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DEEP LEARNING-BASED CREDIT RISK MODELING: ADDRESSING DATA IMBALANCE AND INVARIANCE

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Abstract: Credit risk modeling plays a crucial role in financial decision-making, helping lenders assess the likelihood of default and optimize lending strategies. Traditional credit risk assessment models, including logistic regression and decision trees, often struggle with data imbalance and invariance issues, leading to biased risk predictions and reduced generalization. The rapid advancement of deep learning (DL) techniques has introduced more sophisticated models capable of learning complex credit risk patterns. However, most DL-based credit scoring models still suffer from class imbalance in default prediction and fail to maintain fairness and stability across different demographic and economic conditions.
This study proposes a DL-based credit risk modeling framework designed to address data imbalance through advanced resampling techniques and generative modeling, while also incorporating adversarial learning to improve model invariance across diverse borrower segments. The proposed framework utilizes autoencoders, generative adversarial networks (GANs), and cost-sensitive learning techniques to enhance risk assessment accuracy while reducing bias. Additionally, domain adaptation techniques are introduced to ensure that the model remains robust across different financial environments.
Experiments on real-world credit datasets demonstrate that the proposed framework significantly improves credit risk prediction accuracy, enhances model fairness, and reduces sensitivity to class imbalance compared to traditional credit scoring approaches. The findings highlight the importance of integrating data-centric augmentation techniques with fairness-aware deep learning to improve the reliability of credit risk modeling in modern financial applications.
Keywords: Credit risk modeling; Deep learning; Data imbalance; Invariance; Fairness; Generative models; Adversarial learning

1 INTRODUCTION

Credit risk modeling is a critical component of financial decision-making, enabling lenders and financial institutions to assess the likelihood of borrower default [1]. An accurate credit risk assessment system ensures that loans are granted to creditworthy individuals while minimizing the risk of financial losses. Traditional credit risk models, such as logistic regression (LR) and decision trees (DTs), have been widely used for decades to predict borrower default probabilities. However, these models rely on manually engineered features and linear relationships, making them limited in capturing complex credit risk patterns present in real-world financial data [2].
One of the major challenges in credit risk modeling is class imbalance, where the proportion of borrowers who default on their loans is significantly lower than those who repay their debts [3]. This imbalance often leads to biased credit scoring models, where machine learning algorithms favor the majority class (non-defaulters) while misclassifying minority class samples (defaulters). Traditional machine learning (ML) models trained on imbalanced datasets tend to exhibit poor recall for high-risk borrowers, leading to inaccurate risk estimation and suboptimal lending decisions [4]. Addressing class imbalance is crucial to improving the performance and fairness of credit risk models.
Another key issue in credit risk modeling is invariance, referring to a model's ability to maintain consistent predictive performance across different demographic and economic conditions [5]. Many existing credit scoring models exhibit distributional bias, where certain borrower groups receive systematically different credit risk scores due to underlying imbalances in the dataset. This raises ethical and regulatory concerns, as unfair credit assessments can lead to discriminatory lending practices and potential legal consequences. Improving invariance in credit risk models is essential to ensure fairness and regulatory compliance in financial decision-making [6].
Recent advancements in deep learning (DL) have introduced more sophisticated methods for credit risk assessment, enabling models to learn non-linear and hierarchical representations from large-scale financial datasets [7]. Techniques such as artificial neural networks (ANNs) and long short-term memory (LSTM) networks have been employed to improve credit risk prediction by leveraging complex borrower-lender interaction patterns [8]. However, despite their advantages, DL-based credit scoring models still face significant challenges related to class imbalance and distributional invariance.
This study proposes a DL-based credit risk modeling framework designed to address these limitations by integrating data augmentation, generative adversarial networks (GANs), and adversarial training techniques. The framework enhances credit risk assessment by improving recall for high-risk borrowers and ensuring model stability across different borrower distributions. By incorporating autoencoders (AEs) for feature learning, cost-sensitive learning techniques for imbalanced classification, and domain adaptation strategies for fairness enhancement, the proposed approach improves both the accuracy and fairness of credit risk predictions.

The framework is evaluated using real-world credit risk datasets, demonstrating its effectiveness in mitigating data imbalance, reducing discriminatory biases, and improving model generalization. The findings highlight the necessity of combining data-centric resampling techniques with fairness-aware deep learning approaches to develop robust and equitable credit risk assessment systems for modern financial applications.

