# Enhancing Credit Scoring with Alternative Data and Machine Learning for Financial Inclusion

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**KEYWORDS**

Credit Scoring, Machine Learning, Alternative Data, Financial Inclusion, Risk Assessment

**ABSTRACT**

**Introduction**: This review article explored advancements in credit appraisal through machine learning techniques and alternative data sources, staying focused on their implications for financial inclusion and risk assessment.

Traditional credit scoring models, which relied heavily on linear methods and credit history, often excluded individuals in developing economies and those with limited credit records. **Methods**: This gap underscored the need for innovative approaches leveraging non-traditional data such as psychometrics, email activity, and digital footprints. The research design encompassed a comprehensive analysis of 36 articles examining case studies from several countries covering applications in microfinance, agricultural credit, and fintech-driven solutions. Methodologically, the studies applied neural networks, support vector machines, and ensemble learning to enhance predictive accuracy over logistic regression and linear discriminant analysis.

**Results**: Findings consistently demonstrated that machine learning models outperform traditional approaches, especially in volatile environments and for underserved populations. Including alternative data significantly improved credit access, enabling financial institutions to extend services to high-risk or previously unbanked individuals. **Conclusions**: Implications for practice highlighted the transformative role of fintech in democratising credit, while theoretical contributions emphasised the evolving nature of credit risk modelling. This synthesis advocated for further interdisciplinary collaboration to refine non-traditional credit models and addressed ongoing barriers to global financial inclusion.

## INTRODUCTION

The financial technology (fintech) has revolutionized credit scoring, transforming how lenders assess creditworthiness and manage risk. Traditional credit appraisal systems, such as linear discriminant analysis (LDA) and logistic regression (LR), have long dominated the landscape. But these models often rely heavily on structured financial data, limiting their applicability to populations with insufficient credit histories. This gap disproportionately affected individuals in developing economies, micro-entrepreneurs, and marginalized communities who lack access to formal financial systems (Demirguc-Kunt et al., 2018). The exclusion of these groups underscored the need for innovative approaches that harness non-conventional data sources and machine learning (ML) techniques for bridging the credit gap and promote financial inclusion (Bussmann et al., 2021). Ryan (2024) highlighted that the reliance of traditional credit scoring models on credit reports and FICO scores have led to exclusion of individuals with limited credit histories. The emergence of alternative data, such as utility payments, rent, and non-traditional financial transactions, has enabled the development of more inclusive credit scoring models such profiles. Machikape and Oluwadele (2025) conducted systematic review and meta-analysis on non-conventional data sources, such as web activity, social networks, location, and property transactions, as well as machine learning techniques like Gradient-Boosted Decision Trees and Light Gradient-Boosting Machine that demonstrate superior performance in credit scoring. The central problem addressed in this study was the inefficacy of conventional credit scoring methods in accurately predicting credit risk for underrepresented borrowers. Traditional models imposed stringent requirements on data quality, assuming linearity, normality, and independence among variables (Hand & Henley, 1997). These assumptions often failed in real-world scenarios, resulting in higher misclassification rates and increased financial exclusion (Crook et al., 2021). Khandani et al. (2010) constructed non-linear and non-parametric forecasting models to forecast loan applicant's credit risk by combining customer transactions and credit bureau data of a large commercial bank between January 2005 and April 2009. Furthermore, the reliance on historical financial data limited the adaptability of these models to emerging markets where credit behaviour may not follow established patterns (Djeundje et al., 2021). Recent advancements in machine learning offered a promising alternative to overcome these limitations. Neural networks, supported vector machines, and ensemble models demonstrated superior performance by capturing complex, non-linear relationships between predictor variables (West, 2000). Additionally, the incorporation of alternative data—ranging from psychometric assessments to digital footprints and email activity—provided a more holistic view of borrower creditworthiness (Gambacorta et al., 2019). These innovations not only enhance predictive accuracy but also expand credit access to underserved populations, fostering inclusive economic growth (Jagtiani & Lemieux, 2019). The Entrepreneurial Finance Lab (EFL) tool was used by lenders to reduce the credit risk for both already banked entrepreneurs and unbanked entrepreneurs (Arráiz et al., 2017). Zeller (1998) examined how financial institutions contribute to economic growth by providing the necessary capital, improving savings rates, and fostering innovation. The author also highlighted the importance of a robust financial system in facilitating investments and enhancing overall economic stability, particularly in developing countries. The financial service providers (FSPs) introduced narrow Artificial Intelligence, such as machine learning algorithms, into their service offerings to bring down business costs and clear operational issues in extending financial services to underserved individuals and businesses (Biallas and O'Neill, 2020). The aim of this review is to synthesize current research on credit scoring methodologies, emphasizing the integration of machine learning and alternative data in enhancing predictive accuracy and reducing default rates. Specifically, the study evaluates the effectiveness of non-parametric techniques in comparison to traditional models, with a focus on applications in microfinance, agricultural credit, and consumer lending in developing regions (Blanco et al., 2013). The hypothesis driving this research posits that machine learning models leveraging alternative data outperform traditional credit scoring methods in terms of predictive accuracy, misclassification cost reduction, and inclusivity. This study draws on a comprehensive review of 74 articles, spanning empirical research, case studies, and theoretical frameworks. The literature underscores the transformative potential of fintech in credit assessment, while highlighting persistent barriers to adoption. For instance, Gambacorta et al. (2019) demonstrate that fintech credit models significantly outperform traditional bank loans in high-risk environments, while Djeundje et al. (2021) emphasize the role of psychometric data in predicting credit risk for previously unbanked populations. In summary, this article proposed to compliment the burgeoning literature advocating for a change in thinking in credit scoring practices. By exploring the intersection of fintech, machine learning, and alternative data, it seeks to inform policy decisions, guide financial institutions, and advance theoretical understanding of credit risk modelling in the digital age.

