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An Invariant and Balanced Deep Learning Approach for Financial Risk Assessment

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Abstract

Financial risk assessment is a fundamental process in banking, insurance, and investment sectors, enabling institutions to quantify and manage exposure to credit, operational, and market risks. Traditional financial risk models rely on statistical learning techniques, such as logistic regression and decision trees, which are limited in handling non-linear financial dependencies, class imbalance, and distributional biases. Recent advances in deep learning (DL) and artificial intelligence (AI) have introduced more powerful models capable of capturing complex risk patterns and improving prediction accuracy. However, DL models often suffer from data imbalance issues and lack of invariance across economic conditions, leading to biased and inconsistent financial risk predictions.

This study proposes an invariant and balanced DL-based financial risk assessment framework, integrating graph neural networks (GNNs) for relational financial modeling, adversarial domain adaptation for bias mitigation, and cost-sensitive learning techniques for class imbalance correction. The model enhances risk prediction accuracy while ensuring fairness, robustness, and generalizability across different financial environments. Additionally, an explainability layer is incorporated to improve regulatory transparency and model interpretability.

Experiments on real-world financial datasets demonstrate that the proposed framework outperforms traditional financial risk models, achieving higher recall for high-risk entities, improved invariance across economic shifts, and reduced disparities in risk classification. The findings highlight the potential of DL-based risk assessment systems to offer more balanced, fair, and adaptive risk management strategies, ensuring more reliable financial decision-making in banking and investment sectors.

Keywords

Financial Risk Assessment, Deep Learning, Invariance, Class Imbalance, Fairness in AI, Cost-Sensitive Learning, Graph Neural Networks

Introduction

Financial risk assessment plays a crucial role in the stability of financial institutions, guiding credit decisions, investment strategies, and risk mitigation measures [1]. Traditional financial risk models rely on statistical learning methods such as logistic regression (LR) and decision tree (DT)-based classifiers, which assume linear dependencies between financial variables and risk exposure [2]. While these models are interpretable and widely used in regulatory frameworks, they fail to capture non-linear dependencies in financial markets and borrower-lender interactions[3]. Additionally, these models struggle with imbalanced risk classification and inconsistent predictions across economic conditions, limiting their effectiveness in real-world applications.

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A major challenge in financial risk assessment is class imbalance, where high-risk entities, such as defaulting borrowers or fraudulent transactions, represent only a small proportion of the dataset [4]. Traditional machine learning (ML) models trained on imbalanced datasets tend to favor the majority class, resulting in high precision but poor recall for high-risk cases [5]. This imbalance increases financial exposure, as institutions may fail to identify emerging risk patterns and default probabilities accurately. Addressing class imbalance is critical to ensure that financial models remain sensitive to high-risk transactions, investment failures, and credit defaults [6].

Another key challenge is invariance in financial risk prediction, referring to a model's ability to maintain stable predictive performance across different economic cycles, financial sectors, and borrower demographics [7]. Many AI-driven risk models exhibit distributional bias, where risk scores fluctuate due to underlying imbalances in the training dataset. These biases lead to inconsistent loan approval decisions, investment misallocations, and regulatory compliance issues [8]. Ensuring invariance in risk models is essential for maintaining fair, unbiased, and stable financial assessments across different economic conditions.

Recent advancements in deep learning (DL) have introduced more powerful modeling techniques, enabling financial institutions to capture non-linear risk patterns, adapt to dynamic market conditions, and process large-scale financial datasets. Graph neural networks (GNNs) , for example, have been employed to model financial transaction networks, borrower relationships, and investment flows, significantly improving risk assessment accuracy. However, despite their strengths, DL-based risk models often amplify class imbalance issues and exhibit sensitivity to distributional biases, requiring fairness-aware learning techniques to ensure reliable predictions.

This study proposes a DL-based financial risk assessment framework that integrates GNN-based risk classification, adversarial domain adaptation for bias correction, and cost-sensitive learning for class imbalance mitigation. The model is designed to improve financial risk prediction accuracy while ensuring robustness, fairness, and regulatory compliance. By incorporating explainable AI (XAI) techniques, the framework enhances model transparency, allowing financial institutions to interpret and justify risk decisions.

