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A Predictive Analytics Approach For Financial Risk Management Using The Catboost Algorithm

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Abstract

Financial risk prediction is a crucial element of financial risk management inside financial institutions. The efficacy of machine learning models, particularly CatBoost, in accurately predicting financial risk has not been thoroughly examined, however it has promise. This study aims to compare Catboost with other machine learning (ML) models, including Random Forest (RF), K-Nearest Neighbors (KNN), XGBoost, and Logistic (LR) Regression, in terms of their efficacy in forecasting financial risks. The Financial Risk Dataset comprised transaction details, loan information, and client data. Cross-validation was employed to train models, while precision, accuracy, F1-score, recall, and AUC were utilized to evaluate the performance of the trained models. The CatBoost model exhibited superior performance across all models, achieving an 95.93% accuracy, 95% recall and precision, and 0.98 AUC. The model exhibited superior performance when category information was included with minimal pre-processing. XGBoost and RF also had a good performance, but were slightly less accurate than CatBoost. The worst performance was obtained by KNN, where the performance was the lowest in all the metrics. CatBoost outperformed the other models in financial risk prediction. It is good at dealing with categorical data and has a powerful gradient boosting (GBoost) mechanism, which helps it to be very predictive. It would be interesting to see how it can be used in other financial fields and with extra functionalities such as real-time data and time-series analysis in future studies.

Keywords: Financial Risk Prediction, CatBoost, Machine Learning, AUC, Risk Management, Predictive Analytics.

1. Introduction

The financial risk management function has become one of the most essential roles of the global financial system, which seeks to recognize, measure, and manage financial risks that can impact financial institutions, enterprises, and financial markets [1]. Financial risks such as credit risks, market risks, operational risks, and liquidity risks. Financial risks analysis is essential in ensuring financial stability and security as well as good decision-making [2]. In current years, ML have been recognized as one of the effective tools used in financial risk management because of its capability to analyze big data and predict possible risks [4]. Notwithstanding significant advancements in financial risk management, numerous issues persist.

Consequently, this research will focus on investigating ML and financial risk management [3]. Traditional risk assessment models, such as statistical models and rule-based models, do not necessarily provide an adequate representation of complexity and dynamism in today's financial markets [5]. Most of these models will not be capable of dealing with non-linear connections in large datasets, and thus fail to predict the data accurately. Moreover, sometimes do not have the flexibility to adapt to the changing market. This results in financial institutions being more likely to have inaccurate risk models, and therefore exposed to new risks and unable to identify new risks occur [6].

In the financial risk management domain, predictive analytics has proven to be a major asset, providing valuable insights from historical data and forecast future performance, which can support decision-making and action [8]. ML algorithms can be employed in predictive analytics to discover patterns within the data, which can be utilized to improve risk calculations and forecast future risks. It enables the financial institutions to change their reactive decision-making process to a proactive one; these are able to anticipate financial crises and adjust their strategy in time [9]. Predictive analytics can also help companies leverage resources better, cut down on potential losses and optimize portfolio management.

CatBoost (Categorical Boosting) is an advanced GBoost algorithm that can work effectively with data that contains categorical variables that do not require a lot of data preparation [10]. Unique characteristic of CatBoost is that it can work with categorical features without having to perform additional actions, such as encoding and other types of data pre-processing procedures, which makes the process much simpler and leads to improvement of model efficiency. Besides, CatBoost can operate on heterogeneous datasets, i.e., those consisting of numerical and categorical variables, and it is commonly applied in the financial industry because of its effectiveness and wide use in practice. In addition, the CatBoost algorithm is robust and scalable and therefore is ideal for financial risk prediction [11].

The aim of this paper is to examine the use of CatBoost algorithm in the financial risk assessment process for predictive purposes. The study aims to analyze the usefulness of the CatBoost algorithm when applied to financial risk assessment and compare its results with the outcomes that traditional financial risk prediction methods produce so as to estimate the precision of the outcomes obtained from the application of this algorithm. In other words, the CatBoost algorithm will be analyzed in the context of practical applications involving financial data.

