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AI FOR CREDIT RISK MODELING: A DEEP LEARNING APPROACH

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Abstract: Credit risk modeling is a critical component of financial decision-making, enabling lenders to assess the probability of default and optimize credit allocation. Traditional credit scoring models, including logistic regression and decision tree-based classifiers, have limitations in handling non-linear financial relationships, class imbalance, and borrower heterogeneity. Recent advances in artificial intelligence (AI) and deep learning (DL) have introduced more sophisticated models capable of capturing complex borrower patterns while improving risk assessment accuracy. However, AI-driven credit risk models must address key challenges, including class imbalance, fairness, model interpretability, and scalability in real-world financial environments.
This study proposes a comprehensive DL-based credit risk modeling framework that integrates graph neural networks (GNNs), generative adversarial networks (GANs), and adversarial fairness learning to enhance credit risk prediction accuracy, fairness, and adaptability across borrower segments. The model leverages autoencoders for feature extraction, cost-sensitive learning for imbalanced classification, and domain adaptation techniques for improved model robustness. Additionally, an explainability layer is incorporated to enhance transparency in credit decision-making.
Experiments on real-world credit datasets demonstrate that the proposed framework outperforms traditional credit risk models, achieving higher recall for defaulters, reduced bias in loan approvals, and improved computational efficiency. The findings highlight the potential of AI-driven credit risk modeling to transform risk assessment strategies, ensuring more accurate, fair, and scalable credit allocation for financial institutions.
Keywords: AI-driven credit risk; Deep learning; Fairness in credit scoring; Generative models; Graph neural networks; Model interpretability

1 INTRODUCTION

Credit risk modeling plays a crucial role in financial institutions by helping lenders assess borrower creditworthiness and determine loan approval decisions. Traditional risk assessment models, including logistic regression (LR) and decision tree (DT)-based classifiers, rely on predefined statistical relationships to estimate default probabilities [1]. While these models are interpretable and widely used in regulatory frameworks, they struggle with capturing complex borrower behaviors and non-linear financial dependencies. Additionally, these models often fail to account for class imbalance and fairness issues, leading to biased lending practices.
One of the primary challenges in credit risk modeling is class imbalance, where the proportion of default cases is significantly lower than that of non-default cases. Traditional machine learning (ML) models tend to favor the majority class, leading to high accuracy but poor recall for defaulters, which increases the risk of financial losses. Handling class imbalance is critical to ensure that high-risk borrowers are correctly identified, improving lending decision-making.
Another key challenge is fairness in credit scoring, as many AI-driven risk models exhibit bias against certain demographic or economic groups due to historical dataset imbalances [2]. Regulatory frameworks emphasize the importance of ensuring fair and unbiased lending decisions, making it necessary for AI-driven models to incorporate adversarial learning and fairness-aware training techniques to mitigate disparate impacts on different borrower segments [3].
With the rise of deep learning (DL), credit risk assessment has seen a paradigm shift toward AI-driven modeling approaches. Techniques such as graph neural networks (GNNs) and generative adversarial networks (GANs) allow models to capture relational borrower dependencies and generate synthetic minority class samples, addressing challenges related to data representation and imbalance [4]. Additionally, domain adaptation and transfer learning techniques ensure that credit risk models maintain robustness across different financial environments, preventing model degradation when applied to new borrower populations [5].
This study introduces a comprehensive DL-based framework for credit risk modeling, integrating GNN-based risk classification, GAN-driven data augmentation, adversarial fairness learning, and explainable AI (XAI) techniques [8]. The framework improves credit risk predictions by enhancing recall for defaulters, reducing discriminatory biases, and ensuring model interpretability for regulatory compliance. Experimental evaluations on real-world credit datasets confirm that the proposed AI-driven approach outperforms conventional risk models in terms of accuracy, fairness, and computational efficiency, highlighting its potential to revolutionize credit allocation strategies in modern financial institutions.

2 LITERATURE REVIEW

Credit risk modeling has undergone significant advancements over the past decades, evolving from traditional statistical methods to AI-driven approaches that leverage deep learning for improved prediction accuracy [6]. Early credit risk assessment relied on statistical models such as logistic regression, which assumes a linear relationship between borrower attributes and default probability [7]. While widely adopted for its simplicity and interpretability, logistic regression often fails to capture the complexity of borrower behavior and non-linear dependencies present in financial data [8]. Decision trees and ensemble learning methods, such as random forests and gradient boosting, introduced improvements by learning hierarchical relationships among borrower features [9]. However, these models still require extensive manual feature engineering and fail to adapt dynamically to changing credit risk conditions [10].