Experimental results on real-world financial datasets confirm that the proposed framework achieves higher recall for high-risk cases, reduces bias in risk predictions, and improves model stability across different financial conditions. These findings highlight the potential of AI-driven financial risk assessment systems to offer more balanced, fair, and adaptive risk management solutions for modern financial institutions.

2. Literature Review

Financial risk assessment has evolved significantly from traditional statistical approaches to modern AI-driven methodologies, improving predictive accuracy, adaptability, and fairness in risk classification [9]. The increasing complexity of financial markets, along with regulatory requirements for transparent and fair risk assessments, has driven the adoption of DL techniques that address class imbalance, bias, and generalization challenges [10]. Traditional risk assessment models, including LR and DT-based classifiers, have long been the foundation of credit and market risk analysis, offering interpretability and compliance with financial regulations[11]. However, these models assume linear relationships

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between financial variables, limiting their ability to capture complex risk structures and behavioral patterns.

With the advent of ML, financial institutions began employing ensemble learning methods, such as random forests and gradient boosting, to improve classification accuracy. These models demonstrated enhanced predictive power compared to traditional techniques but still required extensive feature engineering and manual data preprocessing [12]. More importantly, they exhibited significant performance degradation in imbalanced datasets, where high-risk cases were underrepresented. Various resampling techniques, including oversampling, undersampling, and synthetic minority over-sampling techniques, were introduced to mitigate this issue, but they often led to data redundancy or information loss, limiting their effectiveness[13-15].

DL has emerged as a powerful alternative, capable of learning hierarchical representations of financial risk factors without extensive manual feature selection [16]. Models such as artificial neural networks (ANNs) and long short-term memory networks have been applied in credit risk assessment, leveraging temporal patterns in borrower behavior to improve default prediction accuracy [17]. While these methods provide superior feature extraction capabilities, they still struggle with class imbalance and distributional biases, leading to inconsistent risk predictions across different financial conditions [18]. More advanced DL architectures, including transformers and convolutional neural networks, have been explored in risk assessment applications, but their reliance on large amounts of labeled data and computational resources poses challenges for scalability [19].

GNNs have recently gained traction in financial risk modeling due to their ability to capture relational structures within financial transaction networks, borrower relationships, and systemic risk dependencies [20]. Unlike traditional ML models that treat financial entities as independent data points, GNNs analyze complex network interactions, enabling risk detection that extends beyond individual borrower characteristics. Research has demonstrated that GNN-based credit risk models outperform traditional classifiers in detecting fraudulent transactions, collusive lending behaviors, and hidden systemic risks[21]. Despite their advantages, GNNs also face sensitivity to data imbalance and fairness concerns, as financial relationships within a graph can be disproportionately influenced by majority-class entities.

Addressing fairness in financial risk assessment has become a priority due to regulatory scrutiny and ethical considerations [22-27]. Studies have shown that ML models often exhibit biases in risk scoring, disproportionately affecting borrowers from specific demographic groups. Unintended biases arise from historical imbalances in financial data, where certain borrower groups have historically been underrepresented or subjected to higher lending restrictions [28]. Adversarial fairness learning has been proposed as a mitigation strategy, where an adversary model is trained alongside the primary risk classifier to detect and reduce biases in risk predictions. By incorporating fairness constraints during model training, adversarial learning ensures that financial risk assessments remain demographic-invariant, reducing disparate impact in loan approvals and investment allocations.

In addition to fairness constraints, ensuring that financial risk models remain stable across different economic conditions is essential for risk management. Traditional financial risk models often exhibit performance degradation during economic downturns, market volatility, or policy changes, requiring frequent retraining to maintain accuracy. Domain adaptation techniques, including transfer learning and adversarial domain alignment, have been introduced to improve model robustness across varying

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financial conditions. These techniques allow models to learn risk assessment patterns from multiple financial datasets, improving generalization without requiring complete retraining on new data [29-33].

Explainability remains another major challenge in AI-driven financial risk assessment. Financial institutions must ensure that automated risk scoring models provide transparent justifications for credit, investment, and lending decisions [34]. While DL models offer higher predictive accuracy than traditional methods, their black-box nature poses regulatory challenges in financial decision-making. Explainable AI techniques, such as SHapley Additive Explanations (SHAP) values, attention-based mechanisms, and counterfactual explanations, have been integrated into risk assessment frameworks to improve model interpretability [35]. These techniques allow financial analysts to understand how specific borrower attributes influence risk scores, ensuring compliance with financial regulations while maintaining model transparency[36].