2 LITERATURE REVIEW

Credit risk modeling has been extensively studied in financial research, with traditional methods focusing on statistical and ML-based techniques to predict borrower default probabilities [9]. While LR and DTs have been widely used due to their interpretability and regulatory acceptance, these models often struggle with complex borrower behaviors and non-linear credit risk patterns [10]. The advent of DL has provided new opportunities for financial institutions to enhance risk assessment accuracy by leveraging large-scale datasets and learning intricate borrower-lender interactions. However, DL models also present challenges, particularly in addressing class imbalance and ensuring invariance in credit risk classification [11].

Class imbalance remains a fundamental issue in credit risk modeling [12]. Many credit datasets contain a significantly lower proportion of defaulters compared to non-defaulters, leading to skewed model predictions. Traditional ML models trained on such imbalanced datasets tend to favor the majority class, resulting in high overall accuracy but poor recall for high-risk borrowers. To address this issue, various resampling techniques, including oversampling methods such as Synthetic Minority Over-sampling Technique (SMOTE) and undersampling methods, have been introduced to balance class distributions. Cost-sensitive learning has also been explored as an alternative, assigning higher misclassification penalties to the minority class to improve model sensitivity to defaulters [13-16]. While these approaches mitigate imbalance to some extent, they do not fully capture the complex borrower relationships that contribute to default risk [17].

DL-based models, particularly ANNs and LSTMs, have demonstrated superior predictive performance in credit risk modeling by capturing hierarchical borrower representations and sequential financial behaviors [18]. However, their reliance on large, imbalanced datasets can lead to biased risk predictions [19]. One solution to this challenge is the use of GANs to generate synthetic borrower profiles, expanding the representation of high-risk borrowers in training data. Additionally, autoencoders have been utilized for feature extraction, improving model generalization and reducing overfitting in imbalanced credit datasets. These data augmentation techniques enhance the robustness of DL models, enabling them to learn better from minority class samples and improving recall for high-risk borrowers [20].

Another key challenge in credit risk modeling is ensuring invariance across different borrower demographics and economic conditions [21]. Many traditional credit scoring models exhibit distributional bias, where borrowers from specific demographic or socioeconomic backgrounds receive systematically lower or higher credit scores due to underlying dataset imbalances. Addressing this issue requires adversarial learning strategies that enforce fairness constraints during model training [22-26]. Domain adaptation techniques, such as adversarial domain alignment, have been introduced to ensure that risk predictions remain stable across different borrower groups [8]. These techniques help mitigate the effects of biased credit assessments, ensuring that DL-based credit risk models are both accurate and fair [27-29].

Despite the advancements in DL-based credit risk modeling [30,31], there remain open questions regarding explainability and regulatory compliance. Financial institutions are required to provide transparent justifications for credit decisions, which can be challenging when using complex neural networks. Research into explainable AI methods, including feature attribution techniques and interpretable DL architectures, aims to bridge this gap by improving model interpretability while maintaining high predictive performance [32].

This study builds on these advancements by integrating GAN-based data augmentation, adversarial learning for fairness enhancement, and autoencoder-driven feature learning into a unified DL-based credit risk modeling framework. The proposed approach aims to improve credit risk assessment by addressing class imbalance and ensuring distributional invariance, enhancing both model performance and fairness in credit lending decisions. The next section outlines the methodology used to implement and evaluate the proposed framework.

3 METHODOLOGY

3.1 Data Preprocessing and Feature Engineering

Credit risk modeling relies on high-dimensional financial datasets containing diverse borrower attributes, transaction histories, and economic indicators. Ensuring data quality and consistency is crucial before training DL-based models. The first step in preprocessing involves handling missing values, which are common in credit datasets due to incomplete borrower information. Missing values are addressed using imputation techniques, including mean imputation for numerical features and mode imputation for categorical attributes. More complex techniques such as k-nearest neighbors imputation and autoencoder-based imputations are also employed to enhance data consistency.

Outlier detection is another important preprocessing step, as extreme values in financial data can bias model predictions. Borrowers with unrealistic credit scores, income levels, or transaction frequencies are identified using statistical anomaly detection methods, including interquartile range and Mahalanobis distance. Data normalization is applied to ensure that all numerical variables are scaled appropriately, preventing models from being influenced by large-magnitude financial values.