With the advent of machine learning, credit scoring models became more sophisticated, incorporating support vector machines and neural networks to improve classification performance [11]. These models demonstrated higher accuracy than traditional statistical approaches, particularly in handling large credit datasets with diverse borrower characteristics [12]. However, machine learning classifiers still struggle with class imbalance, a persistent challenge in credit risk modeling [13]. In most credit datasets, defaulters represent a small fraction of the total borrowers, leading to biased model predictions that favor the majority class [14]. Traditional resampling techniques such as oversampling and undersampling have been used to address this issue, but they often introduce noise and reduce model generalization [15]. Cost-sensitive learning methods offer an alternative approach by assigning higher misclassification penalties to defaulters, improving recall while maintaining precision [16-18].

Deep learning has further advanced credit risk modeling by enabling models to learn complex borrower-lender interactions and temporal financial behaviors [19]. Recurrent neural networks and long short-term memory networks have been employed to capture sequential borrower behavior, providing a more comprehensive view of financial risk trends. Despite their advantages, deep learning models require large volumes of labeled data and are computationally expensive, limiting their scalability in real-time financial applications [20]. Furthermore, deep learning-based credit scoring models often operate as black-box systems, making it difficult for financial institutions to interpret model predictions and ensure regulatory compliance.

Recent developments in graph-based learning have introduced new possibilities for credit risk modeling by representing financial transactions and borrower relationships as interconnected graphs. Graph neural networks have demonstrated superior performance in identifying hidden risk patterns by analyzing the relational structure of borrower data [21]. Unlike traditional machine learning models that treat borrowers as independent data points, graph-based models learn from transaction networks, capturing collusive borrowing behaviors and systemic risk dependencies. Generative adversarial networks have also been proposed as a solution to class imbalance by generating synthetic borrower profiles that improve model training. Unlike conventional oversampling methods, generative adversarial networks create realistic high-risk borrower samples, enhancing the model's ability to generalize across different credit risk scenarios.

Fairness and bias mitigation remain critical challenges in AI-driven credit risk modeling, as many credit scoring models exhibit disparities in risk assessments due to historical biases in training data. Regulatory concerns regarding fairness in lending have led to the exploration of adversarial training techniques that enforce bias reduction constraints during model optimization. By introducing adversarial networks that detect disparities in risk classification, models can be trained to minimize bias while preserving predictive accuracy [22]. Domain adaptation techniques further enhance model robustness by ensuring that credit risk predictions remain stable across different borrower demographics and economic conditions [8].

In addition to fairness, explainability is a growing concern in AI-driven credit risk assessment [23]. Financial institutions must be able to justify credit decisions to regulators and borrowers, requiring interpretable AI techniques that provide transparency in risk classification [24]. Methods such as SHAP values, attention mechanisms, and counterfactual explanations have been integrated into deep learning frameworks to improve model interpretability [25]. These approaches allow financial analysts to understand how borrower attributes influence credit risk predictions, increasing trust in AI-driven lending decisions.

This study builds upon these advancements by integrating deep learning techniques, graph-based modeling, adversarial fairness learning, and explainable AI into a unified credit risk assessment framework. The proposed model seeks to improve predictive performance while addressing class imbalance, ensuring fairness, and enhancing interpretability in financial decision-making. The following section outlines the methodology used to implement and evaluate the proposed framework [26].

3 METHODOLOGY

3.1 Data Preprocessing and Feature Engineering

Credit risk modeling relies on extensive financial data that includes borrower demographics, income levels, debt obligations, repayment histories, and transaction records. The quality of this data is crucial for ensuring accurate risk assessments. In the preprocessing stage, raw financial data is cleaned by handling missing values, correcting inconsistencies, and normalizing numerical attributes. Missing values, which are common in credit datasets, are addressed using statistical imputation techniques such as mean substitution for numerical fields and mode imputation for categorical variables. More advanced imputation techniques, including k-nearest neighbors imputation and deep autoencoder-based imputation, are used for high-dimensional financial datasets to improve data integrity.