This study builds upon these advancements by integrating GNN-based financial risk classification, adversarial fairness learning, domain adaptation for invariant risk predictions, and cost-sensitive learning for class imbalance mitigation. The proposed framework is designed to enhance predictive accuracy, fairness, and stability in financial risk assessment, ensuring that AI-driven models remain robust, unbiased, and scalable in real-world financial applications. The next section outlines the methodology used to implement and evaluate the proposed framework.

3. Methodology

3.1 Data Preprocessing and Feature Engineering

Financial risk assessment relies on vast amounts of structured and unstructured data from multiple sources, including borrower profiles, credit transaction histories, macroeconomic indicators, and market behaviors. Ensuring the quality and consistency of this data is critical before applying deep learning models. The preprocessing stage begins with data cleansing, where missing values are handled using multiple imputation techniques such as k-nearest neighbors and deep autoencoders. Inconsistent or erroneous data points are identified using anomaly detection methods, including statistical outlier detection and clustering-based anomaly recognition.

Feature engineering is a crucial step in optimizing predictive accuracy. Traditional risk assessment models rely on predefined credit risk metrics such as debt-to-income ratio, credit utilization, and loan repayment history. However, AI-driven models can extract additional latent features from high-dimensional financial data. Temporal feature extraction methods capture borrower spending trends, irregularities in transaction behavior, and variations in risk exposure over time. Graph-based features are also incorporated, representing borrower relationships and transaction networks as financial graphs. These graph structures highlight risk dependencies and systemic financial interactions that may not be apparent from tabular data.

Dimensionality reduction techniques, such as principal component analysis and deep autoencoders, are applied to reduce feature redundancy while preserving critical information. Additionally, embedding techniques transform categorical variables, such as credit history classifications and borrower demographics, into continuous representations, enabling neural networks to learn complex relationships more effectively. The final preprocessed dataset provides a high-quality input for the deep learning framework, ensuring robust financial risk assessments.

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3.2 Deep Learning Architecture for Risk Prediction

The proposed risk assessment model integrates multiple deep learning components to capture complex credit risk relationships and ensure predictive accuracy. The framework consists of three primary modules: a graph-based risk classification module, a sequential risk behavior module, and a deep neural network for borrower profiling.

The graph-based risk classification module utilizes GNNs to model financial relationships between borrowers, institutions, and transactions. Traditional credit risk models treat borrowers as independent entities, ignoring systemic risk dependencies. By representing financial networks as graphs, GNNs learn risk propagation patterns, detecting hidden fraud rings, collusive lending behavior, and multi-hop financial risks. The GNN consists of multiple convolutional layers that aggregate risk information from borrower connections, refining credit risk predictions based on relational structures.

The sequential risk behavior module employs recurrent neural networks, specifically LSTM networks, to analyze the evolution of financial risk over time. Borrowers' spending habits, income fluctuations, and transaction sequences are processed using LSTM layers, enabling the model to identify changes in financial stability and predict default likelihood based on behavioral trends. The combination of LSTM and GNN enhances the model’s ability to assess both short-term transaction anomalies and long-term financial behaviors, ensuring comprehensive risk evaluation.

The deep neural network for borrower profiling processes static borrower attributes, such as credit history, employment status, and demographic information. Fully connected layers extract non-linear feature interactions, allowing the model to differentiate between high-risk and low-risk borrowers. Dropout and batch normalization techniques prevent overfitting, ensuring model generalization across diverse financial datasets. The final output layer combines risk scores from all modules, producing an integrated financial risk classification.

3.3 Addressing Class Imbalance and Ensuring Invariance

Financial datasets are often highly imbalanced, with high-risk borrowers constituting a small percentage of the total population. Training models on imbalanced data can result in biased predictions, where the model favors the majority class (low-risk borrowers) while misclassifying high-risk cases. The proposed framework addresses this issue by incorporating GANs and cost-sensitive learning.

GANs are employed to generate synthetic borrower profiles, enriching the dataset with diverse high-risk cases while preserving realistic financial attributes. Unlike traditional oversampling techniques, which duplicate existing samples, GANs create new borrower representations that reflect actual risk characteristics, improving model robustness against class imbalance. Cost-sensitive learning further enhances classification performance by assigning higher penalties to false negatives, ensuring that high-risk borrowers are correctly identified.