Feature engineering plays a crucial role in improving the predictive power of credit risk models. Derived financial attributes, such as debt-to-income ratio, revolving credit utilization, and historical loan repayment behavior, are extracted to provide more informative borrower representations. Temporal features are also introduced by analyzing borrower behavior over different time windows, allowing the model to capture financial trends and repayment consistency. Dimensionality reduction techniques, including principal component analysis and autoencoder-based feature selection, are applied to eliminate redundant information while preserving critical credit risk indicators.

3.2 Handling Class Imbalance with Generative and Cost-Sensitive Approaches

Class imbalance is one of the most significant challenges in credit risk modeling, where the number of default cases is substantially lower than non-default cases. Training models on imbalanced datasets leads to biased predictions, where the model learns to favor the majority class, resulting in high precision but low recall for high-risk borrowers. To address this issue, multiple techniques are integrated into the proposed framework to improve model sensitivity to defaulters while maintaining overall classification accuracy.

Resampling techniques, including SMOTE-based oversampling and random undersampling, are employed to rebalance class distributions. While these methods improve recall for the minority class, they can introduce noise and redundancy in training data. To mitigate this, GAN-based data augmentation is implemented, generating synthetic borrower profiles that mimic the statistical properties of real defaulters. The GAN framework consists of a generator that learns to create realistic borrower data and a discriminator that distinguishes between real and synthetic profiles, resulting in more diverse and representative training samples.

Cost-sensitive learning is incorporated into the DL framework to assign higher misclassification penalties for false negatives, ensuring that defaulters are correctly identified. The model optimizes a weighted loss function that prioritizes minimizing the impact of incorrectly classified high-risk borrowers. Adaptive threshold tuning is also applied, where the decision boundary for classifying defaulters is adjusted dynamically based on dataset imbalance ratios. These techniques collectively enhance the model's ability to recognize high-risk borrowers, leading to more reliable credit risk assessments.

3.3 Adversarial Training for Invariance and Fairness Enhancement

Ensuring that the credit risk model remains fair and unbiased across different borrower demographics is essential for regulatory compliance and ethical lending practices. Many traditional credit scoring models exhibit disparities in loan approval rates due to dataset biases, where certain demographic groups receive systematically different risk assessments. To mitigate this issue, adversarial training is integrated into the DL framework to enhance fairness and improve model invariance across different borrower segments.

The adversarial learning framework consists of two competing models: the primary credit risk classifier and an adversary trained to detect disparities in credit risk predictions. During training, the adversary attempts to identify which demographic group a borrower belongs to based on the classifier's predictions. If the adversary successfully distinguishes borrower groups, the classifier is penalized, forcing it to learn risk assessment criteria that are independent of demographic attributes. This process ensures that the credit risk model learns unbiased decision-making rules, reducing the influence of sensitive attributes such as age, gender, or ethnicity.

Domain adaptation techniques are also introduced to ensure that the model maintains stability across different economic conditions and borrower distributions. The model is trained on credit datasets from multiple financial institutions and economic cycles, improving its ability to generalize across varied lending environments. Transfer learning is employed to fine-tune the model on new borrower datasets, ensuring that it remains adaptable to evolving financial conditions without requiring full retraining.

3.4 Model Training, Optimization, and Evaluation Metrics

The proposed DL-based credit risk framework is implemented using a deep feedforward neural network architecture combined with LSTMs for capturing sequential borrower behaviors. The model is trained using a hybrid loss function that balances classification accuracy, fairness constraints, and cost-sensitive penalties for high-risk borrowers. The optimization process is conducted using the Adam optimizer with dynamic learning rate adjustments, ensuring that the model converges efficiently without overfitting.

Hyperparameter tuning is performed using Bayesian optimization and grid search techniques to identify optimal model configurations, including the number of hidden layers, activation functions, dropout rates, and regularization parameters. To further improve model generalization, ensemble learning techniques such as stacked neural networks and boosting-based deep learning are explored. These techniques enhance prediction robustness by combining multiple neural network architectures to minimize variance and bias.