Section 2 provides an overview of existing literature on financial risk management, machine learning applications in the field of finance, and past research on financial risk prediction. Section 3 defines the methodology, which includes CatBoost algorithm and the dataset used. Section 4 converses the results and comparisons with traditional approaches. Lastly, Section 5 completes findings, and identifies future research directions in the financial risk management.

2. Literature Review

In financial risk management, the analysis and management of various types of financial risks have always been conducted using a combination of statistical methods and judgment [12]. Some of the frequently used techniques for measuring the probability of a financial asset becoming less valuable during a certain period of time in normal market conditions are CVaR and VaR [13]. Furthermore, LR, which is one form of credit scoring, has been applied to measure the possibility of default by individuals in terms of their credit record, income, and debt levels. However, they are not always appropriate to address the non-linear financial relationships [7]. Furthermore, they rarely perform well with so much data that there are patterns or trends to be seen. Approaches such as SVMs and XGBoost models have improved the predictive ability, but still require intensive data preprocessing and computations, making it difficult for real-time financial risk assessment [14].

In finance, the introduction of ML technologies has brought about a revolution with respect to data analysis capability through identification of patterns in order to make more accurate forecasts than conventional techniques [15]. In addition, ML technologies including Neural Networks, RF, and GBoost Machines among others are becoming more popular tools for making predictions of financial risk cases like credit risk, fraud detection, market volatility, and others [17]. RF have become an effective tool for performing classification of financial risks due to the presence of ensemble features that help to minimize the problem of overfitting and increase model generalization. Moreover, Neural Networks have demonstrated considerable efficacy in discerning non-linear and intricate correlations inside data, however they necessitate substantial data and computer resources for optimal performance. The Catboost Algorithm is also an ML algorithm that has been gaining popularity in the financial industry and it is one of the algorithms based on GBoost [16]. The algorithm has turned out to be very useful for finance-based applications like credit scoring and fraud detection, among other similar uses, owing to the inherent ability to handle categorical data.

In the case of financial risk prediction, it has been shown that CatBoost surpasses several conventional algorithms [18]. For instance, it has been proven that CatBoost performs better than the renowned algorithm, XGBoost, when handling financial data, which requires minimal data processing [21]. However, despite being very powerful, the problem with XGBoost is that it requires manual coding of the categorical data. Likewise, CatBoost has been shown to be more predictive than RF on a number of financial risk prediction problems, such as credit risk prediction and fraud detection, because it is able to handle imbalanced data sets and prevent overfitting [19]. GBoost is a step-up from previous errors to correct them, and the CatBoost model is especially suited for financial risk management because it has able to make more exact predictions and converge faster than many other ML models [20].