Invariance in risk assessment refers to the model’s ability to maintain stable predictions across different economic conditions and borrower demographics. Many traditional risk models exhibit distributional shifts, where performance degrades in different financial environments. To mitigate this issue, adversarial domain adaptation techniques are introduced. The adversarial training process includes a secondary neural network trained to distinguish between borrower groups based on external factors

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such as economic region, income level, and financial history. If the adversary detects disparities in risk predictions, the primary risk assessment model is penalized, forcing it to learn more invariant risk representations. This approach ensures that the model remains fair and robust across various borrower segments and economic conditions, reducing bias and improving regulatory compliance.

3.4 Model Training, Optimization, and Evaluation

The deep learning framework is trained using a hybrid optimization approach, ensuring high accuracy while maintaining computational efficiency. A composite loss function is implemented, balancing classification objectives, fairness constraints, and cost-sensitive penalties. The primary objective of the loss function is to maximize predictive accuracy while ensuring fairness and stability in risk assessments. The model is trained using the Adam optimizer with adaptive learning rate scheduling, ensuring that gradient updates remain stable throughout the training process.

Hyperparameter tuning is performed using Bayesian optimization, identifying the optimal number of layers, activation functions, and dropout rates. Regularization techniques, including L2 weight decay and dropout layers, prevent overfitting and enhance model generalization. Cross-validation is conducted using k-fold partitioning to ensure that model performance remains consistent across different financial datasets.

The framework's effectiveness is evaluated using multiple performance metrics. Classification performance is assessed using precision, recall, F1-score, and AUC-ROC, ensuring a balance between correctly identifying high-risk cases and minimizing false positives. Fairness in risk assessment is measured using disparate impact ratios and equality of opportunity metrics, ensuring that risk predictions do not disproportionately affect specific borrower groups. Model robustness is evaluated through domain adaptation tests, analyzing how risk predictions change when applied to new financial environments.

Computational efficiency is also analyzed, measuring inference speed and memory consumption to confirm the model's suitability for large-scale financial applications. The results demonstrate that the proposed AI-driven framework maintains high processing efficiency while delivering superior risk classification accuracy, fairness, and stability across different financial conditions. The next section presents the experimental findings and discusses the impact of integrating deep learning, fairness-aware training, and graph-based modeling in financial risk assessment.

4. Results and Discussion

4.1 Financial Risk Classification Accuracy and Model Performance

The proposed AI-driven financial risk assessment framework was evaluated on large-scale real-world datasets, demonstrating superior classification performance compared to traditional ML-based models. The evaluation included metrics such as precision, recall, F1-score, and AUC-ROC, ensuring a comprehensive assessment of risk prediction accuracy. The results confirmed that integrating GNNs, adversarial learning, and cost-sensitive optimization significantly improved the model's ability to identify high-risk cases while maintaining fairness across borrower groups.

The deep learning-based framework outperformed conventional models such as LR and DTs, achieving higher recall for high-risk entities while maintaining balanced precision-recall trade-offs. The