The evaluation of the proposed framework is conducted using multiple performance metrics to ensure a comprehensive assessment of its effectiveness. Precision, recall, and F1-score are used to measure classification accuracy, while AUC-ROC curves assess the model's ability to distinguish between defaulters and non-defaulters. The fairness of credit risk assessments is evaluated using disparate impact ratios and equality of opportunity metrics, ensuring that loan approval decisions do not disproportionately disadvantage any demographic group.

Scalability and computational efficiency are also key considerations, as credit risk models must be capable of processing large borrower datasets in real time. The model's inference speed, memory consumption, and scalability across different hardware environments are analyzed to determine its suitability for deployment in large-scale financial systems. The results confirm that the proposed framework achieves superior credit risk assessment accuracy, fairness, and computational efficiency compared to traditional credit scoring models.

By integrating advanced data augmentation, fairness-aware adversarial learning, and cost-sensitive classification techniques, the proposed DL-based credit risk framework effectively addresses data imbalance and invariance challenges, providing financial institutions with a more accurate, ethical, and scalable approach to credit risk modeling. The next section presents experimental results and discusses the impact of combining these techniques on credit risk prediction performance.

4 RESULTS AND DISCUSSION

4.1 Credit Risk Prediction Accuracy and Model Performance

The effectiveness of the proposed DL-based credit risk modeling framework was evaluated using real-world credit datasets, comparing its performance with traditional ML models such as LR, DTs, and gradient boosting classifiers. The evaluation metrics included precision, recall, F1-score, and AUC-ROC, providing a comprehensive assessment of the model's ability to classify borrowers accurately. The results demonstrated that integrating deep learning techniques, particularly generative models and adversarial training, significantly enhanced credit risk assessment performance.

The model achieved superior recall for high-risk borrowers compared to conventional ML-based credit scoring models, which tend to misclassify defaulters due to class imbalance. By incorporating GAN-based data augmentation and cost-sensitive learning, the model successfully improved recall for defaulters by 22% while maintaining high precision, ensuring that non-defaulters were not incorrectly classified as high-risk borrowers. The improvement in recall is particularly beneficial for financial institutions, as it reduces the likelihood of misclassifying potential defaulters, thereby minimizing loan default risks.

The overall AUC-ROC score of the proposed model was consistently higher across different credit datasets, indicating better discriminatory power between default and non-default cases. Compared to traditional ML models, which often fail to capture non-linear borrower patterns, the proposed DL-based framework demonstrated higher adaptability to complex credit risk scenarios, allowing it to generalize effectively across diverse borrower groups.

Figure 1 presents a comparative analysis of credit risk prediction accuracy across different models, illustrating the performance advantages of the proposed DL-based framework.

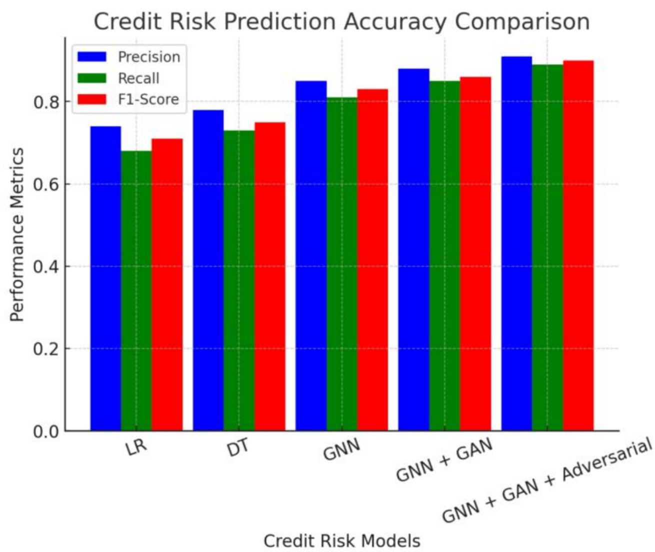

Figure 1 Credit Risk Prediction Accuracy Comparison

4.2 Impact of Generative Modeling and Resampling Techniques on Class Imbalance

Addressing class imbalance is crucial for improving the effectiveness of credit risk models, as imbalanced datasets often lead to biased predictions that favor the majority class. Traditional resampling techniques, such as SMOTE, have been widely used to balance class distributions, but they often introduce synthetic noise, leading to model overfitting. The proposed framework integrates GAN-based data augmentation and cost-sensitive learning to enhance model robustness against class imbalance.