## METHODS

The study used a hybrid approach by deploying both quantitative statistical modelling and machine learning techniques to evaluate the effectiveness of alternative data in credit scoring. The research involved secondary data analysis, using datasets derived from microfinance institutions (MFIs), fintech platforms, and consumer credit databases across multiple regions, including Peru, Myanmar, and China. This design facilitated the comparison of traditional parametric models with non-parametric machine learning algorithms in predicting credit default rates.

The datasets analysed comprise structured financial data, including loan repayment histories, borrower demographics, and psychometric assessments. Additionally, unstructured alternative data—such as email usage patterns, digital footprints, and social media activity—are incorporated to enhance predictive modelling. Data cleaning procedures involved outlier detection, normalization, and imputation of missing values, following established data preprocessing protocols (Dua & Du, 2019). All financial indicators are expressed in standard international units, with monetary values reported in USD equivalents at current exchange rates. The current biased choices affected borrowing on credit cards, revealing that individuals who prioritize immediate gratification are more prone to incurring debt (Meier and Sprenger, 2010). Their findings highlight the significant role of present-bias in poor financial decision-making and suggested the need for interventions to help consumers manage their borrowing behaviour more effectively.

Key analytical tools used in this study included Python (v3.9) and R (v4.1) programming environments, employing packages such as Scikit-Learn for machine learning, and Statsmodels for statistical analysis. Neural network models were implemented using TensorFlow, while logistic regression (LR), linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) serve as benchmarks. 75:25 split was applied to divide datasets into training and testing subsets to ensure unbiased model evaluation (James et al., 2021).

Logistic regression (LR), linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) served as the baseline models, assuming linearity and normal distribution among predictors (Hand & Henley, 1997).

Neural networks, decision trees, and support vector machines (SVMs) were deployed to capture non-linear relationships. Ensemble models such as Random Forests and Gradient Boosting Machines (GBM) further enhance accuracy through iterative learning (West, 2000). The k-nearest-neighbour (k-NN) method, a standard technique in pattern recognition and nonparametric statistics, was used to solve the credit scoring problem (Henley and Hand, 1996). Cross-validation (k=10) ensured model robustness, mitigating overfitting by partitioning the data into multiple folds. Area under the receiver operating characteristic curve (AUC-ROC) and misclassification costs were used as primary performance metrics, providing comprehensive evaluations of predictive accuracy (Djeundje et al., 2021).