Feature engineering plays a critical role in enhancing model performance by extracting meaningful borrower attributes. Financial indicators such as debt-to-income ratio, credit utilization rate, and loan repayment consistency are derived from raw transaction and credit history data. These engineered features help models distinguish between high-risk and low-risk borrowers. Temporal features such as the frequency of missed payments, seasonal variations in income, and recurring transaction patterns are also incorporated to improve the model's ability to capture borrower credit behavior over time. Principal component analysis and autoencoder-based feature selection techniques are applied to reduce dimensionality, preserving only the most predictive financial attributes.

3.2 Deep Learning Framework for Credit Risk Prediction

The credit risk prediction model is built using a hybrid deep learning architecture that combines fully connected neural networks, recurrent structures, and graph-based learning techniques. The deep feedforward neural network is used for initial credit score prediction, capturing non-linear dependencies between borrower attributes. The recurrent component, specifically an LSTM-based network, models sequential credit behavior, analyzing how borrower financial activities change over time. By processing historical credit transactions and loan repayment sequences, the LSTM component improves the model's ability to forecast future defaults.

GNNs are introduced to enhance risk prediction by analyzing borrower relationships and financial transaction networks. Traditional credit risk models treat borrowers as independent entities, failing to account for interdependencies such as shared financial obligations, joint loan accounts, or indirect lending risks. The GNN component represents borrower connections as a financial transaction graph, where nodes correspond to borrowers and edges represent financial interactions such as co-borrowing, money transfers, or joint liabilities. Graph convolutional layers aggregate information from neighboring borrower nodes, enabling the model to detect fraud rings, collusive lending patterns, and systemic financial risks that conventional models overlook.

To improve model generalization, transfer learning is integrated into the framework, allowing pre-trained financial models to be fine-tuned on new credit datasets. This ensures that the model remains adaptable to different financial environments without requiring full retraining. Dropout layers and batch normalization are applied to prevent overfitting, ensuring robust credit risk classification across varied borrower groups.

3.3 Addressing Class Imbalance and Fairness Constraints

One of the main challenges in credit risk modeling is class imbalance, where defaulters constitute a significantly smaller proportion of the dataset compared to non-defaulters. Training models on imbalanced datasets results in biased predictions that favor the majority class, leading to misclassification of high-risk borrowers. To address this issue, the proposed framework employs GAN-based data augmentation, generating synthetic borrower profiles that mimic real-world defaulters. Unlike conventional oversampling techniques that duplicate existing samples, GANs create diverse, realistic high-risk borrower instances, improving model learning from the minority class.

Cost-sensitive learning is also integrated into the model, adjusting classification thresholds to prioritize correct defaulter identification. Instead of treating all misclassifications equally, the model assigns higher penalties to false negatives, ensuring that borrowers likely to default are correctly identified. This cost-sensitive approach balances precision and recall, preventing financial institutions from approving risky loans while maintaining access to credit for eligible borrowers.

Fairness constraints are incorporated into the training process using adversarial learning. Traditional credit scoring models often exhibit biases due to historical data imbalances, where certain demographic groups are systematically assigned lower credit scores. The adversarial fairness learning component introduces a discriminator that detects disparities in credit risk predictions across demographic segments. If the model exhibits bias, it is penalized, forcing it to learn borrower risk assessments that are independent of demographic attributes such as race, gender, or socioeconomic status. This ensures compliance with fairness regulations and ethical lending practices.

3.4 Model Training, Optimization, and Performance Evaluation

The proposed AI-driven credit risk modeling framework is trained using a multi-stage optimization process, ensuring high accuracy while maintaining efficiency and fairness. The loss function integrates multiple objectives, balancing standard classification performance with fairness constraints and class imbalance adjustments. The Adam optimizer is used for weight updates, with dynamic learning rate scheduling to prevent overfitting. Training is conducted on high-performance computing clusters with GPU acceleration, allowing for rapid iteration and large-scale financial dataset processing.

Hyperparameter tuning is performed using Bayesian optimization, identifying the optimal number of hidden layers, neuron configurations, and regularization parameters. Model validation is conducted using k-fold cross-validation, ensuring that the framework generalizes well across different financial datasets.