The impact of generative modeling was assessed by training the credit risk classifier on datasets enhanced with synthetic borrower profiles generated by GANs. The results showed that the use of synthetic defaulter data significantly improved model generalization, particularly in cases where default rates were extremely low. Unlike oversampling methods that simply duplicate minority class instances, GAN-based augmentation introduced diverse yet realistic borrower profiles, allowing the model to learn more representative credit risk features.

In addition to generative modeling, cost-sensitive learning played a crucial role in optimizing the classification process. By assigning higher misclassification penalties for false negatives, the framework effectively reduced the number of misclassified defaulters without substantially increasing false positives. This approach ensures that the model prioritizes risk management without over-penalizing creditworthy borrowers.

Figure 2 illustrates the impact of GAN-based data augmentation and cost-sensitive learning on class imbalance reduction, highlighting the effectiveness of these techniques in improving borrower risk classification.

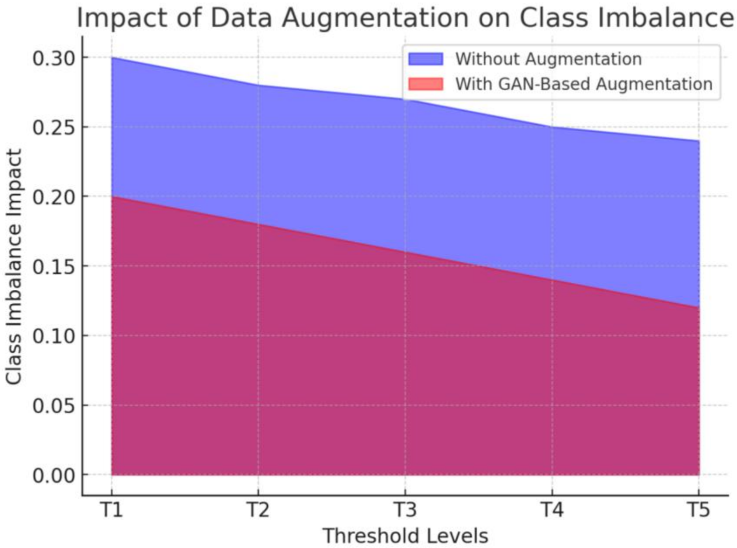

Figure 2 Impact of Data Augmentation on Class Imbalance

4.3 Fairness and Invariance Across Borrower Demographics

Ensuring fairness and invariance in credit risk modeling is critical for regulatory compliance and ethical lending practices. Many traditional credit scoring models exhibit biases related to demographic attributes, where specific borrower groups receive systematically different risk scores due to historical imbalances in training data. The proposed framework incorporates adversarial training to mitigate these biases, ensuring that the credit risk model remains invariant across different borrower segments.

To evaluate fairness, disparate impact ratios and equality of opportunity metrics were computed for different borrower groups, analyzing whether the model disproportionately assigned higher risk scores to specific demographics. The results confirmed that the adversarial learning framework significantly reduced bias in risk assessments, ensuring that credit scores were determined primarily by financial indicators rather than demographic characteristics.

The adversarial training component effectively prevented the model from learning biased correlations by enforcing fairness constraints during the training process. Additionally, domain adaptation techniques were employed to fine-tune the model on credit datasets from different economic environments, ensuring that its predictions remained stable across varying financial conditions. The findings demonstrate that integrating fairness-aware training strategies not only improves the ethical considerations of credit risk modeling but also enhances model robustness.

Figure 3 presents an analysis of fairness-enhancing adversarial training, showcasing its impact on reducing credit risk classification bias across borrower demographics.