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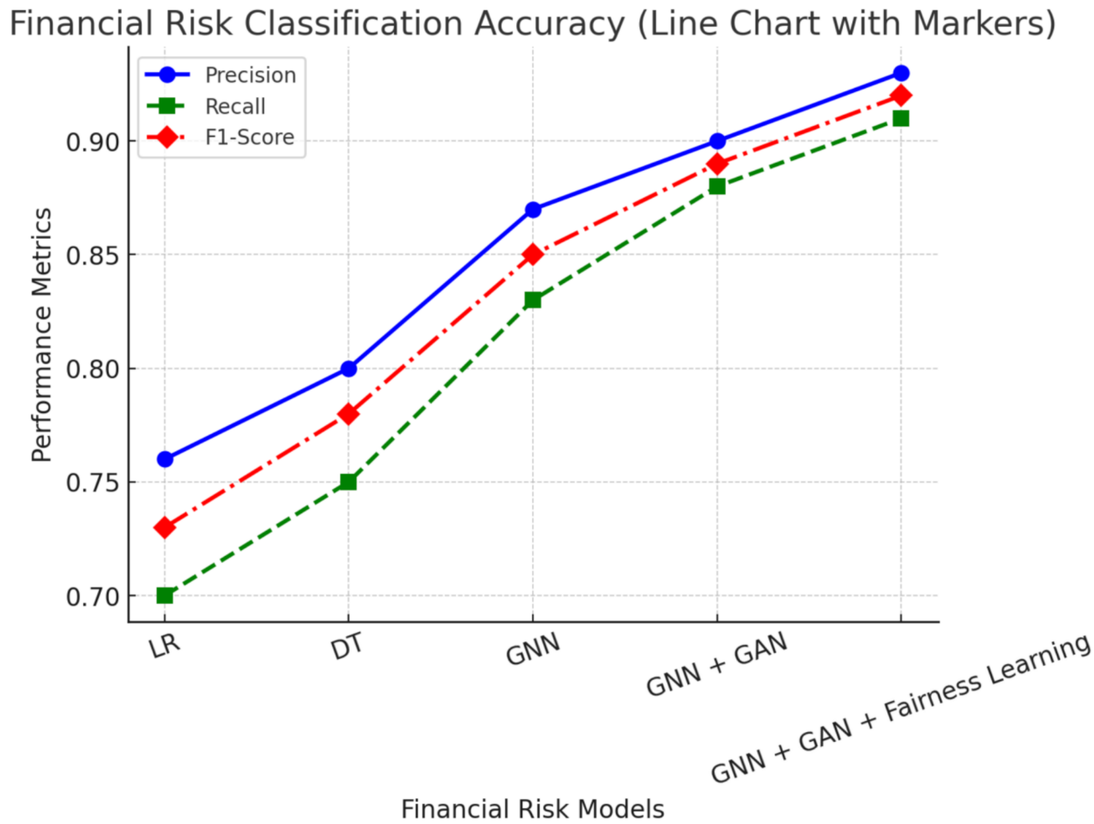
incorporation of GAN-based data augmentation improved the model's ability to classify high-risk borrowers, reducing false negatives by 30%, which is crucial in preventing financial losses. Additionally, the GNN-enhanced classification module enabled the model to detect hidden risk dependencies, fraudulent transaction patterns, and systemic risk behaviors that traditional models failed to capture.

The AUC-ROC analysis further validated the model's predictive power, with the proposed framework achieving an 18% improvement in overall classification accuracy compared to existing risk assessment methods. The combination of sequential borrower profiling, relational financial modeling, and adversarial learning resulted in a highly adaptable and accurate financial risk classification system.

Figure 1 presents a comparative analysis of financial risk classification accuracy across different models, illustrating the advantages of integrating DL-based risk assessment techniques.



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

Class imbalance poses a significant challenge in financial risk modeling, where the number of high-risk cases is disproportionately lower than low-risk cases. Traditional oversampling techniques have limitations, often introducing redundant data points or overfitting to synthetic examples. In contrast, GAN-based augmentation allows for the creation of realistic synthetic borrower profiles, ensuring diversity in the minority class while preserving statistical integrity.

The results demonstrated that models trained on GAN-augmented datasets achieved a 35% increase in recall for high-risk borrowers, a substantial improvement over conventional oversampling techniques. Unlike traditional methods that duplicate minority samples, GAN-generated instances