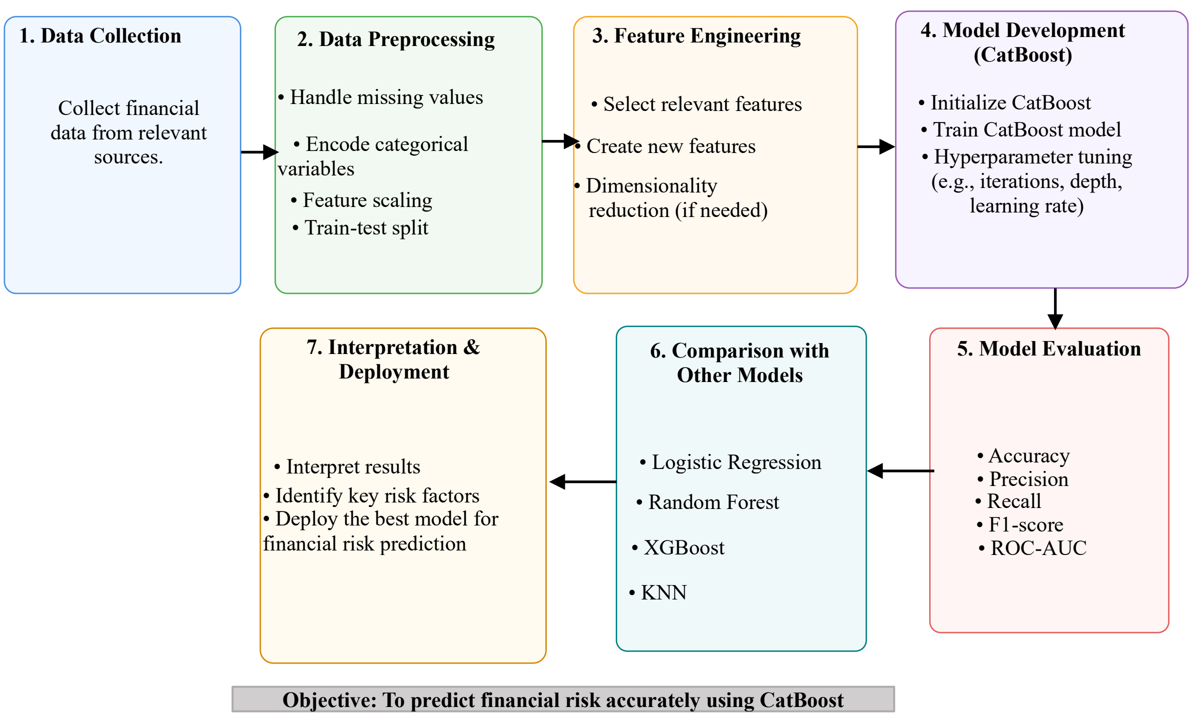
Despite the fact that the ML models have made great achievements in financial risk management, there is a lack of literature about the specific use of CatBoost for financial risk prediction. Although models such as XGBoost and RF have been extensively researched and successfully used, CatBoost has not been studied as much, especially in finance. The literature mostly focuses on models that require a lot of pre-processing of the data or which cannot capture the non-linear relationship in financial data that is of a heterogeneous nature. The study interested in this particular aspect and want to fill this gap in the paper by discussing the applications of CatBoost on the prediction of financial risks, such as the prediction of credit risk, fraud detection, and market forecasting, where this is of high interest. The advantages of CatBoost will be discussed in relation to its ability to deal with categorical information effectively, and its performance in big data sets in financial scenarios will be highlighted.

3. Methodology

3.1 Data Acquisition and Preprocessing

This study employs the Financial Risk Kaggle dataset. The information contained in this comprises financial transaction data, loan application information, credit scores and customer demographics. The data contains both categorical and numerical attributes, making it appropriate for ML models like CatBoost. Medians and modes have been used to replace missing data in the data set. CatBoost uses the native processing of categorical features without the need to encode them as one-hot vectors or any other encoding techniques. The normalization of numerical data is done for effective training of the models, and statistical methods such as Z-scores are used for outlier detection.

Figure 1: Methodology for financial risk prediction using CATBOOST



The prediction of financial risk using the CatBoost model is carried out in the following steps, as shown in figure 1. It showcases the following steps: Data Collection (Financial Data Collection), Data Preprocessing (Data Cleaning and Encoding), Feature Engineering, Model Development (Initialization and Training the CatBoost model), Model Evaluation, Comparison with Other Models, and Interpretation & Deployment (Interpretation of Results, Identification of Key Risk Factors, Deployment of the best model). The goal is to accurately predict the financial risk with CatBoost and to make a comparison with other ML models.