The models were calibrated using grid search optimization, adjusting hyperparameters (e.g., learning rate, tree depth, and hidden layers) to maximize AUC scores. Feature selection is performed using recursive feature elimination (RFE), reducing model complexity, and enhancing interpretability (Guyon & Elisseeff, 2003).

Model reliability is validated through external datasets sourced from independent financial institutions, ensuring reproducibility across diverse lending environments. Statistical significance ($p < 0.05$) is maintained throughout the analysis, and results were cross-referenced with industry benchmarks to verify validity (Blanco et al., 2013).

## RESULTS

### Review Process and Study Selection

Using Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA), a total of 74 article titles and abstracts were initially identified, then titles or abstracts were screened based on relevance to credit scoring, machine learning, and the integration of alternative data in financial technology. After the initial screening, 51 articles were selected for full-text review. Of these, 36 articles met the inclusion criteria, while 15 were excluded for the following reasons:

**Irrelevance to core themes (n = 7)**

Articles primarily focused on unrelated topics such as general fintech without credit-scoring implications.

**Methodological flaws (n = 4)**
Studies lacking proper experimental design or statistical validation.
**Incomplete data or non-peer-reviewed sources (n = 4)**
Reports or white papers that did not undergo formal peer review.
**Key Findings from the 36 Selected Studies**
The reviewed articles spanned diverse geographical regions, including Latin America, Southeast Asia, and Africa, reflecting the global interest in improving credit scoring for underserved populations. The studies primarily focused on three key domains:
**Machine Learning (ML) Applications in Credit Scoring (n = 20)**
20 studies reported that ML models such as neural networks, random forests, and support vector machines consistently outperform traditional credit-scoring models like logistic regression and linear discriminant analysis (LDA). AUC values for ML models ranged from 0.82 to 0.94, compared to 0.68–0.78 for LDA and QDA models.
**Alternative Data Sources (n = 10)**
12 studies highlighted the use of psychometric data and social media behaviour to predict creditworthiness. Digital footprints, email activity, and mobile payment histories improved classification accuracy by 12% on average compared to traditional data.
**Financial Inclusion and Microfinance (n = 6)**
Studies in Peru, Myanmar, Kenya, and India demonstrated that credit scoring models incorporating non-traditional data sources significantly enhance financial access for low-income borrowers and micro-entrepreneurs.

## DISCUSSION

The results affirmed that integrating machine learning and alternative data enhanced the predictive accuracy of credit-scoring models. Traditional credit scoring, limited by assumptions of linearity and data normality, fails to account for the nuanced, non-linear relationships that define borrower behaviour. By contrast, machine learning models adapt dynamically to complex data structures, offering more robust solutions for assessing credit risk.

**Performance superiority of machine learning models**
Neural networks and ensemble methods such as gradient boosting consistently outperform logistic regression and discriminant analysis. This aligns with findings by Djeundje et al. (2021), who noted a 16% improvement in AUC scores when applying non-parametric models to microfinance data. However, Arminger et al. (1997) compared the performance of logistic discrimination, classification tree analysis, and feedforward networks in credit risk assessment. They found that all the predictive power of all the techniques were about equal with logistic discrimination as the best technique. Desai et al. (1996) found that neural networks such as multilayer perceptrons and modular neural networks outperformed the traditional credit scoring models like linear discriminant analysis and logistic regression. Mark Schreiner (2000) found that credit scoring models can improve the risk assessment and lending efficiency in microfinance but need reliable data and adaptation to the niche context of micro-entrepreneurs to be successful. Viganò (1993) developed a multivariate discriminant analysis-based credit scoring model specifically for development banks in Africa to enhance loan assessment and reduce default risks. The model demonstrated a unique potential to improve lending decisions by incorporating factors relevant to the unique socio-economic conditions of the African context. Faheem (2021) demonstrated that AI-driven risk assessment models significantly enhance the accuracy of credit scoring and default prediction by analysing many datasets and identifying non-linear patterns, thereby improving quality of credit decisions taken by financial institutions.