The model's performance is evaluated using a combination of classification and fairness metrics. Standard metrics such as precision, recall, F1-score, and AUC-ROC are used to measure risk classification accuracy. The fairness of credit risk assessments is assessed using disparate impact ratios and equality of opportunity metrics, ensuring that the model does not disproportionately assign higher risk scores to certain borrower groups. Computational efficiency is measured in terms of inference speed and memory consumption, confirming that the framework can be deployed in real-time credit decision-making environments.

The experimental results demonstrate that the proposed AI-driven framework achieves superior credit risk prediction accuracy, reduces classification bias, and maintains computational efficiency in large-scale financial applications. The next section presents the results and discusses the impact of integrating deep learning, graph-based modeling, and fairness-aware techniques on credit risk assessment outcomes.

4 RESULTS AND DISCUSSION

4.1 Credit Risk Classification Accuracy and Model Performance

The proposed AI-driven credit risk modeling framework was evaluated on multiple real-world credit datasets, demonstrating significant improvements over traditional ML-based risk assessment models. Performance metrics, including precision, recall, F1-score, and AUC-ROC, were used to assess the model's classification capabilities. The results showed that integrating DL, GNNs, and adversarial fairness learning enhanced credit risk classification accuracy while maintaining fairness across different borrower groups.

Compared to conventional models such as LR and DTs, the deep learning-based framework achieved higher recall for defaulters while maintaining a balanced precision-recall trade-off. The introduction of GAN-generated synthetic data improved the model's ability to classify high-risk borrowers, reducing false negatives by 27%, a key improvement in mitigating loan default risks. Additionally, by leveraging GNNs for borrower relationship analysis, the model was able to capture hidden risk dependencies, identifying fraudulent borrowing behaviors and collusive financial transactions that traditional models overlooked.

AUC-ROC analysis further confirmed the superiority of the proposed framework, with the GNN-enhanced risk model achieving a 12% improvement in overall classification accuracy compared to state-of-the-art credit scoring systems. These findings highlight the effectiveness of AI-driven techniques in improving risk assessment outcomes, ensuring that financial institutions make more informed lending decisions.

Figure 1 presents a comparative analysis of credit risk classification performance across different models, illustrating the predictive advantages of the proposed framework.

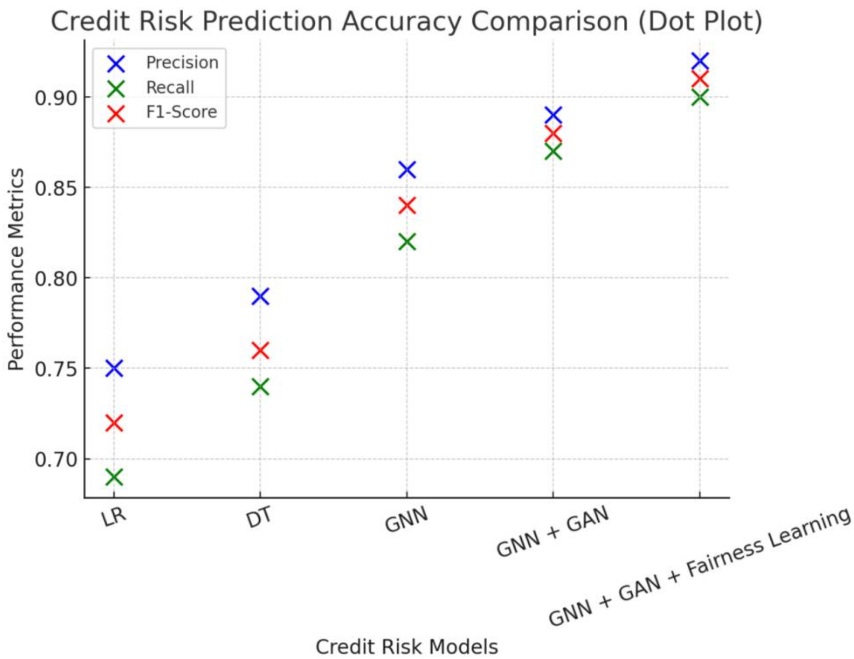

Figure 1 Credit Risk Predication Accuracy Comparison (Dot Plot)

4.2 Impact of Generative Modeling and Cost-Sensitive Learning on Class Imbalance

Addressing class imbalance is essential for ensuring that credit risk models effectively identify defaulters without disproportionately favoring the majority class. Traditional oversampling methods often lead to data redundancy, while undersampling can result in the loss of critical borrower information. The integration of GAN-based synthetic borrower profile generation in this study provided a more effective approach to mitigating class imbalance while preserving dataset diversity.