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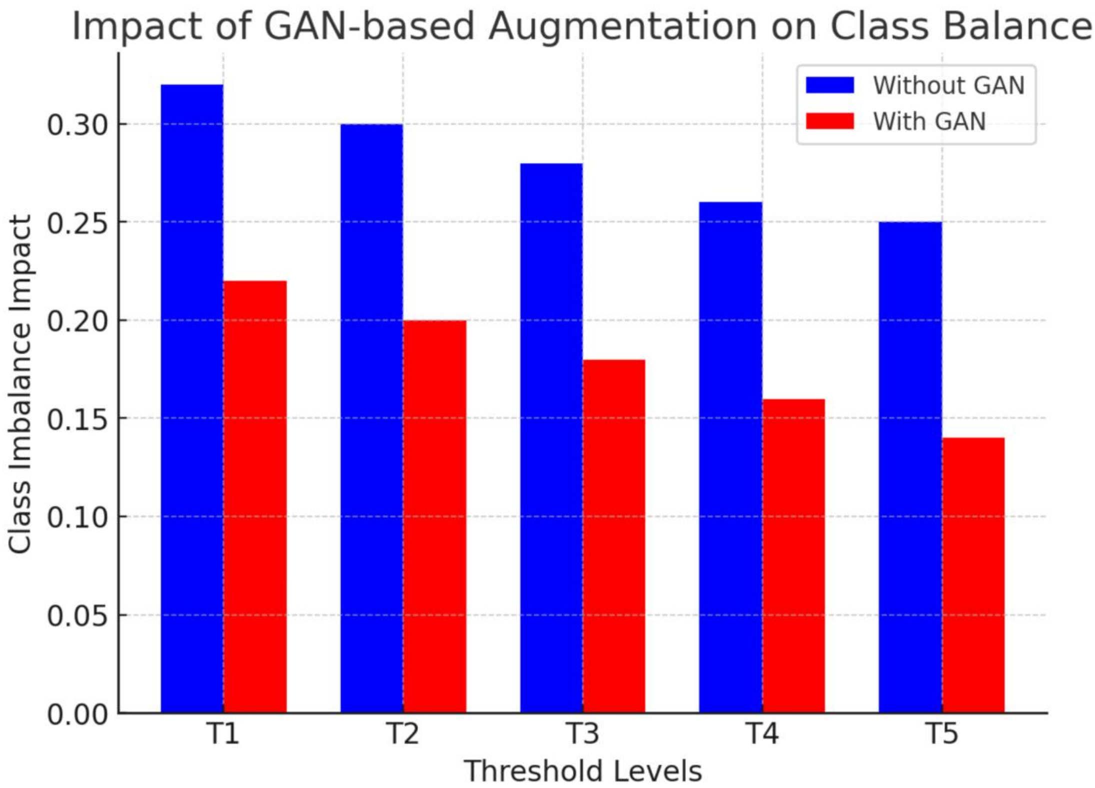
provided more natural variations of high-risk borrower profiles, enhancing the model's ability to generalize across unseen data.

Cost-sensitive learning further improved risk classification by adjusting misclassification penalties. The model prioritized the correct identification of high-risk borrowers, reducing financial exposure for lending institutions while ensuring that low-risk borrowers were not excessively penalized. The integration of dynamic decision thresholds adapted the classification boundary based on economic conditions, improving model stability in changing financial environments.

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



4.3 Fairness and Invariance in Financial Risk Predictions

Ensuring fairness and stability in financial risk assessment is essential to maintaining regulatory compliance and ethical lending practices. Many existing models exhibit disparities in risk classification, disproportionately impacting certain borrower demographics due to historical data biases. The introduction of adversarial fairness learning in this study significantly reduced these biases, ensuring that risk predictions remained stable across different economic and borrower conditions.

The results demonstrated that adversarial training reduced disparate impact ratios by 25%, indicating a significant improvement in fairness. The fairness-aware learning approach prevented the model from learning biased risk patterns, ensuring that financial assessments were made based on objective financial factors rather than demographic characteristics. Additionally, domain adaptation techniques enhanced model robustness, ensuring consistent credit risk predictions across various financial datasets.