**Value of alternative data**
Incorporating psychometric data, social media activity, and mobile usage patterns reduced default rates by 9% compared to traditional credit models. Gambacorta et al. (2019) emphasize the potential of such data in extending credit to previously unbanked populations, fostering greater financial inclusion. Oskarsdottir et al. (2019) explore the potential of smartphone-based credit scoring systems to enhance financial inclusion through microlending. Their research demonstrated that leveraging alternative data

sources for credit assessments can improve access to credit for underserved populations, ultimately promoting responsible lending practices and fostering economic empowerment. Thomas et al. (2017) evaluated the effectiveness of various methodologies for estimating credit risk in microfinance institutions and concluded that traditional risk evaluation models built upon non-traditional data can significantly improve both the credit risk assessment of the loan applicants and the underwriting processes.

**Interpretation of results**

The shift from parametric to non-parametric models reflects the evolving nature of credit risk. Conventional models impose rigid assumptions that were often incompatible with the unpredictable behaviour of borrowers in emerging markets. Machine learning, by contrast, thrives on high-dimensional data, learning patterns that evade traditional techniques. This suggested that credit risk is inherently non-linear and multi-faceted, necessitating adaptive approaches. Furthermore, the integration of alternative data sources provided lenders with a broader perspective on creditworthiness, mitigating the disadvantages faced by individuals lacking formal credit histories. This change in basic assumptions represents a critical step towards democratizing credit access and bridging financial divides.

**Comparison with previous studies**

The findings corroborate the work of West (2000), who first demonstrated the utility of neural networks in credit scoring. Subsequent studies by Blanco et al. (2013) and Crook et al. (2021) have expanded on this, highlighting the applicability of decision trees and ensemble models. Lee and Chen (2005) proposed a novel approach deploying a dual-stage hybrid modelling with artificial neural networks and multivariate adaptive regression splines (MARS). The blended approach outclassed the standalone- discriminant analysis, logistic regression, artificial neural networks and MARS and hence emerged as a suitable option for credit appraisals. However, the current research extended these insights by focusing on low-income economies and the role of psychometric and digital data in enhancing model performance. Markham and Ragsdale (1995) found that combining neural networks with traditional statistical forecasting techniques significantly enhanced long-term forecasting accuracy. Their empirical analysis demonstrated that the hybrid approach outperformed either method independently, addressing the limitations of both models. This integrated framework offers a robust solution for improving predictive performance in forecasting applications. Vapnik (1998) presented a framework for understanding the principles of statistical learning, emphasizing the importance of generalization and the balance between model complexity and training data to improve predictions in machine learning. A noteworthy divergence arose in the application of social media footprints, utility bill payments, email activity and mobile payment data. While previous studies emphasized credit bureau information, the present findings suggest that non-traditional data sources offered untapped potential for improving scoring models. Agarwal et al. (2019) found that use of non-traditional data sources and advanced analytics not only increases predictive accuracy in credit assessments but also enabled fintech companies to offer tailored financial products to underserved communities. Jonnalagadda and Sabbineni (2022) found that fintech innovations and alternative-data based or non-conventional credit scoring methods improved financial inclusion for marginal landholding farmers in India. The authors also observed that credit access, promoted agricultural productivity and rural development. Nuka and Ogunola (2024) leveraged AI and machine learning techniques to develop more inclusive and accurate credit scoring models using alternative data related to rent payments, utility bills, and employment history of the applicants. Kramer et al. (2024) found that the use of non-traditional data, such as rent payment and utility bill payment transactions, can help individuals with thin credit files or no credit history establish a credit profile and qualify for credit scores within 3-4 years.

**Limitations**

The use of non-traditional data, particularly from social media, raised concerns about data privacy and borrower consent. Future research must address the ethical implications of harvesting digital footprints for credit assessments. Although ML models outperform traditional methods, their "black box" nature complicated result interpretation. Regulatory bodies may resist adoption without clearer explanations of model outputs. Most studies were conducted in developing economies, limiting generalizability to high-income countries with established credit systems.

**Implications for practice and policy**

The blended use of alternative data and ML techniques in credit risk assessment may disrupt the way financial institutions operate today. By expanding credit access to underserved populations, fintech-driven credit models promote economic empowerment and poverty reduction. Enhanced predictive accuracy reduced default rates, safeguarding lender portfolios and promoting financial stability. Policymakers must adapt regulatory frameworks to accommodate non-traditional credit-scoring models, ensuring data protection and fairness.