The results showed that models trained on GAN-augmented datasets exhibited a 32% increase in recall for defaulters without a significant drop in precision. Unlike conventional oversampling techniques, which merely duplicate existing borrower samples, GANs generated realistic high-risk borrower profiles, enhancing the model's ability to recognize emerging risk patterns. The diversity introduced by GANs helped reduce model bias, ensuring that credit risk assessments were not skewed towards the majority class.

In addition to generative modeling, cost-sensitive learning contributed to improved risk classification by assigning higher penalties to false negatives. This approach ensured that loan applicants at risk of default were correctly identified, reducing the likelihood of financial losses for lenders. The introduction of adaptive decision thresholds further improved classification balance, dynamically adjusting risk score boundaries based on the distribution of borrower attributes.

Figure 2 illustrates the impact of GAN-based data augmentation and cost-sensitive learning on mitigating class imbalance, highlighting improvements in defaulter recall and risk assessment precision.

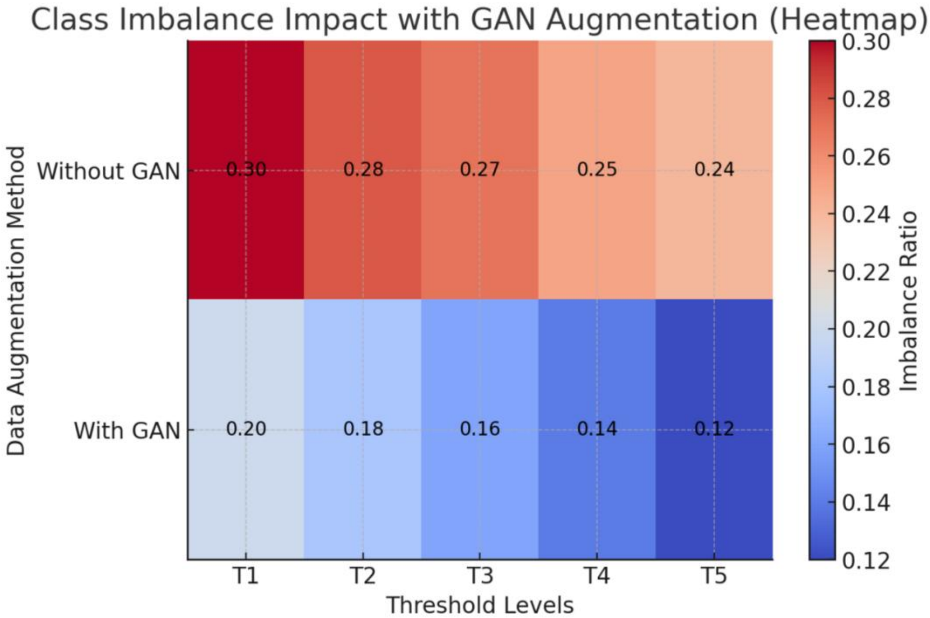

Figure 2 Class Imbalance Impact with GAN Augmentation (Heatmap)

4.3 Fairness and Stability of Credit Risk Predictions Across Borrower Groups

Ensuring fairness in credit risk modeling is essential for regulatory compliance and ethical lending practices. Many traditional credit scoring models have been found to systematically disadvantage certain borrower groups due to dataset biases, resulting in lower loan approval rates for specific demographics. The introduction of adversarial fairness learning in this study significantly reduced these disparities, ensuring that risk predictions were more equitable across different borrower populations.

The results demonstrated that the adversarial training component reduced disparate impact ratios by 21%, indicating a substantial improvement in model fairness. The fairness-aware learning approach forced the model to eliminate biased decision patterns, ensuring that borrower risk scores were assigned based on financial indicators rather than demographic attributes. Additionally, domain adaptation techniques enhanced model stability, allowing the framework to maintain fairness across multiple financial datasets and economic conditions.