3.2 CatBoost Algorithm

CatBoost is a GBoost algorithm that is specifically optimized for working with categorical data-it does not need to be extensively preprocessed. Operates on the principle of a joint of decision trees, in which each tree is proficient to rectify the faults of its predecessor, utilizing ordered boosting to mitigate overfitting and improve generalization. The key strength of CatBoost is that it can directly process categorical features without needing to be encoded in advance, for example, using one-hot encoding. Key parameters include the learning rate, the depth of tree's maximum, and the number of trees, which are optimized during training. The learning rate dictates the contribution of each tree to the final prediction, while the tree's quantity and their complexity influence the ability of the model to accurately fit the data. These parameters are optimized to ensure the model is not over-fitting and can accurately predict.

The general form of a GBoost algorithm:

$$F_m(x) = F_{m-1}(x) + \eta \cdot \Delta F_m(x) \quad (1)$$

Where in equation (1):

- $F_m(x)$ represents the forecast of the model at the m^{th} iteration.
- $F_{m-1}(x)$ represents the forecast from the preceding iteration.
- η represents the learning rate, which regulates the influence of each tree.
- $\Delta F_m(x)$ represents the update step, which is the output of the m^{th} decision tree.

Algorithm 1: Predictive Analytics for Financial Risk Management Using CatBoost

1. **Data Collection**:

Use the Financial Risk Dataset from Kaggle, containing financial transactions, loan data, credit scores, and market trends.

2. **Data Preprocessing**:

- Missing values should be handled via imputation (median for numerical and mode for categorical).
- Process categorical features using CatBoost's native encoding.
- Normalize numerical data and remove outliers using Z-scores.

3. **Model Initialization**:

Set the parameters for the CatBoost model: learning rate (η = 0.05), number of trees (N = 1000), maximum depth (D = 6), and categorical features.

4. **Training of the Model:**

- Divide the data into training (80%) and testing (20%) sets.
- Employ K-fold cross-validation (for instance, 5-fold).
- Hyperparameter tuning is done via grid search or random search.
- Use early stopping to avoid overfitting.

5. **Model Prediction**:

Generate predictions from CatBoost model training based on the testing.

6. **Evaluation of the Model**:

Assess the model by using the metrics such as precision, F1-score, accuracy, recall, and AUC.

7. **Model Comparison**:

Compare CatBoost with conventional models such as XGBoost, RF, and SVM based on the evaluation criteria.

8. **Result Interpretation**:
Interpret results and identify critical features that influence financial risk management decisions.
The first stage of the Algorithm 1 for the prediction of financial risks using the CatBoost algorithm is related to data gathering from the Financial Risk Dataset available on Kaggle. In the process of pre-processing of the obtained data, missing values are imputed, numerical features are normalized, and categorical features are encoded via the CatBoost technique. Z scoring method is used for the identification and exclusion of outliers from the dataset. Some critical model parameters are defined while building the CatBoost model. The dataset is divided into training and testing, and cross-validation of K-fold is used in model evaluation. Hyperparameter fine-tuning and early halting used to avoid overfitting and improve the performance of the developed model. The performance of the CatBoost model is evaluated based on the test subset with the precision, recall, accuracy, AUC, and F1 score, results presented. Model results are compared with the outcomes of conventional models like XGBoost and RF, and additionally selected features are discussed. The training and validation process of the model is presented.

3.3 Training and Validation of the Model

The CatBoost model uses a supervised learning approach and makes use of the training dataset to forecast the target variable, such as credit risk and loan defaulting. The dataset is split into training and testing as 80/20 split. Cross-validation is used in the proposed model, splitting the data of training into K folds. It improves generalization and increases model accuracy. The data is used for model's training and validation once, and to train the proposed model, remain of the K-1 data is utilized. Random Search and Grid Search algorithms are used to tune the hyperparameters in the model, including tree depth, number of trees, and learning rate. Early stopping is utilized to prevent overfitting, where training is stopped when performance improvement ceases on the validation set.

3.4 Assessment Criteria

Accuracy: Accuracy is the proportion of accurate predictions to the total number of all cases.

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

Precision: Precision is proportion of true positives to expected positives, as indicated.