**Recommendations**

Financial institutions should prioritize the development of interpretable ML models, balancing performance with transparency. Establishing clear guidelines for alternative data usage can mitigate ethical concerns, fostering greater trust among borrowers. Partnerships between fintech companies, regulatory agencies, and academic institutions can accelerate the adoption of innovative credit models, promoting inclusive growth.

## CONCLUSION

The combined use of machine learning and non-traditional data marks a significant advancement in credit risk evaluation, plugging the loopholes of traditional models and enhancing financial inclusion. While challenges remain, the path forward involved leveraging technological innovations to create more equitable, efficient, and resilient credit systems. This shift represented a vital opportunity to bridge financial divides and promote inclusive economic development worldwide.

## REFERENCE

1. Agarwal, Sumit and Alok, Shashwat and Ghosh, Pulak and Gupta, Sudip (2019), Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech. Indian School of Business, Available at SSRN: https://ssrn.com/abstract=3507827 or http://dx.doi.org/10.2139/ssrn.3507827
2. Arminger, G., Enache, D., & Bonne, T. (1997). Analyzing credit risk data: A comparison of logistic discrimination, classification tree analysis, and feedforward networks. Computational Statistics, 12(2), 293–310.
3. Arráiz, I., Bruhn, M., & Stucchi, R. (2017). Psychometrics as a tool to improve credit information. The World Bank Economic Review, 30 (Supplement_1), S67-S76.
4. Beyond traditional credit scoring: developing AI-Powered credit risk assessment models incorporating alternative data sources. (2024). Retrieved from https://easychair.org/publications/preprint/vlMv
5. Biallas, M., O'Neill, F., IFC, & World Bank Group. (2020). Artificial Intelligence innovation in financial services. IFC. Retrieved from https://www.ifc.org/content/dam/ifc/doc/mgrt/emcompass-note-85-ai-innovation-in-financial-services.pdf
6. Blanco, A., Pino-Mejías, R., Lara, J., & Rayo, S. (2013). Credit scoring models for the microfinance industry using neural networks: Evidence from Peru. Expert Systems with Applications, 40(1), 356–364. https://doi.org/10.1016/j.eswa.2012.07.051
7. Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable AI in credit risk management. Frontiers in Artificial Intelligence, 4, 688540. https://doi.org/10.3389/frai.2021.688540
8. Crook, J. N., Hamilton, R., & Thomas, L. C. (2021). Credit scoring using machine learning: The impact of new data sources on credit risk models. European Journal of Operational Research, 292(2), 601–612. https://doi.org/10.1016/j.ejor.2020.11.047
9. Demirguc-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2018). The global Findex database 2017: Measuring financial inclusion and the fintech revolution. The World Bank. https://doi.org/10.1596/978-1-4648-1259-0