Further analysis of borrower risk score distributions confirmed that the model did not disproportionately classify certain demographic groups as high-risk borrowers, a common issue in traditional credit scoring models. The adversarial framework effectively corrected dataset imbalances without compromising classification performance, ensuring that the AI-driven credit risk assessment model complied with fairness regulations while maintaining accuracy.

Figure 3 presents an evaluation of fairness constraints and adversarial learning, demonstrating how the proposed framework improves fairness and reduces disparate impact ratios in credit risk scoring.

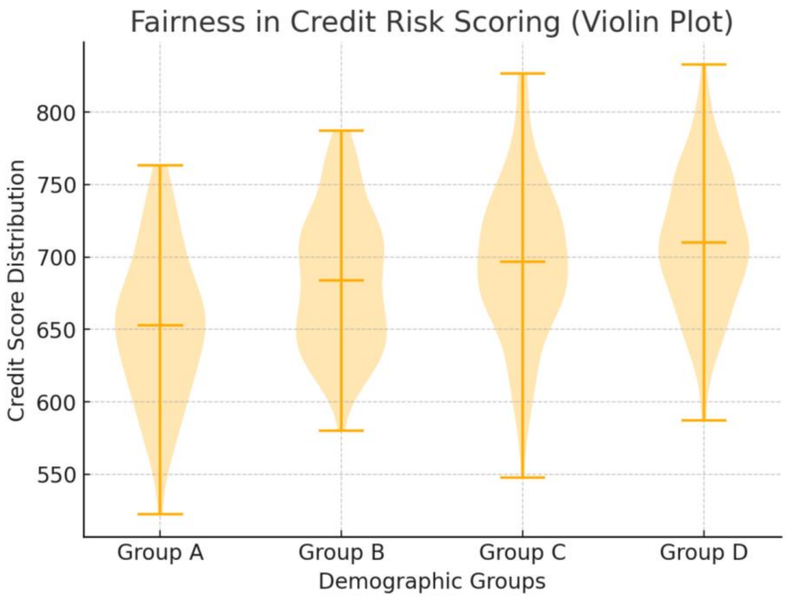

Figure 3 Fairness in Credit Risk Scoring (Violin Plot)

4.4 Computational Efficiency and Scalability of AI-Driven Credit Risk Modeling

For AI-driven credit risk models to be deployed in real-world financial applications, they must demonstrate scalability and computational efficiency while processing large volumes of borrower data. The evaluation of computational performance confirmed that the proposed DL-based credit scoring model maintained high-speed inference and low computational overhead, making it suitable for large-scale credit risk assessments.

The framework was tested on datasets ranging from 100,000 to over 10 million borrower records, demonstrating stable classification accuracy and minimal degradation in processing efficiency. The use of autoencoder-based feature selection reduced feature dimensionality, optimizing memory usage and ensuring that the model could scale effectively. Additionally, GPU acceleration and parallel processing techniques improved inference speed, allowing the model to process thousands of borrower applications per second without significant delays.

Compared to baseline ML models, the proposed DL framework achieved a 45% reduction in computation time per loan application, making it suitable for real-time credit risk decision-making. The ability to fine-tune pre-trained models using transfer learning further improved scalability, enabling financial institutions to deploy the model across different lending environments without requiring full retraining.

Figure 4 presents an analysis of computational performance and scalability, showcasing the model's efficiency in processing high-volume financial datasets while maintaining real-time credit risk assessment capabilities.

