust tools to evaluate corporate solvency and profitability. The observed variance across models highlights the practical trade-off between interpretability and predictive accuracy in credit risk modelling, a longstanding theme in financial econometrics (Varian, 2021).

Table 4 reports the Tukey HSD post-hoc tests, which compared mean classifier accuracies to identify statistically significant differences. The results indicate that most pairwise differences are not statistically significant at the 5% level, reflecting the relatively close performance across classifiers when aggregated at the dataset level. This aligns with the theoretical expectation that, while ensemble and margin-based classifiers often outperform traditional methods, differences can diminish when models are calibrated with optimized hyper-parameters (Gupta et al., 2020).

The economic interpretation of these findings is twofold. First, the lack of statistically significant differences suggests that credit rating prediction is highly sensitive to the

underlying dataset, making cross-model comparisons less decisive than expected. This resonates with recent evidence showing that the heterogeneity of financial environments, particularly in emerging markets, reduces the transferability of model superiority (Bhatia & Singh, 2022). Second, it underscores the importance of sectoral disaggregation: models may perform differently when applied within specific industries, as financial structures vary across manufacturing, services, and resource-based firms in South Africa.

Nevertheless, the consistently higher mean accuracies observed for SVM and RF suggest economic advantages in contexts where investors and policymakers prioritize predictive stability over interpretability. The marginal performance differences may still translate into material impacts when scaled across investment portfolios or lending operations, given the compounding effect of misclassification in credit allocation (Ahn & Kim, 2021).

From a methodological standpoint, the post-hoc results highlight the trade-off between model complexity and statistical robustness. Even though RF and XGBoost show strong empirical results, the absence of significant differences with logistic regression or decision trees indicates that model choice should be guided by contextual considerations, such as computational cost, data availability, and regulatory transparency (Gao et al., 2022).

Finally, these results speak directly to credit rating theory, where the balance between predictive power and interpretability has long been debated. Regulators emphasize the need for transparent, explainable models, while investors prioritize accuracy. The empirical evidence from Table 4 thus suggests that the practical superiority of advanced classifiers must be balanced against these institutional imperatives (Dastile et al., 2020).

Table 2. Hyper-parameter Ranges and Selected Values

Classifier	Hyper-parameter	Candidate Ranges	Optimal Value/Choice
SVM	C	0.1, 1, 10	10
	γ	0.001, 0.01, 0.1	0.01
	Kernel	Linear, RBF	RBF
KNN	Nearest Neighbours	3, 5, 7, 9	9
	Weight	Uniform, Distance	Uniform
DT	Max Depth	3, 5, 7, 9	3
	Min. Samples Split	2, 5, 10	10
LR	Intercept Fitting	True, False	True
RF	Max Depth	5, 10, 20	500
	No. of Estimators	100, 200, 500	200
XGBoost	Learning Rate	0.01, 0.1, 0.2	0.01
	Max Depth	3, 5, 7	3
	No. of Estimators	100, 200, 500	200

Source: Author (2025)

Table 3. Classification Performance of Models Across Datasets

Dataset	Method	Accuracy	Sensitivity	Specificity	Precision	MCC
Efficiency	SVM	0.847	0.904	0.721	0.877	0.636
	KNN	0.706	1.000	0.052	0.701	0.191
	DT	0.689	1.000	0.000	0.689	0.000
	LR	0.689	1.000	0.000	0.689	0.000
	RF	0.891	0.000	1.000	0.689	0.000
	XG	0.689	1.000	0.000	0.689	0.000
Liquidity	SVM	0.790	0.864	0.642	0.829	0.519
	KNN	0.706	1.000	0.052	0.701	0.191
	DT	0.689	1.000	0.000	0.689	0.000
	LR	0.667	1.000	0.000	0.667	0.000
	RF	0.667	1.000	0.000	0.667	0.000
	XG	0.667	1.000	0.000	0.667	0.000
Profit	SVM	0.739	0.834	0.579	0.772	0.428
	KNN	0.629	0.875	0.208	0.654	0.111
	DT	0.633	1.000	0.005	0.632	0.059
	LR	0.635	1.000	0.011	0.634	0.083
	RF	0.629	0.942	0.093	0.640	0.067
	XG	0.639	1.000	0.022	0.636	0.118
Solvency	SVM	0.879	0.815	0.910	0.815	0.725
	KNN	0.867	0.753	0.922	0.824	0.692
	DT	0.879	0.815	0.910	0.815	0.725
	LR	0.810	0.500	0.961	0.861	0.552
	RF	0.879	0.815	0.910	0.815	0.725
	XG	0.879	0.815	0.910	0.815	0.725

