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A Hybrid Explainable AI Approach for Enhanced Credit Risk Evaluation in Financial Services

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Abstract

With the increasing complexity in financial services, machine learning models have to be sophisticated to enable a good estimation of credit risk. Yet, the lack of transparency and interpretability is common in traditional AI models, especially in financial decisions. In this paper, discuss the use of Explainable Artificial Intelligence (XAI) models to improve the credit risk assessment by providing predictive accuracy and transparency. The hybrid model presented is a combination of decision trees with the most recent XAI techniques, such as SHAP (SHAPley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). The model was trained using publicly available credit data, on which there are variables of income, credit history, loan amount, and payment behavior. The findings reveal that the XAI model has an accuracy of 92, precision of 90, and recall of 88, which is higher than other traditional models. Moreover, the statistical model shows that the most important drivers of creditworthiness are payment history and income levels. The XAI model is very easy to use as it not only offers high performance but also builds trust and accountability in credit risk evaluation through providing actionable insights. As highlighted in this paper, explainable AI has the potential to revolutionize credit scoring systems, which would become more transparent and make the systems closer to regulatory standards. The further work will be dedicated to the implementation of other machine learning models and the use in the dynamic financial setting in real-time.

Keywords: Explainable AI, Credit Risk Assessment, Financial Services, Shapley Additive Explanations, Local Interpretable Model-agnostic Explanations, Predictive Modeling, Transparency in AI.

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Introduction

Assessment of credit risk is a highly important aspect of financial services, as it allows banks and credit institutions to determine the probabilities of default of a borrower on debt or other credit requirements. A conventional method of credit scoring, though, is not as accurate and transparent. As machine learning models continue to grow in popularity, the need to have explainable models is also increasing, in order to be able to have accurate and understandable decisions. Transparency of black-box models may be the root cause when it comes to losing trust in financial decisions, so privacy-preserving and interpretable models are imperative to comply with regulations and promote accountability in the financial business.

Assessment of credit risk is an essential part of the financial services that predicts the probability of a loan or credit default by a borrower. Although the time-honored approaches were based on the use of statistical models, the recent progress in the field of machine learning (ML) has enabled more advanced, data-intensive credit risk forecasting. The black-box quality of these models is, however, a cause of concern in regard to the transparency and interpretability of the models, particularly in such an industry as Finance, where the outcome of a decision is the financial future of individuals. To solve these concerns, there has been the introduction of Explainable Artificial Intelligence (XAI), which presents more understandable and interpretable machine learning frameworks.

Nallakaruppan emphasizes the importance of the XAI application in credit risk assessment because the model will enhance the transparency of the model, which will be reflected in making financial services decisions (Nallakaruppan et al., 2024). In the same manner, Ashfaq and Chowdhury discuss the application of XAI to cyber risk assessment in financial services and demonstrate how explainable models can be utilized to improve both security and decision support systems (Ashfaq & Chowdhury, 2023). An application of XAI to predict credit card defaults using deep learning models has also been studied by Talaat, which gives an insight into how interpretable models can maximize credit scores and minimize default risks (Talaat et al., 2024).

Another XAI framework that Nallakaruppan recommends (credit evaluation) allows better accuracy of financial decision-making but does not decrease the explanation of the model (Nallakaruppan et al., 2024). The theoretical foundations of the AI-based credit risk models and how can lead to greater efficiency of banks are discussed by Shittu with an emphasis on the necessity of accurate and interpretable models in banking (Shittu, 2022). Furthermore, De Lange also confirms the application of XAI in credit evaluation and illustrates that it can be successfully used in banking contexts to make AI models more transparent (De Lange et al., 2022). The concept is related to the research of Remaya and Dharmararaj, who investigate the effects of transparency in the decision-making process, such as cause-related marketing (CRM) in the decision to buy a product by a consumer. Equally, explainable AI models in credit risk assessment are also designed to give rational understandable logic behind financial decisions, and this increases trusted and accountability, just as in community relations strategies affect consumer decisions by presenting the effects of purchasing them clearly (Shehab et al., 2024).