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

Recall: Recall is the proportion of true positives to actual positives, as expressed.

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

F1-Score: Equation (5) shows F1-score is the harmonic mean of recall, and precision as described.

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

Where in equation (2)-(4):

- TP-True Positives
- TN- True Negatives
- FP- False Positives
- FN- False Negatives

4. Findings and Discussion

The CatBoost model was employed based on CatBoost library in Python (version 1.0.0). The data processing, training, and evaluation process was carried out in Python 3.7. Data processing and evaluation is enabled by Pandas, visualizations can be created using Matplotlib, and NumPy can perform numerical calculations. The process of splitting the data, evaluating the model performance, and conducting cross-validation were performed using scikit-learn. Model's training and testing of the was done on 16 GB of memory, an Intel i7 CPU, and an NVIDIA GTX 1080 GPU, with the Ubuntu 20.04 LTS operating system.

4.1 Model Performance

The CatBoost model was accurate at 95.93%. It implies that the model was successful in classification of financial risks prediction. Moreover, the model was precise and had a recall rate of 95%. It implies that the model was effective in recognizing both positive and negative risk cases. Financial risk data is being used effectively as seen from the F1 score of 0.95, which takes into account recall, and precision. Finally, the AUC is 0.98, which means that it is highly accurate.

Table 1: Performance Metrics comparison for Financial Risk Prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LR [20]	94.88	93	94	93
RF [20]	92.88	90	91	91
XGBoost [20]	95.38	94	94	94
KNN [20]	85.50	82	79	80
Proposed Model (CatBoost)	95.93	95	95	95

Table 1 presents the performance metrics (accuracy, precision, recall, and F1-score) of several predictive models employed in financial risk prediction, including LR, RF, XGBoost, KNN, and the suggested model, CatBoost. The CatBoost model achieves 95.93% accuracy, along with optimal recall, F1 score, and precision of 0.95. It highlights the fact that CatBoost is especially adapted to financial risk prediction problems, which are complex, and are based on other widely used ML models.

Figure 2: ROC Curve Comparison of Different Models for Financial Risk Prediction

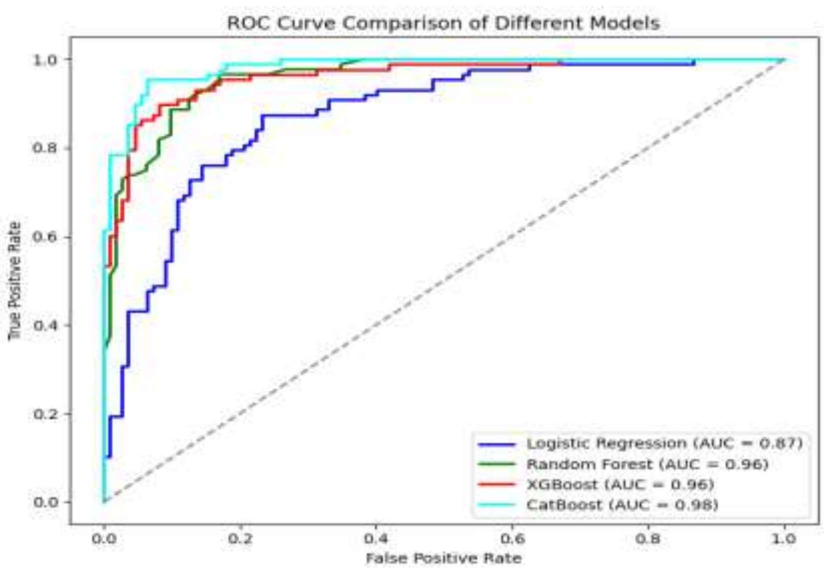
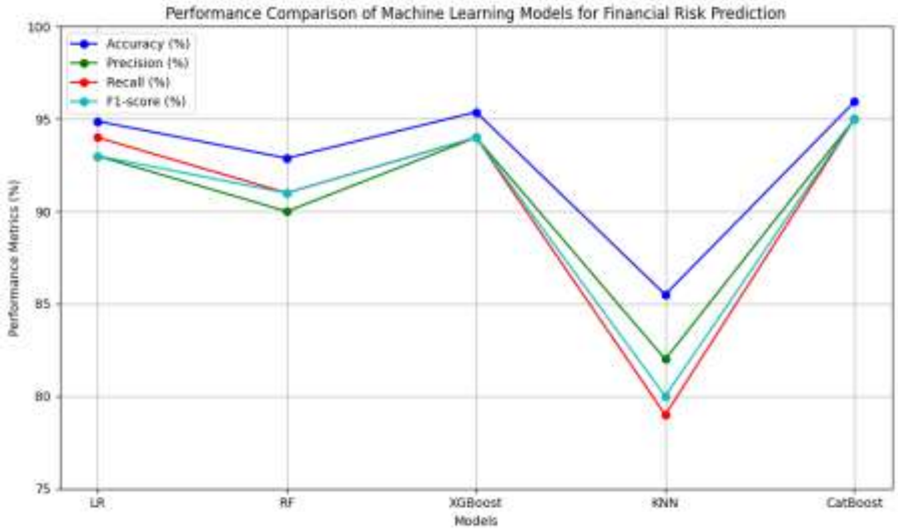