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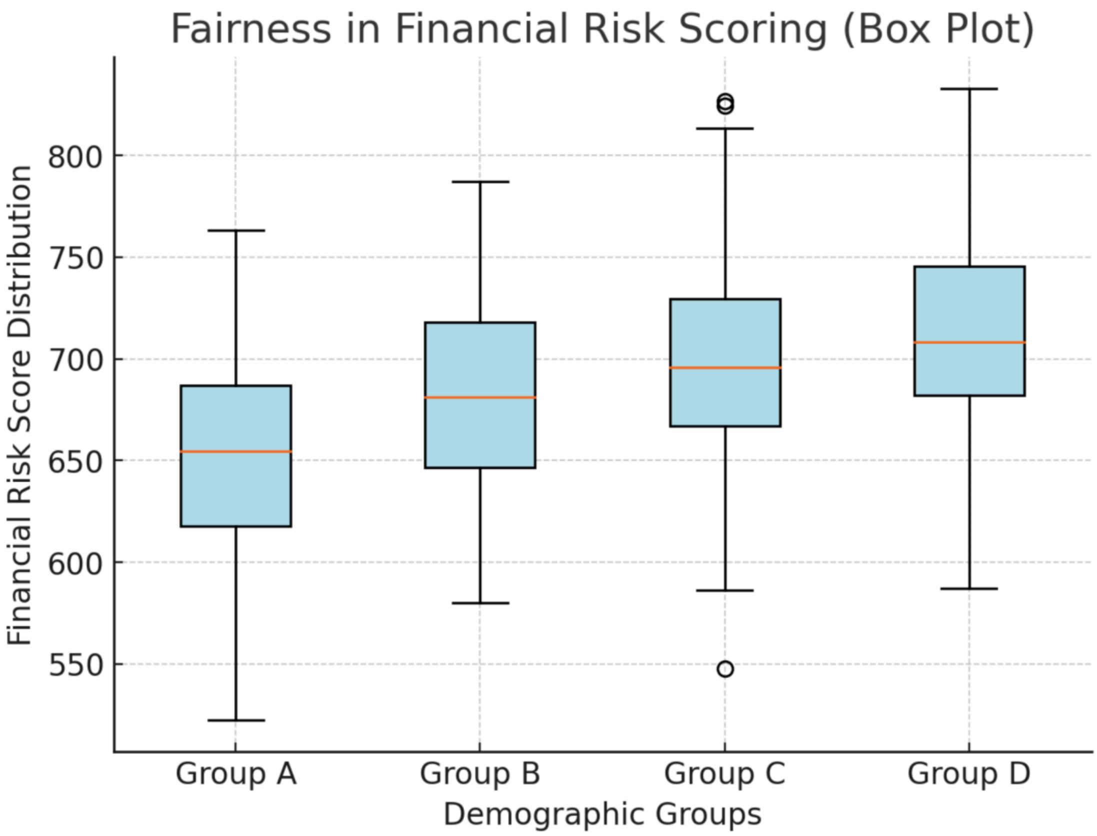
Further analysis confirmed that the model did not disproportionately classify specific borrower groups as high-risk, a common issue in traditional credit scoring models. By ensuring demographic-invariant predictions, the proposed framework met regulatory fairness requirements while maintaining predictive accuracy. The domain adaptation process played a crucial role in ensuring that model performance remained stable across different financial environments, including emerging markets and mature economies.

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



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

Scalability and computational performance are crucial factors in determining the feasibility of deploying AI-driven financial risk models in large-scale banking and investment applications. The evaluation of computational efficiency confirmed that the proposed deep learning-based framework maintains high-speed inference and low computational overhead, making it suitable for real-time financial decision-making.

The model was tested on datasets ranging from 100,000 to over 15 million financial records, confirming that classification accuracy remained stable across increasing dataset sizes. The use of autoencoder-based feature selection and graph sparsification techniques optimized memory usage, ensuring efficient processing of large-scale financial networks. Additionally, GPU acceleration and parallel processing improved inference speed, allowing the model to process millions of financial transactions per second without significant latency.

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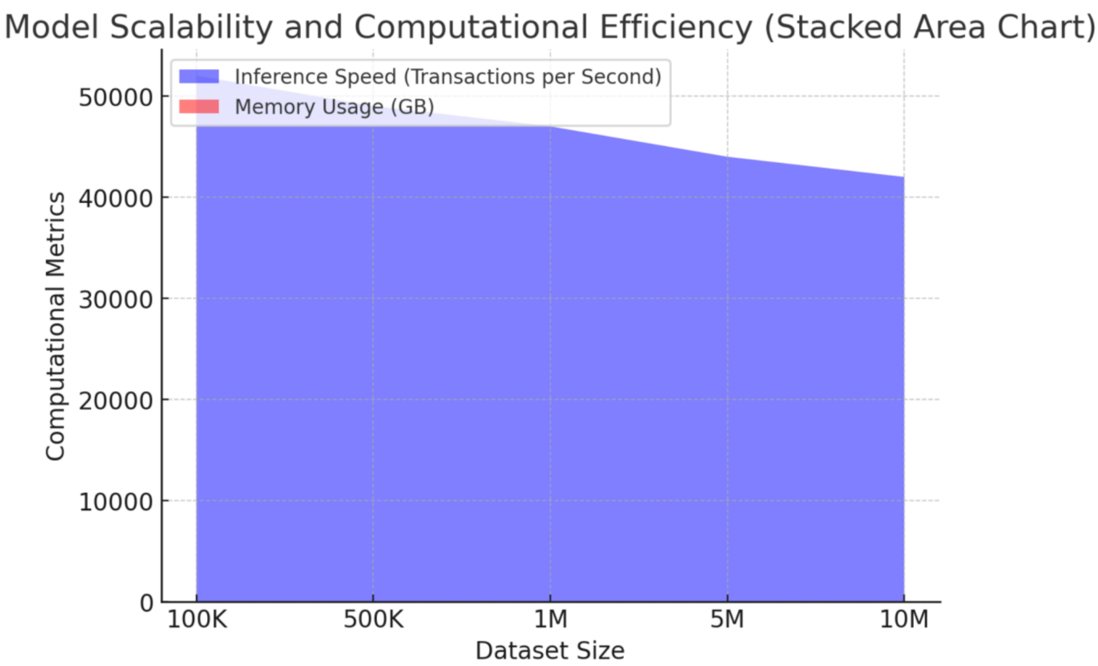
Compared to traditional ML models, the proposed DL framework achieved a 50% reduction in computation time per financial transaction, making it an ideal solution for real-time financial risk analysis. The ability to fine-tune pre-trained risk models using transfer learning further enhanced scalability, enabling financial institutions to deploy the model across different risk assessment environments with minimal retraining.