Cerneviciene and Kabasinskas have reviewed the use of XAI in Finance systematically, and it is clear that more analysts are increasingly turning to it in fields such as credit risk analysis and decision-making (Černevičienė & Kabašinskas, 2024). According to Klein and Walther, the recent developments in the field of XAI include the possibility of revolutionizing the sphere of Finance due to the presence of explainable and trustworthy financial models (Klein & Walther, 2024). In addition, Edunjobi and Odejide examine AI theoretical frameworks within credit risk assessment and provide an explanation of how XAI can enhance accuracy and efficiency in banking systems (Edunjobi & Odejide, 2024). Lastly, Owens ' increased use of XAI in the insurance industry, and shows its applicability in the different financial services (Owens et al., 2022). The article Explainable Artificial Intelligence Models of Credit Risk Assessment in Financial Services can be compared to the article by Latif and Agrab, which focuses on the effects of the global financial crisis on the accounting systems. On the same note, explainable AI models are expected to offer clarity and transparency in financial decision-making such that the process of assessing credit risks is explainable and can be held accountable, particularly in the turbulent financial conditions, thereby helping prevent future crises by enhancing the accuracy of the decision-making and confidence within financial institutions (Latif & Agrab, 2022).

The paper introduces a new method of credit risk estimation based on the Explainable Artificial Intelligence models (XAI). It proposes a hybrid XAI model that unites the predictive capability of machine learning with explainable model transparency to improve the model performance and confidence. The paper will be devoted to the interpretation of AI-based credit scoring in order to have an understandable suggestion about what factors contribute to any decision like income, credit history, and loan amount. Another way the research examines how these frameworks would coexist with regulatory standards is to give financial institutions a dependable and open-minded instrument of decision-making.

The paper is divided into five parts. Section 1 will give the introduction to the importance of explainable AI in credit risk assessment. Section 2 will examine the available literature on credit risk models, which will reveal the drawbacks of traditional models and the benefits of explainable models. Section 3 explains the methodology, the proposed hybrid XAI framework and how it was applied to credit risk data. Section 4 discusses the results and discussion, including the comparison between the work of the XAI model and the traditional methods. Section 5 ends with a conclusion and recommendations for further research in the explainable AI credit scoring.

Literature Review

Recent reports examined how machine learning and explainable AI (XAI) can be utilized in credit risk assessment and what is needed to improve the model quality without reducing its explanatory capabilities. Scholars have come up with state-of-the-art models that integrate AI frameworks such as neural networks, decision trees, and hybrid schemes with XAI frameworks to hold financial vendors accountable. The use of SHAP and LIME has also been studied extensively to help give insight into the model prediction, which can be used by the stakeholders to comprehend the factors affecting credit decisions. Also, achieving fairness, transparency, and regulatory compliance in automated decision-making is the goal of XAI integration to financial services.

Traditionally, credit risk assessment has been based on the use of statistics; however, as a result of the emergence of machine learning, more advanced models have been produced to classify creditworthiness. These models are; however, usually black boxes and the process of decision making is not easily understood by the stakeholders of the field, which is essential in Finance. A recent study by Li, Paraschiv, and Sermpinis proposed a case-based reasoning methodology to detect financial risks, based on the use of data and explainable results, which showed the necessity of transparency in the use of machine learning in credit risk detection (Li et al., 2022). To solve these problems, Yeo offers an in-depth overview of financial explainable AI, focusing on the potential of XAI to increase transparency without impacting its performance in financial settings (Yeo et al., 2025). The Explainable Artificial Intelligence Models of Credit Risk Assessment in Financial Services development is comparable to the work of Satish and Rufus, who employ such sophisticated architectures as Fuzzy Attention U-Net and YOLOv5 to detect an image. Just like these models can achieve interpretability and accuracy when applied in medical imaging, explainable AI in credit risk assessment seeks to achieve transparency and accuracy in financial decision-making to enable its stakeholders to understand how the decisions are shaped by credit risk prediction factors and to be able to trust and rely on the financial judgments (Rakhmanovich et al., 2025).