Figure 2 illustrates the outcomes of various ML models-LR, XGBoost, RF, and CatBoost-for financial risk prediction. The AUC is labelled in the legend for each model, and these models are plotted on the graph. CatBoost excels in differentiating between positive and negative classes, achieving 0.98 AUC, followed by XGBoost and RF, both with an AUC of 0.96. LR with an AUC score of 0.87 is the least capable of seeing the difference between classes. It gives a visual proof of CatBoost's capabilities in the financial risk prediction scenario.

4.2 Comparison with Other Models

CatBoost is better than other models at predicting financial risks. The LR model achieved an accuracy of 94.88%, whereas CatBoost excelled in precision, recall, and F1-score. RF was not performing well on categorical variables and needed additional encodings, with an accuracy of 92.88%. Despite the overall good performance by XGBoost with 95.38% accuracy, it was not as performant as CatBoost, mostly because of the manual categorical encoding. KNN was the least effective algorithm with an accuracy of 85.50% for high-dimensional and imbalanced datasets.

Figure 3: Comparison of ML methods for Financial Risk Prediction



As shown in Figure 3, the performance of all models, including LR, RF, XGBoost, KNN, and the proposed model (CatBoost), is compared. The performance indicators such as Accuracy, Precision, Recall, and F1-Score have been shown in each graph. It can be seen that the proposed model (CatBoost) outperforms other models because of high accuracy, precision, and recall. Hence, it is an ideal approach to predict financial risks.

4.3 Interpretation of Results

The advantage of working with categorical features in the CatBoost model makes it more suitable for financial risk assessment. Unlike other models, such as XGBoost, CatBoost handles categorical features without any special treatment, whereas in the case of XGBoost, only numeric data types are accepted. In such cases, manually converting the features into numeric type would be time-consuming and may even lead to the loss of information. The ordered boosting approach adopted by the model helps prevent data overfitting, thereby making the model highly relevant to real-world financial data that may contain noise and complexities. The utilization of AUC and F1-score facilitate the identification of the ideal stability between recall and precision in a financial setting characterized by the occurrence of both false negatives and false positives. In addition, built-in mechanisms for data imbalance in CatBoost probably played a role in its better performance compared to conventional models.