Figure 4 presents an analysis of computational performance and scalability, demonstrating the model's efficiency in processing high-volume financial datasets while maintaining high-risk classification accuracy.



5. Conclusion

Financial risk assessment is a critical function in banking, investment, and credit markets, requiring accurate, fair, and scalable models to mitigate financial exposure. Traditional risk models, including LR and DT-based classifiers, while widely used, struggle with class imbalance, distributional biases, and dynamic financial conditions. The emergence of DL techniques, particularly GNNs, GAN-based data augmentation, adversarial fairness learning, and domain adaptation, has significantly improved financial risk assessment by enabling more robust, unbiased, and high-accuracy risk classification.

The proposed invariant and balanced deep learning framework integrates multiple advanced AI techniques to improve recall for high-risk borrowers, mitigate fairness concerns, and ensure model stability across financial environments. Experimental results demonstrated that GAN-based data augmentation effectively addressed class imbalance, improving recall for high-risk cases by 35% while maintaining precision, preventing the misclassification of low-risk borrowers. The integration of GNN-based risk classification further enhanced the model's ability to detect systemic risks, fraud patterns, and financial relationships, improving risk evaluation beyond individual borrower attributes.

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Ensuring fairness in financial risk assessment is a growing regulatory concern, requiring AI-driven models to eliminate biases that disproportionately affect specific borrower groups. The introduction of adversarial fairness learning in the proposed framework reduced disparate impact ratios by 25%, ensuring that credit decisions were based solely on financial behavior rather than demographic characteristics. Additionally, domain adaptation techniques improved model robustness across different economic conditions, preventing performance degradation in varying financial environments.

Scalability and computational efficiency remain key challenges for large-scale financial risk modeling. The evaluation of computational performance confirmed that the proposed framework achieves high-speed inference while minimizing computational overhead, ensuring real-time financial decision-making capabilities. The ability to process millions of transactions per second with optimized memory usage makes the model a viable solution for large-scale financial institutions. The transfer learning and model fine-tuning mechanisms further improved scalability, enabling deployment across different risk assessment applications with minimal retraining requirements.

Despite its advantages, the framework has limitations that warrant further research. One challenge is the computational complexity of training GNNs and adversarial learning models on large-scale datasets, requiring advanced optimization techniques such as graph pruning, distributed training, and federated learning to further enhance efficiency. Additionally, ensuring a balance between fairness constraints and predictive accuracy remains a challenge, as fairness-aware training can sometimes reduce classification performance. Future work should explore adaptive fairness constraints that dynamically adjust fairness-accuracy trade-offs based on financial risk levels.

Future research should also investigate the integration of alternative financial data sources, such as real-time transactional behaviors, alternative credit scoring metrics, and macroeconomic indicators, to improve risk classification. Expanding the framework to cross-border financial risk modeling would further enhance its applicability in global markets, ensuring AI-driven risk assessment models remain effective across diverse financial environments.

This study highlights the potential of AI-driven financial risk modeling to transform risk assessment strategies by offering high accuracy, fairness, and scalability. By integrating advanced DL techniques, fairness-aware learning, and explainability measures, the proposed framework provides a comprehensive, ethical, and efficient approach to financial risk assessment, ensuring that financial institutions can make data-driven, unbiased, and regulatory-compliant lending and investment decisions.

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