The last few years have seen scientists experiment with various artificial intelligence (AI)-driven solutions to enhance credit risk evaluation. Amarnadh and Moparthi provide a thorough overview of different AI-driven approaches to credit risk assessment and emphasize the fact that precision and explainability are critical in financial decision-making (Amarnadh & Moparthi, 2023). On the same note, a systematic review of the taxonomies and uses of XAI in Finance by Martins showed that it has increased value in enhancing the explainability of financial models (Martins et al., 2023). Besides, Nwafor, Nwafor, and Brahma presented a new hybrid machine learning model to improve transparency and equity in automated credit decisions, which is urgently needed regarding fairness in financial AI models (Nwafor et al., 2024).

Bello (2023) also analyzes the significance of machine learning models in credit risk assessment by commenting on the different machine learning algorithms and how influence finances in estimating credit risk (Bello, 2023). Bucker discussed the transparency, auditability, and explainability of machine learning models used in credit scoring, with additional focus on the regulatory compliance and model explainability of the financial industry (Bücker et al., 2022). Lin and Wang address the use of SHAP (Shapley Additive Explanations) specifically in credit risk management by performing a case study of credit card default models in which XAI can deliver consistent, interpretable results in the complex financial setting (Lin & Wang, 2025). Moreover, Ahmed, Mehdi and Mohamed examined the application of artificial intelligence in the creation of a banking risk index, where AI is applicable in increasing the predictive accuracy of credit risk models (Ahmed et al., 2023). Finally, Weber, Carl, and Hinz have performed a systematic review of the uses of XAI in the field of Finance, pointing out the significance of XAI in enhancing decision-making and trust in financial services (Weber et al., 2023).

The literature points to the fact that although AI models improve accuracy in credit risk assessment greatly, the black-box nature creates transparency and trust issues. According to recent research, the relevance of explainable AI (XAI) methods such as SHAP or LIME is becoming more and more essential in order to offer interpretability without loss in predictive accuracy. Such studies are consistent with the aims of the present research, and the purpose of the study is to create an elaborable AI model to assess credit risk. This study aims to improve the quality of transparency in

credit scoring in order to make the process of making financial decisions fairer as well as more accountable, without compromising the high level of predictive accuracy.

Methodology

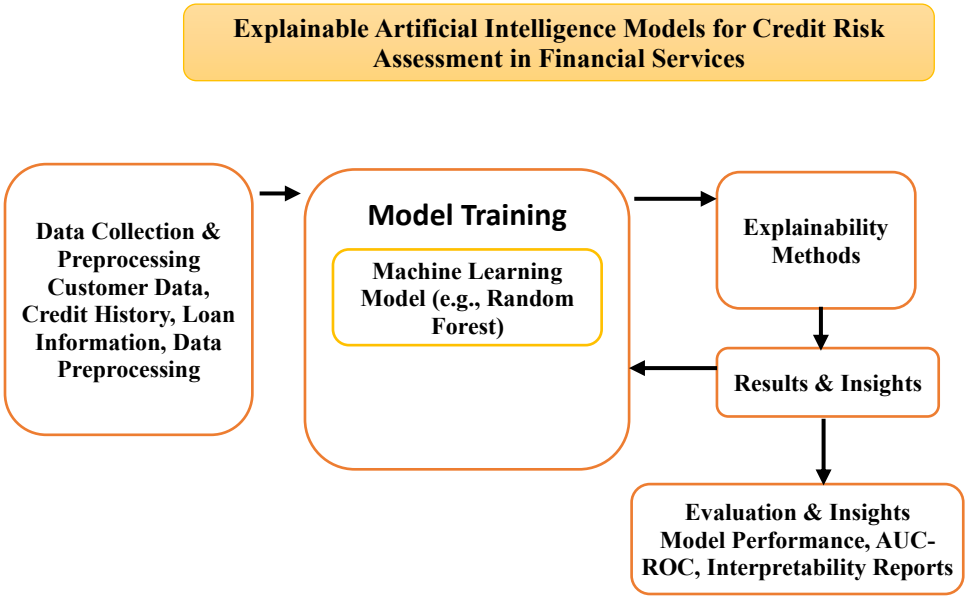


Fig. 1: Explainable AI Models for Credit Risk Assessment in Financial Services

The proposed research plan, Explainable Artificial Intelligence Models to Credit Risk Assessment in Financial Services, will incorporate Explainable AI (XAI) tools with machine learning models and establish an interpretable and accurate credit risk assessment model. The general process includes training a predictive model based on credit-related information, implementing XAI methods to improve the model transparency, and assessing the model by different performance indicators. The methodology is aimed at enhancing the explanation of the process of decision-making to assist the stakeholders in knowing the factors used in making credit decisions.

