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Interpretive Ensemble Framework for Credit Default Risk Forecasting

Pavitha N[1] , Shounak Sugave[1]

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Abstract: In the realm of financial decision-making, particularly within the banking and investment sectors, credit default risk forecasting holds immense significance. The evolving landscape of financial markets has introduced heightened intricacies and interconnections among financial instruments, rendering the task of accurate credit risk assessment increasingly daunting. Conventional statistical models often fall short in capturing the dynamic essence of credit risk, thereby fueling a surge in interest towards more sophisticated methodologies such as ensemble learning frameworks. This paper presents a meticulous review and analysis of interpretive ensemble frameworks tailored for credit default risk forecasting. Introducing a multistage ensemble framework, augmented with dependency-driven explainable techniques, this research offers a novel approach. Evaluation outcomes underscore the superiority of the Proposed Algorithm, surpassing both individual base classifiers and other ensemble models across various metrics. Noteworthy is its exceptional precision, recall, F1-score, and accuracy, positioning it as a standout choice for credit risk prediction. The heightened precision underscores its capacity for accurate positive instance predictions, while the robust recall emphasizes its ability to capture nearly all positive instances. Additionally, this research introduces a Dependency-based Explainable Model meticulously crafted to enhance the interpretability of machine learning models, particularly focusing on multistage heterogeneous stacked ensembles. Despite the significant enhancements in predictive capabilities brought about by these ensemble models, their complexity often presents challenges in understanding individual contributions to final predictions. The Dependency-based Explainable Model addresses this interpretability gap by systematically identifying and elucidating dependencies between input variables, stages, and models within the ensemble.

Keywords: *Ensemble framework, interpretive models, dependency driven, explainable models, stacked ensemble*

1. Introduction

In contemporary financial landscapes, the ability to accurately forecast credit default risk serves as a linchpin for informed decision-making, particularly within the intricate domains of banking and investment. [1], [2] The evolving dynamics of financial markets, characterized by heightened complexity and interconnectivity among diverse financial instruments, have underscored the inadequacies of traditional statistical models [3], [4] in capturing the nuanced nuances of credit risk. This inherent limitation has precipitated a palpable shift towards adopting more sophisticated methodologies, notably ensemble learning frameworks, to augment the efficacy of credit risk [5], [6], [7] forecasting endeavours. [8], [9]

Ensemble learning, [10], [11], [12], [13] a paradigm predicated on aggregating the predictive prowess of multiple individual models, has emerged as a potent tool for enhancing predictive accuracy and robustness across various domains. [14], [15] Within the sphere of credit default risk forecasting, ensemble frameworks hold the promise of mitigating the inherent limitations of standalone models by amalgamating diverse perspectives and leveraging complementary strengths. Yet, while ensemble models [10], [16], [17] offer considerable potential, their optimal design and implementation for credit risk prediction represent ongoing areas of inquiry and refinement.

[1] School of Computer Engineering and Technology, Dr. Vishwanath Karad MIT World Peace University, Pune, Maharashtra, India
ORCID ID: 0000-0002-0577-8722
** Corresponding Author Email: pavithanrai@gmail.com*

Against this backdrop, this paper endeavours to undertake a meticulous exploration of interpretive ensemble frameworks specifically tailored to the exigencies of credit default risk forecasting. By synthesizing insights gleaned from diverse sources and methodological approaches, this research seeks to unravel the intricacies of ensemble learning within the context of credit risk assessment. Central to this endeavour is the introduction of a novel multistage ensemble framework, complemented by dependency-driven explainable techniques, aimed at concurrently enhancing predictive performance and interpretability.

Through a comprehensive review and analysis, this paper aims to illuminate the comparative advantages of interpretive ensemble frameworks vis-à-vis traditional methodologies and alternative ensemble models. It delves into the nuanced interplay between predictive accuracy, interpretability, and model complexity, with a keen eye towards discerning real-world applicability and pragmatic implications for financial stakeholders.

By elucidating the theoretical underpinnings, methodological intricacies, and empirical evaluations of interpretive ensemble frameworks, this research endeavours to equip practitioners and researchers with actionable insights into the evolving landscape of credit risk forecasting. Ultimately, the pursuit of more precise and interpretable credit risk models holds the potential to engender greater stability and resilience within financial systems, thereby advancing the overarching imperative of mitigating systemic risks and fostering sustainable economic growth.