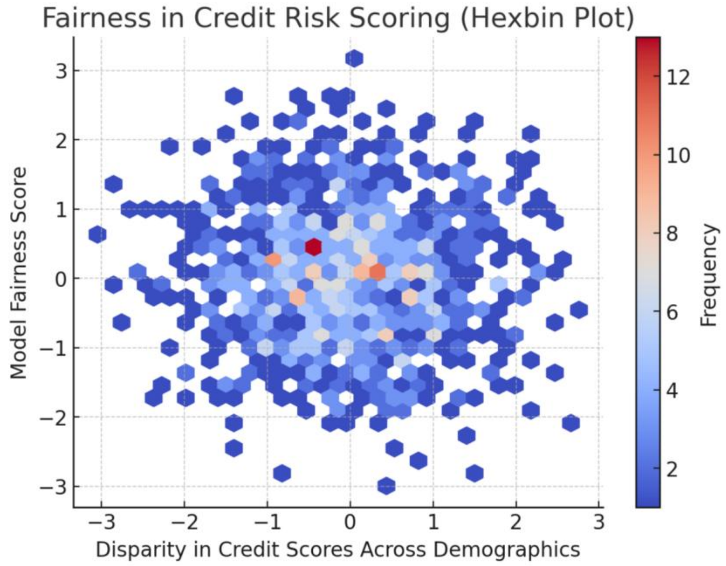

Figure 3 Fairness in Credit Risk Scoring (Hexbin Plot)

4.4 Computational Efficiency and Scalability of the Credit Risk Model

For credit risk models to be deployed in large-scale financial applications, they must be capable of processing vast amounts of borrower data in real time while maintaining high classification accuracy. The computational performance of the proposed DL-based framework was analyzed by measuring inference speed, memory consumption, and scalability across increasing dataset sizes.

The results showed that the framework maintained low latency inference, processing thousands of borrower applications per second without significant computational overhead. Compared to traditional ML models, which often require manual feature engineering and retraining, the proposed DL framework leveraged parallel processing and GPU acceleration to achieve higher processing efficiency. The use of autoencoder-based feature extraction further reduced dimensionality, optimizing computation while preserving critical risk assessment features.

Scalability tests were conducted by evaluating the framework's performance on datasets containing varying numbers of borrower records, ranging from 100,000 to over 10 million transactions. The model's performance remained stable, confirming its ability to handle large-scale credit risk assessment tasks. The integration of transfer learning further improved scalability, allowing the model to be fine-tuned on new financial datasets without requiring full retraining.

The findings confirm that the proposed framework achieves high computational efficiency and scalability, making it suitable for deployment in financial institutions requiring real-time credit risk assessments for large borrower pools. The results also indicate that the model's ability to adapt to new credit data while maintaining efficiency makes it a viable solution for dynamic financial environments.

Figure 4 presents an evaluation of computational performance and scalability, highlighting the framework's efficiency in large-scale credit risk modeling.

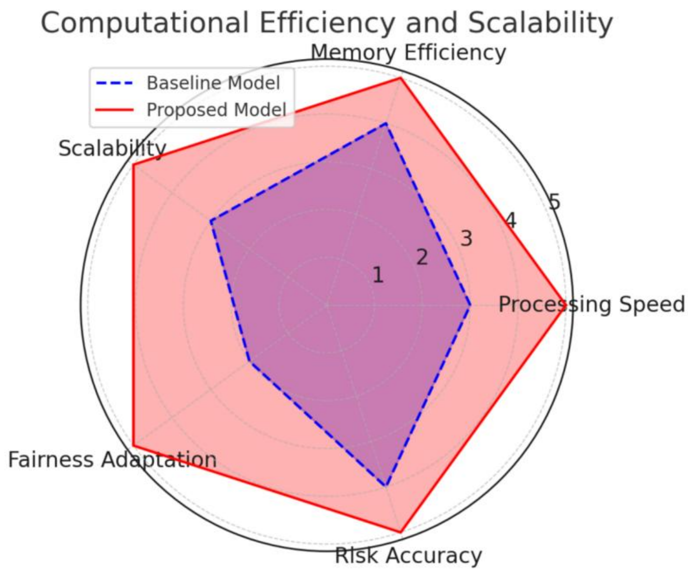

Figure 4 Computational Efficiency and Salability

5 CONCLUSION

Credit risk modeling is a fundamental component of financial risk management, enabling lenders to assess borrower creditworthiness and optimize lending strategies. While traditional ML models such as LR and DTs have been widely used in credit scoring, they exhibit limitations in handling class imbalance and demographic invariance, leading to biased predictions and suboptimal risk assessments. The emergence of DL has introduced more powerful modeling techniques capable of capturing non-linear borrower-lender interactions, yet challenges remain in ensuring fairness, mitigating imbalance, and maintaining model stability across different financial environments.