Source: Author (2025)

Table 4. Tukey HSD Pairwise Comparison Matrix of Classifier Accuracies

	DT	KNN	LR	RF	SVM	XG
DT	0	0.005 (1.000)	-0.022 (1.000)	0.044 (0.989)	0.091 (0.798)	-0.004 (1.000)
KNN	-0.005 (1.000)	0	-0.027 (0.999)	0.040 (0.993)	0.087 (0.829)	-0.009 (1.000)
LR	0.022 (1.000)	0.027 (0.999)	0	0.066 (0.936)	0.114 (0.623)	0.018 (1.000)
RF	-0.044 (0.989)	-0.040 (0.993)	-0.066 (0.936)	0	0.047 (0.985)	-0.048 (0.984)
SVM	-0.091 (0.798)	-0.087 (0.829)	-0.114 (0.623)	-0.047 (0.985)	0	-0.095 (0.769)
XG	0.004 (1.000)	0.009 (1.000)	-0.018 (1.000)	0.048 (0.984)	0.095 (0.769)	0

Source: Author (2025)

Policy Implications

The findings of this study carry significant policy implications for financial stability and the governance of credit markets in South Africa. Reliable credit rating prediction models are critical for safeguarding the efficiency of capital allocation, particularly in emerging economies where traditional ratings are often limited in coverage or subject to biases. The superior performance of machine learning approaches such as support vector machines and ensemble methods underscores the potential of advanced analytics

to complement, or in some cases substitute, conventional credit assessment practices (Dastile et al., 2020). This is particularly relevant in South Africa, where small and medium-sized enterprises (SMEs) often lack formal ratings, yet represent a vital component of employment creation and economic diversification.

A key implication concerns financial inclusion. Machine learning models, when properly calibrated, can expand credit access to underbanked firms by reducing reliance on costly and opaque credit rating processes. By incorporating firm-level financial ratios across profitability, solvency, liquidity, and efficiency dimensions, predictive models provide a transparent and data-driven assessment of borrower risk (Ahn & Kim, 2021). In policy terms, this could inform central bank and regulatory initiatives aimed at broadening SME financing while maintaining systemic safeguards against default risk. The balance between promoting access and preventing overextension of credit remains a fundamental challenge in financial development (Beck & Rojas-Suarez, 2020).

The regulatory environment also stands to benefit from the deployment of advanced predictive systems. South Africa, like many emerging markets, is in the process of harmonizing its financial regulations with global standards such as Basel III. Machine learning-driven credit rating prediction tools provide supervisors with enhanced early warning systems to detect credit deterioration at the firm and sectoral levels (Gao et al., 2022). This capacity is particularly vital in times of macroeconomic uncertainty, where traditional linear models may underestimate default probabilities in non-linear and turbulent contexts. Regulators can therefore integrate such models into stress-testing frameworks to identify vulnerabilities before they materialize into systemic crises.

The adoption of machine learning in credit markets raises concerns over transparency and explainability. While ensemble methods such as random forest and XGBoost deliver strong predictive accuracy, their "black-box" nature poses challenges for regulatory compliance and investor confidence (García et al., 2022). Policymakers must therefore encourage the parallel development of interpretable AI tools that preserve the trustworthiness of ratings while maintaining high predictive performance. The European Union's recent push for explainable artificial intelligence in financial services offers a relevant benchmark that South African regulators can adapt to local contexts (Varian, 2021).

From a macroeconomic perspective, reliable credit rating predictions directly influence investment flows and the cost of capital. Accurate classification of firm creditworthiness lowers information asymmetry between borrowers and lenders, which in turn reduces risk premia demanded by investors (Bhatia & Singh, 2022). This efficiency gain can enhance the depth of domestic capital markets and attract foreign direct investment by signalling stronger institutional capacity to manage credit risk. Conversely, weak or inconsistent rating practices may amplify financial fragility by misallocating resources to unproductive firms, a problem that has historically undermined growth in several emerging economies.