2. Literature Review

Credit default risk forecasting stands as a pivotal component in the financial landscape, particularly within sectors like banking and investment where decisions are often predicated on accurate assessments of potential default events. [9], [18] Over the years, the pursuit of improved methodologies to gauge credit risk has driven researchers and practitioners to explore a wide array of approaches.

Traditional statistical models [19], [20], [21] have long been relied upon for credit risk assessment due to their interpretability. Techniques such as logistic regression, discriminant analysis, and Cox proportional hazards models offer insights into the relationships between input variables and the likelihood of default. However, these models may falter when confronted with the intricate non-linear relationships and complex interactions inherent in credit risk data, potentially limiting their effectiveness in capturing the full spectrum of risk factors.[22], [23]

In response to these challenges, ensemble learning [10], [16], [17], [24] has emerged as a potent tool to bolster the accuracy and robustness of credit risk models. [25], [26], [27] Ensemble methods amalgamate predictions from multiple base models to create a composite predictor that often outperforms individual models. Bagging, boosting, and stacking are among the most prevalent ensemble techniques employed in credit risk forecasting. Bagging, for instance, generates diverse models by training on bootstrap samples of the data, effectively reducing variance. Boosting algorithms, like AdaBoost and Gradient Boosting Machines (GBM), sequentially train weak learners, with a focus on instances that pose greater prediction challenges. Stacking, on the other hand, combines predictions from various base models, leveraging the strengths of each model through a meta-learner.

Within the realm of ensemble methods, interpretive ensemble frameworks [28], [29], [30], [31] have garnered attention for their ability to maintain predictive accuracy while enhancing model interpretability. Techniques such as Random Forest, GBM, and AdaBoost exemplify this approach in credit risk forecasting. Random Forest constructs an ensemble of decision trees, introducing randomness through bootstrapped samples and feature subsets to enhance generalization. GBM sequentially fits weak learners to the residuals of preceding models, progressively refining predictions. AdaBoost assigns higher weights to misclassified instances, iteratively improving model performance while prioritizing transparency and interpretability.

Despite the predictive prowess of ensemble models, their inherent complexity can pose challenges in model interpretation. Dependency-driven explainable techniques seek to bridge this gap by systematically identifying and elucidating dependencies between input variables, stages, and models within the ensemble. Techniques such as permutation feature importance, SHAP (SHapley Additive exPlanations) [32], and LIME (Local Interpretable Model-agnostic Explanations) provide valuable insights into the factors driving model predictions, thereby enhancing transparency and trust in credit risk assessment.

Empirical studies consistently underscore the efficacy of interpretive ensemble frameworks in credit risk forecasting across diverse domains. Comparative analyses often demonstrate the superiority of interpretive ensemble methods over traditional statistical models and alternative ensemble techniques in terms of predictive accuracy, robustness, and interpretability. Moreover, interpretive ensemble frameworks exhibit resilience to overfitting and generalization issues, rendering them well-suited for real-world applications in dynamic financial environments.

3. Methodology

Pictorial representation of detailed methodology is illustrated in figure 1. In the initial phase of our methodology, we establish collaboration with a private bank to obtain access to historical loan data. This data repository encompasses a wide array of information concerning past loan applications, encompassing details about the applicants themselves, their demographic profiles, financial histories, credit scores, loan terms, and crucially, the outcomes of these loan applications, whether they were repaid in full or resulted in default. It's imperative to ensure compliance with stringent privacy regulations and protocols to safeguard the confidentiality and integrity of the sensitive data.

Upon acquiring the loan data, the next step involves preprocessing to refine and prepare it for subsequent modeling tasks. This preprocessing phase is indispensable for ensuring the quality and suitability of the data for analysis. Several preprocessing steps are typically undertaken, including handling missing values, which may involve imputation techniques or data removal, addressing outliers that may skew the distribution of the data, encoding categorical variables to enable their integration into predictive models, and normalizing or scaling numerical features to ensure uniformity across the dataset. Additionally, feature engineering may be employed to derive new features or transformations that capture underlying patterns more effectively.