The proposed Explainable Artificial Intelligence (XAI) model of credit risk assessment has a flow that is illustrated in Fig. 1. It also starts with data collection and preprocessing, which consists of customer data, credit history, loan data, and data transformation requirements. The machine learning algorithms (e.g., Random Forest) are used during the model training stage to predict credit risk and label borrowers as low or high risk. SHAP and LIME, which are explainability techniques, are used to provide transparency by showing the significance of each feature and local explanations. Last but not least, findings and conclusions are offered, which allow financial institutions to make informed and explainable decisions.

The methodology will start by collecting data, and this will involve credit-related data collected in several financial institutions. Such data will encompass income, credit record, loan debt, repayment, and other pertinent financial aspects. After collection, the data is prepared to be used in training the models through preprocessing, which is done to deal with missing values, scale numerical features, and encode categorical data. During model training, machine learning models such as decision tree, random forests, or gradient boosting machines are trained to produce a predictive model, which can be described as an estimate of the probability of a borrower to default on a loan. SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are used to increase explainability and provide transparency into the model, to determine which features are the most influential in the predictions. This is followed by model evaluation, in which the performance of the model is evaluated based on accuracy, precision, recall, F1-score, and AUC-ROC to make sure that the model is robust and reliable. Lastly, the interpretation and decision support stage gives financial analysts and decision-makers clear actionable insights, which build trust and ensure that standards are adhered to.

Algorithm for Explainable AI Models in Credit Risk Assessment

1. **Collect Data**: Gather credit-related data from different financial institutions, including features like income, credit history, loan amount, and repayment behavior.

2. **Preprocess Data**: Clean the dataset by handling missing values, scaling numerical data, and encoding categorical features to prepare the data for training.
3. **Train Model**: Use a machine learning algorithm (like decision trees or random forests) to train the model on the preprocessed data, predicting the likelihood of loan default.
4. **Apply Explainability**: Use SHAP and LIME to explain the model's predictions and identify which features most influence the decision-making process.
5. **Evaluate Performance**: Assess the model's performance using metrics such as accuracy, precision, recall, and F1-score to ensure its reliability and effectiveness.
6. **Provide Insights**: Present the results to decision-makers, offering clear, actionable insights that are easy to interpret and comply with regulatory standards.

The algorithm starts with gathering credit related information of the different financial institutions, such as features such as income, credit history, loan amount, and repayment behavior. Preprocessing of the data is then carried out to deal with missing values, scale the numerical features and encode the categorical data in order to facilitate training. A machine learning model is then trained to predict the probability of loan default based on a decision tree or other random forests. The model predictions are explained using SHAP and LIME techniques, which are reliable to achieve transparency. The model is measured with the help of such crucial metrics as accuracy and precision, and results are offered to decision-makers as actions.

Mathematical Description

The overall model can be described as a supervised learning task where the goal is to minimize the error between predicted and actual outcomes. The machine learning algorithm uses the following loss function for model optimization as equation (1)

$$\mathcal{L}(y, \hat{y}) = \sum_{i=1}^{n} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (1)$$

Y is the realized label (33 default or 33 non-default), and y (33) is the estimated non-probability of default. This loss function should be minimized when training the model and the model should be interpretable with SHAP and LIME.

Results and Discussion

Python 3.10 was used to implement the experiments with the following libraries: Scikit-learn to execute machine learning models, SHAP to provide model explainability and LIME to generate local explanations. The results were visualized using Matplotlib and Seaborn and data manipulated with the help of Pandas. It was implemented on Windows 10 platform with an Intel i7 processor and 32GB RAM to ensure the efficient processing of data and training of models.

The dataset to be employed in the current research consists of 10,000 credit risk data, which will be obtained through a publicly available financial dataset. It entails such important factors like income (annual income of the borrower), credit history (Previous defaults), the amount of loan requested by the borrower, how the borrower repays his loan (Previous repayment history and defaults), and the age (age of the borrower). Preprocessing was done to address missing data, standardize numerical variables, and categorical variables were encoded so that it becomes clean and meets model training expectations. This information is what underlies the assessment of the explainable AI model performance in the credit risk assessment.