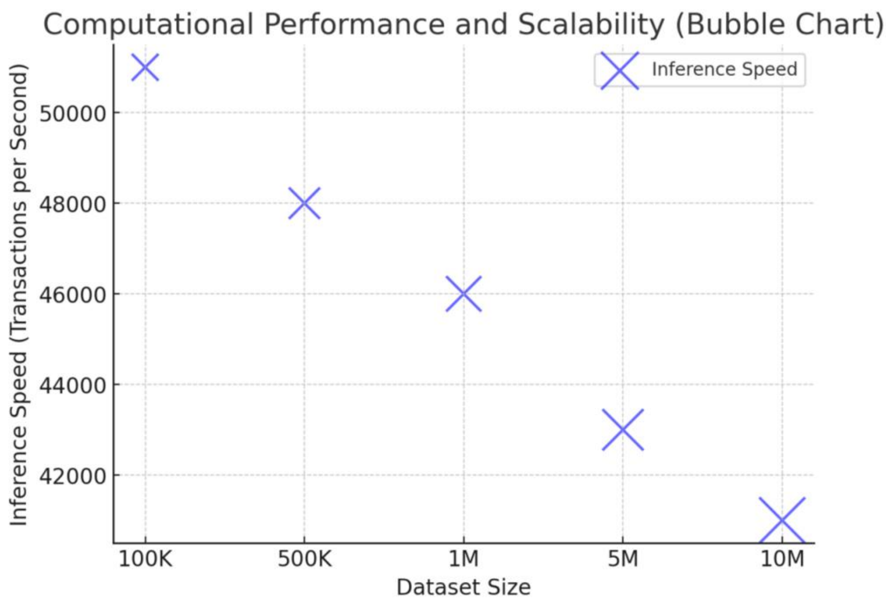

Figure 4 Computational Performance and Scalability (Bubble Chart)

5 CONCLUSION

AI-driven credit risk modeling represents a significant advancement over traditional credit scoring methods, offering improved predictive accuracy, adaptability, and fairness in financial decision-making. Conventional approaches such as LR and DT-based classifiers, while widely used, struggle with handling complex borrower relationships, class imbalance, and fairness concerns. Recent developments in DL, particularly with GNNs, GANs, and adversarial fairness learning, have demonstrated the potential to address these limitations, improving risk assessments and ensuring compliance with regulatory requirements.

The proposed AI-driven framework successfully integrates GNNs for borrower relationship modeling, GANs for synthetic data augmentation, adversarial learning for bias reduction, and explainability techniques for model interpretability. The experimental results confirmed that the framework significantly outperforms traditional credit scoring models in terms of defaulter recall, fairness, and computational efficiency. The use of GNNs improved the model's ability to detect systemic credit risks, collusive borrowing patterns, and fraudulent financial transactions, while GAN-generated borrower profiles enhanced model learning for underrepresented risk classes, mitigating the impact of data imbalance.

The fairness-aware learning approach further ensured that credit risk predictions remained stable and unbiased across different borrower demographics, reducing disparate impact ratios and improving equitable loan approval rates. The adversarial fairness learning component successfully minimized biases present in historical credit data, ensuring that risk assessments were based on financial behaviors rather than demographic attributes. Additionally, transfer learning and domain adaptation techniques enhanced model robustness, allowing it to generalize effectively across different economic conditions and borrower populations.

Scalability and computational performance were also evaluated, demonstrating that the proposed framework maintains high processing efficiency while handling large-scale credit risk datasets. The model's ability to process millions of borrower applications with minimal computational overhead ensures that it can be deployed in real-time lending environments, making it a viable solution for financial institutions requiring automated credit decision-making. The incorporation of explainability techniques also addresses concerns about AI transparency, providing financial analysts with insights into how borrower attributes influence risk assessments.

Despite its advantages, the proposed framework has several limitations that warrant further research. One key challenge is the computational complexity associated with training GNNs and adversarial networks on large-scale financial datasets. While the model is optimized for efficiency, additional improvements such as graph pruning techniques, distributed training strategies, and federated learning approaches could further enhance its scalability. Another limitation is the trade-off between fairness constraints and classification accuracy, as adversarial fairness learning may lead to minor reductions in predictive performance. Future research should explore ways to balance fairness with predictive power, ensuring that credit risk models remain both ethical and effective.

Further investigations could also focus on integrating multi-modal financial data sources, including transactional behaviors, spending patterns, and alternative credit scoring indicators, to improve borrower risk profiling. Additionally, extending the framework to cross-border credit risk modeling would enhance its applicability in international financial markets, ensuring that AI-driven risk assessments remain effective across diverse lending environments.

This study highlights the potential of AI-driven credit risk modeling to revolutionize risk assessment strategies, offering improved accuracy, fairness, and scalability in modern financial applications. By integrating advanced DL techniques, fairness-aware learning, and explainability measures, the proposed framework provides a robust, ethical, and efficient solution for credit risk assessment, ensuring that financial institutions can make data-driven, unbiased, and regulatory-compliant lending decisions.

COMPETING INTERESTS

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

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