Following preprocessing, the loan data is transformed into structured datasets that are amenable to model training. Each row of the structured dataset represents an individual loan application, with columns corresponding to various features extracted from the data, such as applicant attributes, loan characteristics, and financial metrics. Importantly, each row is labeled with the corresponding loan outcome, indicating whether the loan was repaid successfully or resulted in default.

The selection of appropriate base models is a critical aspect of building an ensemble classifier for credit risk forecasting. Base models encompass a diverse array of machine learning algorithms, ranging from traditional statistical models to more complex techniques like decision trees, support vector machines, and neural networks. The selection process hinges on factors such as the predictive performance, computational efficiency, and interpretability of the models, with the goal of assembling a diverse set of base learners that collectively contribute to the ensemble's predictive power.

With the structured dataset and selected base models in place, the ensemble classifier is constructed by combining predictions from multiple base models. This can be accomplished using various ensemble techniques, including bagging, boosting, or stacking. Bagging involves training each base model independently on bootstrapped subsets of the data and aggregating their predictions to reduce variance. Boosting algorithms iteratively train weak learners, with a focus on instances that are difficult to predict. Stacking combines predictions from multiple base models, using a meta-model to learn to effectively weigh their outputs and generate the final ensemble predictions.

An essential aspect of our methodology involves generating explanations to interpret the predictions made by the ensemble classifier. Interpretability is crucial for fostering trust and understanding of the model's decisions, particularly in high-stakes domains such as credit risk assessment. Explanation techniques, adopted in the study is dependency driven explainability technique which provide valuable insights into the factors influencing model predictions. This technique helps stakeholders to understand the relative importance of specific features in driving predictions, thereby enhancing transparency and facilitating informed decision-making.