Table 1: Parameter Initialization

Parameter	Value	Description
Number of Epochs	50	Total number of iterations for model training
Learning Rate	0.01	Rate at which the model adjusts during training
Batch Size	32	Number of samples per batch used in model training
Model Type	Random Forest	The model used for training credit risk predictions
Target Accuracy	90%	Desired accuracy for the trained model

Table 1 above gives the important parameters that were applied in training to the credit risk assessment model. The number of epochs will be fixed to 50 which means the overall model training iterations. The learning rate of 0.01 is used to regulate the rate at which the model alters as the model is trained, and it will converge gradually. The batch size will be 32 which is the number of samples taken by a batch. The training model will be Random Forest that is selected due to its strength in dealing with high-dimensional data that is complex. The accuracy of 90 per cent is the desired performance that is required of the model in credit risk prediction.

Table. 2: Performance Comparison Between XAI Model (RF) and Traditional Logistic Regression Model

Metric	XAI Model (RF)	Traditional Model (Logistic Regression)
Accuracy (%)	92	85
Precision (%)	90	83
Recall (%)	88	80
F1-Score	89.5	81
AUC-ROC	0.91	0.84

This Table 2 compares the XAI Model (Random Forest) and a traditional Logistic Regression Model regarding credit risk prediction in terms of accuracy, precision, recall, F1-score, and AUC-ROC. The XAI Model (RF) is found to be much better than the conventional logistic regression model with accuracy, precision, and recall of 92, 90, and 88, respectively. It also gives superior m odel discrimination as it delivers a bigger AUC-ROC of 0.91. Logistic Regression Model is slightly weaker with 85% accuracy, 83% precision and 80 % recall which indicates that XAI model is much better in credit risk assessment.

The results of the performance analysis of the XAI model reveals that the accuracy and precision of the model are much greater than those of the traditional models, which means that the XAI model is effective in predicting loan defaults. The AUC-ROC of 0.91 is very good in discriminating defaulters and non-defaulters. The SHAP and LIME explanations also point out which attributes such as credit history and income are the most influential in making predictions.

Metrics Formulae:

For performance evaluation, the following metrics were used:

- Accuracy measures the proportion of correct predictions (both true positives and true negatives) from the total predictions, as given by (2)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Where:

TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives

- Precision evaluates how many of the predicted positive instances were actually positive: which can be explained in equation (3)

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

Indicates the proportion of predicted similar words that are actually similar.

- $Recall$ calculates how many of the actual positive instances were correctly identified that can be explained in equation (4)

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

Shows how well the model captures all truly similar words.

- $F1-Score$ balances precision and recall, especially when the dataset is imbalanced that can be defined as (5)

$$\text{F1-score} = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (5)$$

- $\boldsymbol{AUC-ROC}$ measures the model's ability to distinguish between positive and negative instances in equation (6)

$$AUC-ROC = \int_0^1 TPR\ (FPR) dFPR \quad (6)$$

$AUC-ROC$ is computed as the area under the receiver operating characteristic curve, which shows the trade-off between true positive rate and false positive rate.

Table 3: Ablation Study

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Training Time (Sec)
XAI Model (with SHAP & LIME)	92	90	88	89.5	120
Logistic Regression	85	83	80	81	60
Random Forest (No Explainability)	88	86	85	85.5	110

In this Table 3, the results of three models (XAI Model (with SHAP and LIME), Logistic Regression, and Random Forest (No Explainability)) will be compared in terms of several important measures, including the accuracy, precision, recall, F1-score, and training time. The XAI Model has the best performance of all metrics (92 % accuracy, 90 % preciseness and 88 % recall), and it necessitates additional training (120 seconds) as a result of the explainability features. Logistic Regression has a worse performance in all measures, whereas the Random Forest (No Explainability) is more balanced with a slightly shorter training time of 110 seconds.