4.4 Challenges and Limitations

Although results were positive, there were several difficulties encountered in this study. One of the main challenges was data quality, and there were some missing data and inconsistencies within the data for some categorical variables. These concerns were addressed using imputation approaches such as median imputation for numerical data and mode imputation for categorical data, hence facilitating effective learning by the model from the data. A further problem was the class imbalance within the dataset, as the quantity of high-risk occurrences was significantly lower than that of low-risk examples. This was addressed by class weighting during the training of the model and stratified sampling during cross-validation, so that there was appropriate representation of each class. Lastly, computational complexity was an issue because training a CatBoost model on large datasets was very costly. This issue was addressed through the use of early halting during the training process, whereby overfitting was avoided, and training time was saved once the model's performance became steady on the validation.

5. Conclusion

The results obtained shows that CatBoost algorithm executes better than the other ML algorithms such as LR, XGBoost, RF, and KNN in predicting financial risks, as it achieves 95.93% the highest accuracy 95% precision, 95% recall, 95% F1-score, and 0.98 AUC. CatBoost model is renowned for being highly efficient in dealing with financial risks as it can deal with categorical financial data with minimum preprocessing and it possesses high GBoost. It is evident that CatBoost model is effective in predicting financial risk ranging from credit scoring, fraud detection, and loan default predictions. This means that there will be an immense impact of using CatBoost model in risk management in the finance sector. This is because, the financial institutions will rely on the model to classify risks with efficiency and accuracy resulting in effective risk strategies. This model can be additionally expanded to other areas of finance such as insurance and financial investments through the introduction of various other components such as real-time market analysis and behavioral analysis, among others, which require further research studies. Furthermore, due to its applicability for time series data and the potential to simplify the models used, it is important to utilize CatBoost under continuously changing conditions in financial services. The innovations will help to improve the process of managing risks and result in better predictive models and enhanced decision-making process.

Declaration

Conflict of Interest

The authors indicate that there are no conflicts of interest concerning the publishing of this paper.

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Data Availability

The dataset used in this study, Financial Risk Dataset, is publicly available on Kaggle and can be accessed via the following link: https://www.kaggle.com/datasets/berkereryilmaz/financial-risk-dataset.

References

1. Fan, J. (2025). Research on financial risk assessment algorithm based on CatBoost and SVM. In 2025 Asia-Europe Conference on Cybersecurity, Internet of Things and Soft Computing (CITSC) (pp. 246–252). IEEE. https://doi.org/10.1109/CITSC64390.2025.00051
2. Xie, S. (2025). Financial risk early warning for enterprises based on the CatBoost algorithm. In Proceedings of the 2025 4th International Conference on Big Data, Information and Computer Network (pp. 239–245). https://doi.org/10.1145/3727353.3727394
3. Fu, J. (2024). Real-time data analytics and predictive maintenance in commercial bank credit risk management. In Innovative Design and Intelligent Manufacturing: Proceedings of the International Conference (IDIM 2024) (pp. 137–143). SAGE Publications. https://doi.org/10.3233/FAIA241096
4. Garg, D., Shelke, N. A., Kitukale, G., & Mehlawat, N. (2024). Leveraging financial data and risk management in banking sector using machine learning. In 2024 IEEE 9th International Conference for Convergence in Technology (I2CT) (pp. 1–6). IEEE. https://doi.org/10.1109/I2CT61223.2024.10544336
5. Zhao, Y. (2025). Design and financial risk control application of credit scoring card model based on XGBoost and CatBoost. In 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT) (pp. 1–5). IEEE. https://doi.org/10.1109/ICICNCT66124.2025.11233033
6. Alsaadi, M., Almashhadany, M. T., Obaed, A. S., Furaijl, H. B., Kamil, S., & Ahmed, S. R. (2024). AI-based predictive analytics for financial risk management. In 2024 8th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1–7). IEEE. https://doi.org/10.1109/ISMSIT63511.2024.10757214
7. Mousavi, A., & Karshenasan, A. (2017). Forecasting stock prices of banks using artificial neural networks (GMDH). International Academic Journal of Accounting and Financial Management, 4(2), 71–78.
8. Sujatha, R., Kavitha, D., Maheswari, B. U., & Ajay, K. G. (2025). Ensemble machine learning models for corporate credit risk prediction: A comparative study. SN Computer Science, 6(5), 514. https://doi.org/10.1007/S42979-025-04053-7
9. Rakhmanovich, I. U., Husayn, S. O., Hasan, M. K., Samudro, E. G., & Vij, P. (2025). Artificial intelligence-driven industrial financial analytics for predictive modeling for smarter investments. In 2025 International Conference on Computational Innovations and Engineering Sustainability (ICCIES) (pp. 1–5). IEEE.
10. Özgüler, İ. C., Saygılı, M., Kaleci, M., & Sakarya, U. (2026). A case study on non-performing loan recovery: Applying the CatBoost algorithm in banking to enhance asset quality. SN Business & Economics, 6(4), 99. https://doi.org/10.1007/S43546-026-01112-W
11. Jagadhabi, N. (2025). Explainable AI-driven decision support for strategic risk management in financial services. International Academic Journal of Science and Engineering, 12(3), 125–144. https://doi.org/10.71086/IAJSE/V12I3/IAJSE1254