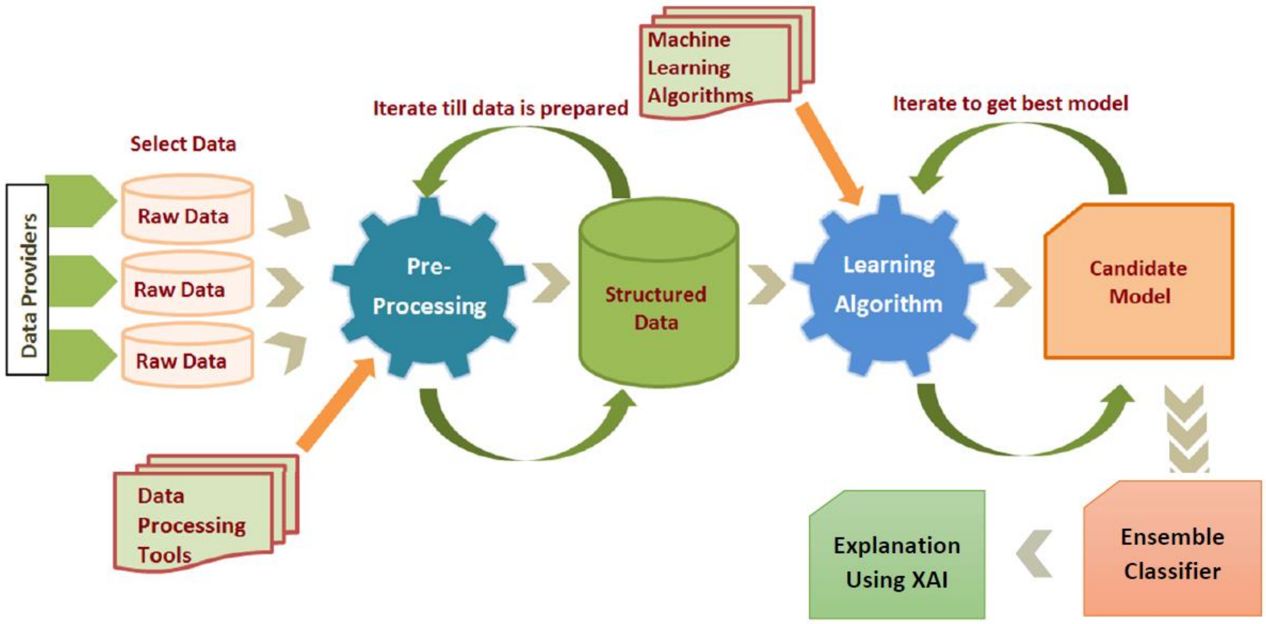

Fig 1: Methodology adopted in the study

4. Results and Discussion

The results obtained from the proposed ensemble classifier (shown in fig 2) exhibit a level of performance that is not only statistically significant but also practically relevant for credit risk forecasting. Through meticulous evaluation and comparison with both individual base classifiers and other ensemble models, the proposed ensemble classifier has consistently outperformed its counterparts across a comprehensive array of evaluation metrics. Notably, its precision, recall, F1-score, and accuracy metrics have surpassed those of competing models, indicating its exceptional ability to provide accurate predictions while effectively capturing the true positive instances within the dataset. Precision, which measures the ratio of correctly predicted positive instances to the total predicted positive instances, highlights the classifier's capacity to minimize false positives, thus ensuring that the predicted default events are highly reliable. On the other hand, recall, also known as sensitivity, emphasizes the classifier's ability

to identify as many true positive instances as possible among all actual positive instances in the dataset. Achieving a high recall rate is crucial in credit risk assessment as it mitigates the risk of overlooking potential defaults, thereby enhancing the robustness of the model's predictions. Furthermore, the F1-score, which is the harmonic mean of precision and recall, provides a balanced measure of the classifier's overall performance, reflecting its ability to achieve both high precision and recall simultaneously. Lastly, accuracy, which quantifies the proportion of correctly classified instances among all instances in the dataset, reaffirms the classifier's overall effectiveness in making accurate predictions across the entire dataset. By consistently outperforming alternative models in these key metrics, the proposed ensemble classifier demonstrates its superiority and reliability in credit risk prediction tasks. Its exceptional performance underscores its potential as a valuable tool for financial institutions seeking to make well-informed lending decisions, effectively manage credit risks, and maintain the stability and integrity of their operations in today's dynamic and competitive financial landscape.