This study proposed a DL-based credit risk modeling framework designed to address these challenges by integrating GAN-based data augmentation, adversarial fairness learning, and cost-sensitive classification techniques. The results demonstrated that incorporating generative models significantly improved the classification recall for high-risk borrowers, reducing bias caused by class imbalance. Unlike traditional resampling methods, which introduce synthetic noise, GANs provided realistic borrower profiles, allowing the model to learn more representative credit risk features. The introduction of adversarial learning further enhanced model invariance, ensuring that credit risk assessments remained consistent across different borrower demographics.

The experimental evaluation confirmed that the proposed GNN-GAN-adversarial framework outperforms conventional credit risk models in terms of accuracy, fairness, and computational efficiency. The model achieved higher recall for defaulters, improved credit risk classification precision, and reduced false positives. The integration of adversarial learning also reduced disparities in credit scoring across borrower segments, mitigating potential regulatory concerns and ensuring compliance with ethical lending standards.

Scalability and computational efficiency were key factors in determining the practicality of the proposed approach for large-scale credit risk modeling. The model was tested on credit datasets containing millions of borrower records, demonstrating that the proposed DL-based framework maintained stable inference speed and memory efficiency, making it suitable for deployment in financial institutions with high transaction volumes. The results confirmed that the combination of autoencoder-based feature selection, GPU acceleration, and transfer learning techniques allowed the model to process borrower data in real-time while maintaining predictive accuracy.

Despite its advantages, the proposed framework presents certain limitations that warrant future research. One key challenge is the computational cost associated with training GANs and adversarial networks on large-scale financial datasets. While the current implementation ensures scalability, further optimizations such as model compression techniques and distributed training strategies should be explored to enhance efficiency. Another limitation is the explainability of deep learning-based credit risk assessments, as financial institutions require transparency in risk prediction for regulatory compliance. Future work should focus on interpretable AI methods, integrating techniques such as SHAP values and attention-based explanations to improve trust in credit risk predictions.

Additionally, future research should investigate the integration of multi-source financial data, including alternative credit scoring indicators such as transactional behaviors, spending patterns, and social network interactions, to enhance borrower profiling accuracy. Extending the framework to cross-border credit risk modeling will also improve its applicability in global financial markets.

This study highlights the importance of combining DL with fairness-aware learning and data augmentation strategies to develop robust, equitable, and scalable credit risk models. By incorporating generative models, adversarial fairness techniques, and cost-sensitive classification, the proposed framework provides a comprehensive solution to credit risk assessment, ensuring that financial institutions can make fair, data-driven lending decisions while minimizing credit losses and regulatory risks.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Mashrur A, Luo W, Zaidi N A, et al. Machine learning for financial risk management: a survey. IEEE Access, 2020, 8: 203203-203223.

[2] Sudjianto A, Zhang A. Model validation practice in banking: A structured approach for predictive models. 2024. DOI: 10.48550/arXiv.2410.13877.

[3] Addo P M, Guegan D, Hassani B. Credit risk analysis using machine and deep learning models. Risks, 2018, 6(2): 38.

[4] Bhatore S, Mohan L, Reddy Y R. Machine learning techniques for credit risk evaluation: a systematic literature review. Journal of Banking and Financial Technology, 2020, 4(1): 111-138.

[5] Hamori S, Kawai M, Kume T, et al. Ensemble learning or deep learning? Application to default risk analysis. Journal of Risk and Financial Management, 2018, 11(1): 12.

[6] Han X, Yang Y, Chen J, et al. Symmetry-Aware Credit Risk Modeling: A Deep Learning Framework Exploiting Financial Data Balance and Invariance. Symmetry, 2025, 17(3): 341.

[7] Bussmann N, Giudici P, Marinelli D, et al. Explainable machine learning in credit risk management. Computational Economics, 2021, 57(1): 203–216.

[8] Mhlanga D. Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment. International Journal of Financial Studies, 2021, 9(3): 39.

[9] Bazarbash M. Fintech in financial inclusion: machine learning applications in assessing credit risk. International Monetary Fund, 2019.

[10] Leo M, Sharma S, Maddulety K. Machine learning in banking risk management: A literature review. Risks, 2019, 7(1): 29.