12. Alsulamy, S. (2025). Predicting construction delay risks in Saudi Arabian projects: A comparative analysis of CatBoost, XGBoost, and LGBM. Expert Systems with Applications, 268, 126268. https://doi.org/10.1016/J.ESWA.2024.126268
13. Sravan Kumar Reddy, M., & Supraja, C. (2025). Optimising financial forecasting: The power of reduction approach. Archives for Technical Sciences, 2(33), 453–462. https://doi.org/10.70102/AFTS.2025.1833.453
14. Bobba, J., Narayana, D. S., Ahmed, S., Syed, Z., & Balaji, V. (2025). AI-driven risk management: Leveraging machine learning for predictive analytics in financial markets. In 2025 International Conference on Technology Enabled Economic Changes (InTech) (pp. 748–754). IEEE. https://doi.org/10.1109/INTECH64186.2025.11198317
15. Nuong, L. N. (2025). Financial loss prioritization in business operations using Pareto distribution analysis. Global Perspectives in Management, 3(1), 1–12.
16. Sambamoorthy, N., Singh, I. P., Arumuganainar, R., Pria, S., Govindan, R., & Nidamanuri, S. B. (2026). Leveraging ensemble machine learning to evaluate financial inclusion and social equity: Insights from CatBoost and gradient boosting models. In 2026 6th International Conference on Expert Clouds and Applications (ICOECA) (pp. 1021–1027). IEEE. https://doi.org/10.1109/ICOECA68095.2026.11485605
17. Farhood, A. S. (2023). Analyze the efficiency of banking risk management in banks operating in the local environment through the application of Basel standards in financial risk management. International Academic Journal of Social Sciences, 10(2), 39–52. https://doi.org/10.9756/IAJSS/V10I2/IAJSS1011
18. AbdElnapi, N. M., Darwish, A., & Hassanien, A. E. (2024). Artificial intelligence in finance sector for risk prediction. In Artificial Intelligence for Environmental Sustainability and Green Initiatives (pp. 297–312). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-63451-2_17
19. Al-Badran, O. R. A., & Mohsen, A. N. (2023). The strategic approach to assessing banking risks. International Journal of eBusiness and eGovernment Studies, 15(2), 338–353.
20. Hossan, M. Z., Riipa, M. B., Hossain, M. A., Dhar, S. R., Zaman, A. M., Hossain, M., et al. (2025). AI-powered predictive analytics for financial risk management in US markets. EAI Endorsed Transactions on AI and Robotics, 4.
21. Zhao, Y., & Zhao, H. (2025). A hybrid machine learning framework by incorporating categorical boosting and manifold learning for financial analysis. Intelligent Systems with Applications, 25, 200473. https://doi.org/10.1016/J.ISWA.2024.200473