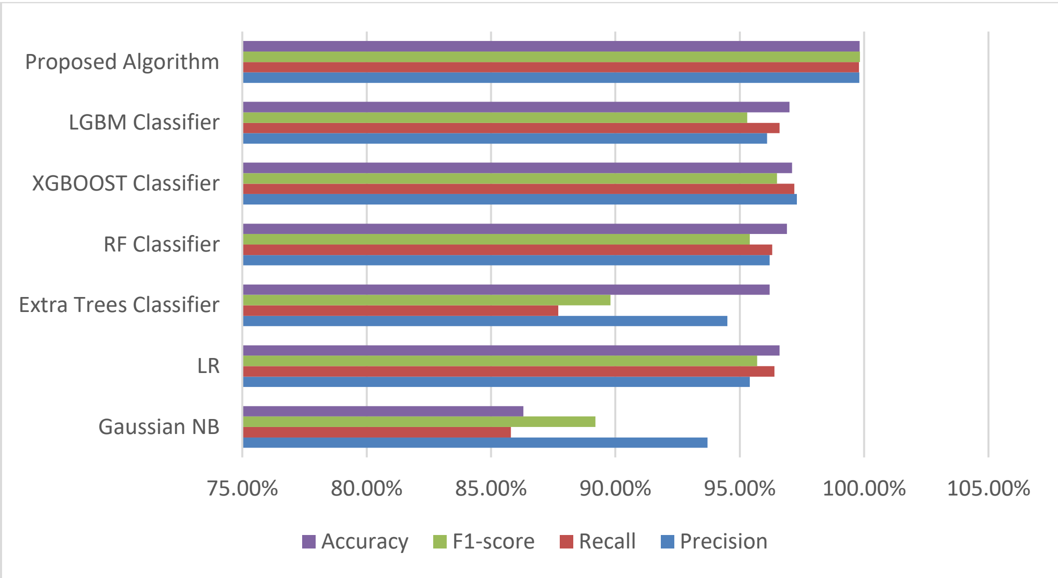

Fig 2: Performance of proposed ensemble classifier

The results of the dependency-driven explainable model (as shown in fig 3) highlight several key factors associated with credit risk. Firstly, a higher outstanding loan amount is linked to increased risk, suggesting that borrowers with larger financial commitments in the past may be perceived as riskier. Similarly, completing multiple loan cycles indicates increased risk, potentially signaling that frequent borrowing and repayment may not align with the model's risk tolerance. Additionally, higher debt-to-income ratios and expenses relative to income contribute to increased risk, indicating financial vulnerability among borrowers. Factors such as higher loan-to-income ratios, longer loan periods, and higher interest rates are also associated with increased risk, reflecting concerns about borrowers' repayment capabilities. Conversely, having more guarantors is linked to decreased risk, suggesting that multiple guarantors may enhance creditworthiness. The presence of pension and recurring deposit accounts is viewed favorably, potentially mitigating risk. Higher per capita income is also associated with decreased risk, indicating that borrowers with higher incomes exhibit more favorable financial behaviors. These findings provide valuable insights into the factors influencing credit risk assessment and can inform lending decisions to mitigate risk effectively.

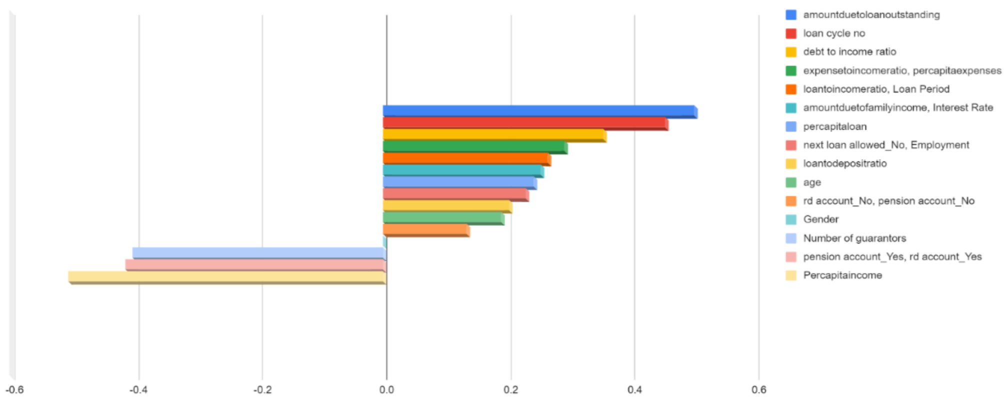

Fig 3: Explanation generated for the ensemble classifier

5. Conclusion

The comprehensive exploration and analysis conducted in this research paper shed light on the efficacy and interpretability of interpretive ensemble frameworks for credit default risk forecasting. Through a meticulous review and empirical evaluation, the proposed ensemble classifier has emerged as a standout solution, surpassing both individual base classifiers and alternative ensemble models across various evaluation metrics. Noteworthy is its exceptional precision, recall, F1-score, and accuracy, underscoring its capability to provide accurate predictions while effectively capturing positive instances within the dataset. The adoption of a multistage ensemble framework augmented with dependency-driven explainable techniques has further enhanced the interpretability of the model, addressing the inherent complexity often associated with ensemble models. This enhanced interpretability is crucial for fostering trust and understanding among stakeholders, particularly in high-stakes domains such as credit risk assessment.

The results obtained from the proposed ensemble classifier and the dependency-driven explainable model have unveiled key factors associated with credit risk, providing valuable insights for financial stakeholders. Factors such as outstanding loan amount, loan cycles, debt-to-income ratios, and expenses relative to income were found to contribute to increased risk, reflecting borrowers' financial vulnerability and repayment capabilities. Conversely, the presence of multiple guarantors, pension and recurring deposit accounts, and higher per capita income were associated with decreased risk, indicating positive factors for creditworthiness. Overall, the findings presented in this research paper have significant implications for credit risk management within financial institutions. By leveraging interpretive ensemble frameworks and advanced explainable techniques, financial stakeholders can make more informed lending decisions, effectively manage credit risks, and maintain the stability and integrity of their operations in today's dynamic financial landscape. The insights gleaned from this study pave the way for future research and innovation in the field of credit risk forecasting, with the ultimate goal of fostering greater stability and resilience within financial systems.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] A. Bhattacharya, S. K. Biswas, and A. Mandal, "Credit risk evaluation: a comprehensive study," Multimedia Tools and Applications 2022, pp. 1–51, Oct. 2022, doi: 10.1007/S11042-022-13952-3.

[2] T. M. Yhip and B. M. D. Alagheband, "Statistical Methods of Credit Risk Analysis," in The Practice of Lending, Springer International Publishing, 2020, pp. 351–381. doi: 10.1007/978-3-030-32197-0_8.