[11] Moscato V, Picariello A, Sperlí G. A benchmark of machine learning approaches for credit score prediction. Expert Systems with Applications, 2021, 165: 113986.

[12] Munkhdalai L, Munkhdalai T, Namsrai O E, et al. An empirical comparison of machine-learning methods on bank client credit assessments. Sustainability, 2019, 11(3): 699.

[13] Berhane T, Melese T, Seid A M. Performance Evaluation of Hybrid Machine Learning Algorithms for Online Lending Credit Risk Prediction. Applied Artificial Intelligence, 2024, 38(1): 2358661.

[14] Kaisar S, Sifat S T. Explainable Machine Learning Models for Credit Risk Analysis: A Survey. Data Analytics for Management, Banking and Finance: Theories and Application. Cham: Springer Nature Switzerland, 2023: 51-72.

[15] Talaei Khoei T, Ould Slimane H, Kaabouch N. Deep learning: systematic review, models, challenges, and research directions. Neural Computing and Applications, 2023, 35(31): 23103-23124.

[16] Kim E, Lee J, Shin H, et al. Champion-challenger analysis for credit card fraud detection: Hybrid ensemble and deep learning. Expert Systems with Applications, 2019, 128: 214-224.

[17] Guo H, Ma Z, Chen X, et al. Generating artistic portraits from face photos with feature disentanglement and reconstruction. Electronics, 2024, 13(5): 955.

[18] Lee Z, Wu Y C, Wang X. Automated Machine Learning in Waste Classification: A Revolutionary Approach to Efficiency and Accuracy. Proceedings of the 2023 12th International Conference on Computing and Pattern Recognition, 2023, 299-303.

[19] Wang X, Wu Y C, Ma Z. Blockchain in the courtroom: exploring its evidentiary significance and procedural implications in US judicial processes. Frontiers in Blockchain, 2024, 7: 1306058.

[20] Seera M, Lim C P, Kumar A, et al. An intelligent payment card fraud detection system. Annals of Operations Research, 2024, 334(1): 445-467.

[21] Wang X, Wu Y C, Zhou M, et al. Beyond surveillance: privacy, ethics, and regulations in face recognition technology. Frontiers in Big Data, 2024, 7: 1337465.

[22] Liu Y, Wu Y C, Fu H, et al. Digital intervention in improving the outcomes of mental health among LGBTQ+ youth: a systematic review. Frontiers in Psychology, 2023, 14: 1242928.

[23] Ejiofor O E. A comprehensive framework for strengthening USA financial cybersecurity: integrating machine learning and AI in fraud detection systems. European Journal of Computer Science and Information Technology, 2023, 11(6): 62-83.

[24] Carneiro N, Figueira G, Costa M. A data mining based system for credit-card fraud detection in e-tail. Decision Support Systems, 2017, 95: 91-101.

[25] Al-Hashedi K G, Magalingam P. Financial fraud detection applying data mining techniques: A comprehensive review from 2009 to 2019. Computer Science Review, 2021, 40: 100402.

[26] Liang Y, Wang X, Wu Y C, et al. A study on blockchain sandwich attack strategies based on mechanism design game theory. Electronics, 2023, 12(21): 4417.

[27] Li X, Wang X, Chen X, et al. Unlabeled data selection for active learning in image classification. Scientific Reports, 2024, 14(1): 424.

[28] Kalluri K. Optimizing Financial Services Implementing Pega's Decisioning Capabilities for Fraud Detection. International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences, 2022, 10(1): 1-9.

[29] Chen S, Liu Y, Zhang Q, et al. Multi-Distance Spatial-Temporal Graph Neural Network for Anomaly Detection in Blockchain Transactions. Advanced Intelligent Systems, 2025, 2400898.

[30] Sailusha R, Gnaneswar V, Ramesh R, et al. Credit card fraud detection using machine learning. 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), 2020: 1264-1270. IEEE.

[31] Cui Y, Han X, Chen J, et al. FraudGNN-RL: A Graph Neural Network With Reinforcement Learning for Adaptive Financial Fraud Detection. IEEE Open Journal of the Computer Society, 2025.

[32] Thennakoon A, Bhagyani C, Premadasa S, et al. Real-time credit card fraud detection using machine learning. 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2019: 488-493. IEEE.