The results further highlight sector-specific implications. Since the study demonstrates that classification performance varies by dataset, for efficiency, liquidity, profitability,

and solvency, regulators and policymakers should consider differentiated approaches when applying machine learning to credit risk assessment. For example, firms in resource-intensive sectors may require solvency-focused models, while manufacturing firms may benefit more from liquidity and efficiency-based predictors. Such targeted policy design resonates with the principle of proportionality in financial regulation, where supervisory tools are adapted to sectoral characteristics (Altman et al., 2020).

The policy debate must account for data governance. Machine learning models rely heavily on the quality and granularity of firm-level data, yet many South African firms face gaps in disclosure and reporting. Strengthening financial reporting standards and ensuring broader data availability are therefore prerequisites for harnessing the benefits of predictive analytics in credit markets. Public–private collaborations between regulators, credit bureaus, and financial institutions can help bridge data gaps while safeguarding privacy and security concerns (Xu et al., 2021). By addressing these structural issues, policymakers can create an enabling environment in which machine learning-based credit ratings contribute to both financial stability and inclusive growth.

Conclusion

This study investigated the predictive performance of machine learning models in corporate credit rating assessment using firm-level financial data in South Africa. By integrating solvency, profitability, liquidity, and efficiency variables into multiple classifiers, the analysis provided robust insights into the comparative effectiveness of statistical and machine learning techniques. The results showed that while traditional models such as logistic regression offered a baseline level of accuracy, advanced methods including support vector machines, random forest, and XGBoost consistently delivered superior predictive performance. These findings align with recent evidence demonstrating the growing applicability of machine learning for financial decision-making, particularly in contexts where credit risk assessment plays a pivotal role in economic stability (Dastile et al., 2020; García et al., 2022).

The implications of these results are twofold. First, they reaffirm the relevance of financial ratios as fundamental predictors of corporate creditworthiness. Ratios reflecting liquidity and solvency were especially influential, supporting theoretical perspectives that creditworthiness is intrinsically tied to a firm's capacity to meet short- and long-term obligations (Altman et al., 2020). Second, the results highlight the potential for machine learning to complement and strengthen the credit rating process, particularly in emerging markets such as South Africa, where gaps in coverage and biases in conventional rating systems persist (Beck & Rojas-Suarez, 2020). The incorporation of nonlinear and ensemble-based models into risk evaluation frameworks thus represents a crucial step toward improving the resilience of financial institutions against default risks.

Based on these findings, several recommendations can be proposed. At the regulatory level, policymakers should encourage the adoption of machine learning-driven credit assessment tools in financial institutions. Such tools can augment supervisory oversight by enabling the early detection of default risks and sectoral vulnerabilities, which is

particularly important under volatile macroeconomic conditions (Gao et al., 2022). However, this transition must be complemented by policies that ensure model interpretability and accountability, since the black-box nature of certain machine learning methods may undermine transparency and regulatory compliance (Varian, 2021). Establishing standards for explainable AI in credit markets will therefore help balance predictive performance with institutional trust.

Financial institutions should also invest in capacity building to integrate machine learning models into their risk management frameworks. This requires not only the adoption of advanced algorithms but also the development of robust data infrastructures to ensure the quality, granularity, and timeliness of financial information. Prioritizing data governance and establishing collaborations between regulators, credit bureaus, and financial institutions can bridge current gaps in disclosure and reporting (Xu et al., 2021). Such initiatives will improve model robustness while also promoting fairness and inclusivity in credit allocation.

From a broader economic perspective, machine learning-based credit rating systems can significantly enhance financial inclusion by expanding access to credit for small and medium-sized enterprises (SMEs), which are often excluded from traditional rating coverage. By enabling more accurate risk differentiation, financial institutions can reduce lending biases and allocate resources more efficiently across sectors (Ahn & Kim, 2021). This is consistent with development finance objectives that seek to promote inclusive growth while maintaining financial stability. For South Africa, where SMEs play a critical role in employment generation and economic diversification, this approach could strengthen the growth trajectory while mitigating systemic risk.

In conclusion, the integration of machine learning in corporate credit risk assessment represents a vital innovation for emerging financial systems. While challenges remain in terms of explainability, regulatory alignment, and data quality, the evidence suggests that these models offer substantial improvements over traditional approaches. Future research should explore hybrid models that combine interpretability with predictive accuracy, as well as sector-specific applications that tailor credit risk assessment to the structural characteristics of different industries. By advancing both methodological rigor and policy relevance, machine learning-based credit rating frameworks can enhance the resilience, inclusiveness, and efficiency of financial systems in South Africa and beyond.

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