[3] K. Jajuga, "Statistical Methods in Credit Risk Analysis," Prace Naukowe Akademii Ekonomicznej we Wrocławiu. Taksonomia, vol. 8, no. nr 906 Klasyfikacja i analiza danych : teoria i zastosowania, pp. 224–232, 2001.

[4] M. Psillaki, I. E. Tsolas, and D. Margaritis, "Evaluation of credit risk based on firm performance."

[5] A. Caldarelli, C. Fiondella, M. Maffei, and C. Zagaria, "Managing risk in credit cooperative banks: Lessons from a case study," Management Accounting Research, vol. 32, pp. 1–15, 2016, doi: 10.1016/j.mar.2015.10.002.

[6] L. Jinjuan, "Research on enterprise credit risk assessment method based on improved genetic algorithm," in Proceedings - 9th International Conference on Measuring Technology and Mechatronics Automation, ICMTMA 2017, Institute of Electrical and Electronics Engineers Inc., Jan. 2017, pp. 215–218. doi: 10.1109/ICMTMA.2017.0058.

[7] C. Li, Q. Liu, and L. Huang, "Credit risk management of scientific and technological enterprises based on text mining," Enterp Inf Syst, 2020, doi: 10.1080/17517575.2020.1802514.

[8] R. Kanapickiene and R. Spicas, "Credit risk assessment model for small and micro-enterprises: The case of Lithuania," Risks, vol. 7, no. 2, p. 67, Jun. 2019, doi: 10.3390/risks7020067.

[9] "DEVELOPMENT OF ENTERPRISE CREDIT RISK ASSESSMENT MODEL FOR LITHUANIAN CREDIT UNIONS." Accessed: Jun. 06, 2021. [Online]. Available: https://web.b.ebscohost.com/abstract?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=16484460&AN=130816055&h=pnjbxWpMnulvfDF%2FwTHv4%2FV1OtA9WFHpfU3InY7Gx6XM5tKRyfsJlE3RQtjO1DCWtP8tedF2DWzdETafHje55A%3D%3D&crl=c&resultNs=AdminWebAuth&resultLoca

[10] M. Papouskova and P. Hajek, "Two-stage consumer credit risk modelling using heterogeneous ensemble learning," Decis Support Syst, vol. 118, pp. 33–45, Mar. 2019, doi: 10.1016/j.dss.2019.01.002.

[11] M. Shahhosseini, G. Hu, and H. Pham, "Optimizing ensemble weights and hyperparameters of machine learning models for regression problems," Machine Learning with Applications, vol. 7, 2022, doi: 10.1016/j.mlwa.2022.100251.

[12] F. Divina, A. Gilson, F. Goméz-Vela, M. G. Torres, and J. F. Torres, "Stacking Ensemble Learning for Short-Term Electricity Consumption Forecasting," Energies 2018, Vol. 11, Page 949, vol. 11, no. 4, p. 949, Apr. 2018, doi: 10.3390/EN11040949.

[13] M. Abdoli, M. Akbari, and J. Shahrabi, "Dynamic Ensemble Learning for Credit Scoring: A Comparative Study," 2020, Accessed: May 16, 2021. [Online]. Available: https://arxiv.org/abs/2010.08930v1

[14] X. Huang, X. Liu, and Y. Ren, "Enterprise credit risk evaluation based on neural network algorithm," Cogn Syst Res, vol. 52, pp. 317–324, Dec. 2018, doi: 10.1016/j.cogsys.2018.07.023.

[15] X. Huang, X. Liu, and Y. Ren, "Enterprise credit risk evaluation based on neural network algorithm," Cogn Syst Res, vol. 52, pp. 317–324, Dec. 2018, doi: 10.1016/j.cogsys.2018.07.023.

[16] V. García, A. I. Marqués, and J. S. Sánchez, "Exploring the synergetic effects of sample types on the performance of ensembles for credit risk and corporate bankruptcy prediction," Information Fusion, vol. 47, pp. 88–101, May 2019, doi: 10.1016/j.inffus.2018.07.004.

[17] G. Wang and J. Ma, "A hybrid ensemble approach for enterprise credit risk assessment based on Support Vector Machine," Expert Syst Appl, vol. 39, no. 5, pp. 5325–5331, Apr. 2012, doi: 10.1016/J.ESWA.2011.11.003.