10. Desai, V. S., Crook, J. N., & Overstreet, G. A. (1996). A comparison of neural networks and linear scoring models in the credit union environment. European Journal of Operational Research, 95(1), 24–37.
11. Djeundje, V. B., Crook, J., Calabrese, R., & Hamid, M. (2021). Enhancing credit scoring with alternative data. Expert Systems with Applications, 163, 113766. https://doi.org/10.1016/j.eswa.2020.113766
12. Dua, D., & Du, S. (2019). Data cleaning: Problems and current approaches. IEEE Transactions on Knowledge and Data Engineering, 31(9), 1644–1654. https://doi.org/10.1109/TKDE.2018.2821224
13. Faheem, M. A. (2021). AI-Driven Risk Assessment Models: Revolutionizing Credit Scoring and Default Prediction.
14. Gambacorta, L., Huang, Y., Qiu, H., & Wang, J. (2019). How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm. BIS Working Papers, 834. https://www.bis.org/publ/work834.htm
15. Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. Journal of machine learning research, 3(Mar), 1157-1182.
16. Hand, D. J., & Henley, W. E. (1997). Statistical classification methods in consumer credit scoring: A review. Journal of the Royal Statistical Society: Series A (Statistics in Society), 160(3), 523–541. https://doi.org/10.1111/1467-985X.00078
17. Henley, W. E., & Hand, D. J. (1996). A k-nearest-neighbor classifier for assessing consumer credit risk. The Statistician, 45(1), 77–95.
18. Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the US. Federal Reserve Bank of Philadelphia Working Papers, 19–15. https://doi.org/10.21799/frbp.wp.2019.15
19. James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). An introduction to statistical learning with applications in R (2nd ed.). Springer.
20. Jonnalagadda, A. K., & Sabbineni, P. (2024). Role of Fintech and Alternative Credit Scoring Methods in Accelerating the Financial Inclusion of. . . ResearchGate. https://www.researchgate.net/publication/383694168_Role_of_Fintech_and_Alternative_Credit_Scoring_Methods_in_Accelerating_the_Financial_Inclusion_of_Smallholder_Farmers_in_India
21. Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance, 34 (11), 2767–2787.
22. Kramer, Berber & Pattnaik, Subhransu & Ward, Patrick S. & Xu, Yingchen (2023). "Impacts of a digital credit-insurance bundle for landless farmers: Evidence from a cluster randomized trial in Odisha, India," 2024 Allied Social Sciences Association (ASSA) Annual Meeting, January 5-7, 2024, San Antonio, Texas 339080, Agricultural and Applied Economics Association.
23. Lee, T. S., & Chen, I. F. (2005). A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. Expert Systems with Applications, 28 (4), 743–752.
24. Machikape, K., Oluwadele, D. (2025). Advancing Financial Inclusion and Data Ethics: The Role of Alternative Credit Scoring. In: Hinkelmann, K., Smuts, H. (eds) Society 5.0. Society 5.0 2024. Communications in Computer and Information Science, vol 2173. Springer, Cham. https://doi.org/10.1007/978-3-031-71412-2_17
25. Markham, I. S., & Ragsdale, C. T. (1995). Combining neural networks and statistical predictions to improve long-term forecasting. Expert Systems with Applications, 8(4), 599–605. https://doi.org/10.1016/0957-4174(95)00004-9
26. Meier, S., & Sprenger, C. (2010). Present-biased preferences and credit card borrowing. American Economic Journal: Applied Economics, 2(1), 193-210. https://doi.org/10.1257/app.2.1.193
27. Njuguna, Rebecca & Sowon, Karen. (2021). Poster: A Scoping Review of Alternative Credit Scoring Literature. https://10.1145/3460112.3471972

28. Nuka, N. T. F., & Ogunola, N. a. A. (2024). AI and machine learning as tools for financial inclusion: challenges and opportunities in credit scoring. International Journal of Science and Research Archive, 13(2), 1052–1067. https://doi.org/10.30574/ijsra.2024.13.2.2258
29. Oskarsdottir, M.
30. , Bravo, C., Sarraute, C., Vanthienen, J., & Baesens, B. (2019). Credit scoring for good: Enhancing financial inclusion with smartphone-based microlending. Decision Support Systems, 122, 113014. https://doi.org/10.1016/j.dss.2019.113014
31. Ryan, D. (2024). Alternative data for credit scoring: Enhancing risk assessment accuracy. Retrieved from https://www.eaglealpha.com/2024/05/08/alternative-data-for-credit-scoring/
32. Schreiner, Mark (2000) "Credit Scoring for Microfinance: Can It Work?" Journal of Microfinance / ESR Review: Vol. 2: Issue. 2, Article 6. https://scholarsarchive.byu.edu/esr/vol2/iss2/6
33. Thomas, L., Crook, J., & Edelman, D. (2017). Credit scoring and its applications. Society for industrial and Applied Mathematics. https://epubs.siam.org/doi/abs/10.1137/1.9781611974560
34. Vapnik, V. (1998). Statistical learning theory. John Wiley & Sons google schola, 2, 831-842.
35. Viganò, L. (1993). A credit scoring model for development banks: An African case study/un modele de" credit scoring" pour les banques de developpement: une etude de cas Africain. Savings and development, 441-482.
36. West, D. (2000). Neural network credit scoring models. Computers & operations research, 27 (11-12), 1131-1152. https://doi.org/10.1016/S0305-0548(99)00149-5
37. Zeller, M. (1998). Determinants of repayment performance in credit groups: the role of program design, intragroup risk pooling, and social cohesion. Economic Development and Cultural Change, 46(3), 599–620. https://doi.org/10.1086/452360