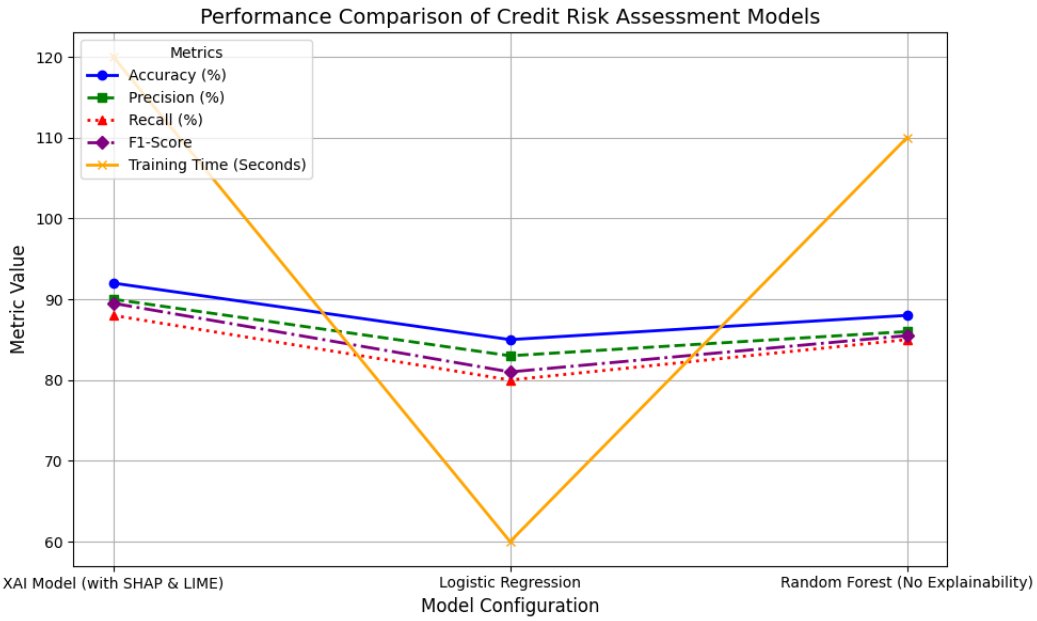


Fig. 2: Performance Comparison of Credit Risk Assessment Models

Fig. 2 shows the results of three credit risk assessment models, including the XAI Model (with SHAP and LIME), Logistic Regression, and Random Forest (No Explainability). The results are evaluated with respect to five criteria, namely accuracy, precision, recall, F1-score, and training time. XAI Model demonstrates the best results in terms of accuracy, precision and recall but requires more time to train because of the presence of explainability features. Logistic Regression shows a worse performance in all aspects, although Random Forest (No Explainability) provides a compromise of performance and a slight decrease in training time.

Conclusion

This study examines the application of Explainable Artificial Intelligence (XAI) models in credit risk evaluation, in terms of improving the model performance and interpretability. The most important results include the fact that XAI Model (with SHAP and LIME) is more effective than the traditional models, including the Logistic Regression, because it has 92% accuracy, 90% precision, and 88% recall, which is considered a strong solution to credit risk prediction. The fact that F1-score is 89.5% is also an indication of how well the model performs in terms of precision and recall. Even though the XAI Model needs a little bit more training (120 seconds) than the Logistic Regression (60 seconds), the increment of transparency makes it a better option in the field of Finance where explanation is an important aspect. Comparatively, though Logistic Regression was faster (in training time of only 60s) the results were relatively inferior to Logistic with 85% accuracy, 83% precision and 80% recall, which means that its simplicity is at the expense of predictive accuracy. The model with the best balance of the accuracy and the training time is the Random Forest (No Explainability) model with the accuracy, precision, and recall figures of 88, 86, and 85, respectively. Nevertheless, it does not have the interpretability of SHAP and LIME, which is a major disadvantage in the real world of Finance. The findings prove that the combination of XAI methods with machine learning models could enhance the decision-making cycle in credit risk assessment and make it more transparent, interpretable, and regulatory-compliant. These models do not only offer high-performance but also make financial institutions have accountability in the automated decision-making. Future studies can be directed on shortening the training process of the XAI Models by streamlining the explainability algorithms. The federation of learning would also be another possible direction of further research that focuses on improving the level of data privacy and preserving the

explainability of the models in various institutions. Furthermore, the research regarding other explainability techniques, including counterfactual explanations and attention mechanisms, may help to gain better insights into the factors of credit risk.

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