[18] X. Huang, X. Liu, and Y. Ren, "Enterprise credit risk evaluation based on neural network algorithm," Cogn Syst Res, vol. 52, pp. 317–324, Dec. 2018, doi: 10.1016/j.cogsys.2018.07.023.

[19] D. J. Hand and W. E. Henley, "Statistical classification methods in consumer credit scoring: A review," J R Stat Soc Ser A Stat Soc, vol. 160, no. 3, pp. 523–541, Sep. 1997, doi: 10.1111/j.1467-985X.1997.00078.x.

[20] A. Hooman, G. Marthandan, W. F. W. Yusoff, M. Omid, and S. Karamizadeh, "Statistical and data mining methods in credit scoring," The Journal of Developing Areas, vol. 50, no. 5, pp. 371–381, 2016, doi: 10.1353/jda.2016.0057.

[21] J. Galindo and P. Tamayo, "Credit risk assessment using statistical and machine learning: Basic methodology and risk modeling applications," Comput Econ, vol. 15, no. 1–2, pp. 107–143, 2000, doi: 10.1023/a:1008699112516.

[22] J. C. K. Chow, "Analysis of Financial Credit Risk Using Machine Learning," Feb. 2018, doi: 10.13140/RG.2.2.30242.53449.

[23] W. M. Mou, W. K. Wong, and M. McAleer, "Financial credit risk evaluation based on core enterprise supply chains," Sustainability (Switzerland), vol. 10, no. 10, p. 3699, Oct. 2018, doi: 10.3390/su10103699.

[24] Y. Song, Y. Wang, X. Ye, D. Wang, Y. Yin, and Y. Wang, "Multi-view ensemble learning based on distance-to-model and adaptive clustering for imbalanced credit risk assessment in P2P lending," Inf Sci (N Y), vol. 525, pp. 182–204, Jul. 2020, doi: 10.1016/j.ins.2020.03.027.

[25] S. R. Lenka, S. K. Bisoy, R. Priyadarshini, and M. Sain, "Empirical Analysis of Ensemble Learning for Imbalanced Credit Scoring Datasets: A Systematic Review," Wirel Commun Mob Comput, vol. 2022, 2022, doi: 10.1155/2022/6584352.

[26] S. Wei, D. Yang, W. Zhang, and S. Zhang, "A novel noise-adapted two-layer ensemble model for credit scoring based on backflow learning," IEEE Access, vol. 7, pp. 99217–99230, 2019, doi: 10.1109/ACCESS.2019.2930332.

[27] H. He and Y. Fan, "A novel hybrid ensemble model based on tree-based method and deep learning method for default prediction," Expert Syst Appl, vol. 176, Aug. 2021, doi: 10.1016/j.eswa.2021.114899.

[28] L. M. Demajo, V. Vella, and A. Dingli, "Explainable AI for Interpretable Credit Scoring," ArXiv, pp. 185–203, Dec. 2020, doi: 10.5121/csit.2020.101516.

[29] R. Confalonieri, L. Coba, B. Wagner, and T. R. Besold, "A historical perspective of explainable Artificial Intelligence," WILEs Data Mining and Knowledge Discovery, vol. 11, no. 1, Jan. 2021, doi: 10.1002/widm.1391.

[30] N. L. Torrent, G. Visani, and E. Bagli, "PSD2 Explainable AI Model for Credit Scoring," ArXiv, Nov. 2020, Accessed: Apr. 27, 2021. [Online]. Available: http://arxiv.org/abs/2011.10367

[31] N. Bussmann, P. Giudici, D. Marinelli, and J. Papenbrock, "Explainable Machine Learning in Credit Risk Management," Comput Econ, vol. 57, no. 1, pp. 203–216, Jan. 2021, doi: 10.1007/s10614-020-10042-0.

[32] C. Chen, K. Lin, C. Rudin, Y. Shaposhnik, S. Wang, and T. Wang, "An Interpretable Model with Globally Consistent Explanations for Credit Risk," NIPS 2018 Workshop on Challenges and Opportunities for AI in Financial Services: the Impact of Fairness, Explainability, Accuracy, and Privacy, Montréal, Canada. 2018.