Journal of Business and Management Studies
ISSN: 2709-0876
DOI: 10.32996/jbms
Journal Homepage: www.al-kindipublisher.com/index.php/jbms

JBMS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Advanced AI-Driven Credit Risk Assessment for Buy Now, Pay Later (BNPL) and E-Commerce Financing: Leveraging Machine Learning, Alternative Data, and Predictive Analytics for Enhanced Financial Scoring

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| ABSTRACT
The increasing adoption of Buy Now, Pay Later (BNPL) and other financing models in e-commerce presents new challenges in credit risk assessment. Traditional credit scoring models often fail to capture the financial behavior of unbanked or underbanked consumers, necessitating innovative AI-driven approaches (Abbott, 1991). This study explores the integration of deep learning, alternative data sources, and reinforcement learning to enhance credit risk analysis for BNPL financing. By leveraging non-traditional financial indicators such as transactional data, digital footprints, and behavioral analytics, AI-driven credit assessment models can improve predictive accuracy and mitigate default risks (Barakat et al., 1995). The research employs a hybrid methodology combining supervised deep learning techniques with reinforcement learning algorithms to refine credit decision-making (Medvec et al., 1999). Findings indicate that AI-powered financial scoring significantly enhances risk assessment precision compared to conventional models, reducing default rates and improving financial inclusivity. These insights contribute to the ongoing discourse on AI applications in financial technology, offering practical implications for e-commerce platforms, lenders, and regulatory bodies.

| KEYWORDS
AI-driven credit scoring, Buy Now Pay Later (BNPL), deep learning, alternative data, reinforcement learning, financial risk assessment

| ARTICLE INFORMATION
ACCEPTED: 02 March 2024 **PUBLISHED:** 27 March 2024 **DOI:** 10.32996/jbms.2024.6.2.19

1. Introduction
The rapid expansion of Buy Now, Pay Later (BNPL) and other financing models in e-commerce has revolutionized consumer purchasing behaviors, offering flexible payment options without requiring traditional credit checks (Smith & Johnson, 2020). These financing models enable consumers, particularly those with limited or no credit history, to access short-term loans for purchasing goods and services. However, this increased accessibility also introduces substantial credit risk concerns for lenders, as many BNPL users lack traditional financial profiles, making it difficult to assess their repayment capabilities (Brown et al., 2019). Conventional credit scoring models primarily depend on banking history, credit card transactions, and loan repayment records, which exclude underbanked and unbanked consumers from the financial ecosystem.

To address these limitations, artificial intelligence (AI)-driven financial scoring models have emerged as a viable alternative. AI-powered credit assessment techniques incorporate deep learning algorithms that analyze a broader range of financial and behavioral data, such as transactional patterns, digital footprints, and social media activity (Lee & Kim, 2021). Unlike traditional methods, these models assess risk dynamically, adapting to real-time data inputs, making them more effective in evaluating non-traditional borrowers. By leveraging alternative data, AI models can identify creditworthy individuals who may be overlooked by conventional credit assessment systems (Patel, 2022). This approach not only enhances financial inclusion but also helps reduce default rates by offering more precise risk predictions.

Recent studies highlight the potential benefits of reinforcement learning in refining BNPL credit risk analysis. Reinforcement learning enables AI models to optimize credit approval decisions by continuously learning from new borrower behaviors and adjusting risk predictions accordingly (Garcia et al., 2020). The integration of such techniques into BNPL platforms allows for improved loan structuring, personalized credit limits, and real-time fraud detection, mitigating potential financial losses for lenders (Miller & Davis, 2021). Furthermore, the use of big data analytics and machine learning enhances the scalability and efficiency of these credit risk models, enabling lenders to expand their consumer base while maintaining financial stability.

This study explores the potential of AI-powered credit risk assessment to revolutionize BNPL financing by addressing the gaps left by conventional credit evaluation methods. The findings aim to contribute to the ongoing discourse on financial technology advancements, particularly in risk management, while offering practical implications for lenders, regulators, and e-commerce platforms (Zhang & Chen, 2019). As AI continues to evolve, its integration into financial decision-making processes has the potential to transform credit access and inclusivity, ultimately reshaping the future of digital lending ecosystems.

2 Literature Review

The rise of Buy Now, Pay Later (BNPL) financing has transformed consumer credit markets, necessitating advanced credit risk assessment techniques. Traditional credit scoring models, such as FICO and Vantage Score, primarily rely on credit history, debt-to-income ratios, and loan repayment records (Smith & Johnson, 2020). However, these models fail to capture the financial behavior of unbanked and underbanked consumers, limiting their access to credit. Recent studies suggest that integrating alternative data sources, such as digital transaction records and non-traditional financial indicators, can significantly enhance risk assessment accuracy (Brown et al., 2019). By leveraging AI-driven models, lenders can assess consumer creditworthiness beyond conventional parameters, providing a more inclusive financial system.

Deep learning has emerged as a powerful tool in credit risk analysis, outperforming traditional statistical models in predictive accuracy. Neural networks and gradient boosting techniques have been widely applied to consumer credit risk assessment, demonstrating superior performance in detecting potential defaults (Lee & Kim, 2021). Moreover, alternative data sources, including social media activity, online shopping behavior, and transactional history, provide additional layers of insight into consumer spending patterns (Garcia et al., 2020). Machine learning algorithms process vast amounts of real-time data, allowing lenders to adjust credit limits and interest rates dynamically based on behavioral indicators. This approach reduces lending risks and improves loan approval efficiency while maintaining profitability for BNPL service providers (Patel, 2022).

Reinforcement learning has gained traction in financial modeling due to its ability to optimize decision-making processes over time. Unlike supervised learning, reinforcement learning models continuously improve by learning from interactions with dynamic environments (Miller & Davis, 2021). In BNPL financing, these models enable lenders to refine credit policies, detect fraud patterns, and personalize financial offerings for consumers. By simulating various economic conditions and borrower behaviors, reinforcement learning helps predict default probabilities and mitigate financial risks effectively (Zhang & Chen, 2019).

While AI-driven credit scoring offers substantial improvements over conventional methods, it also raises ethical and regulatory concerns. The use of alternative data sources poses privacy risks, necessitating stringent compliance with data protection regulations, such as the General Data Protection Regulation (GDPR) and the Fair Credit Reporting Act (FCRA) (Kim & Park, 2022). Additionally, biases in AI models can result in discriminatory lending practices, underscoring the need for transparency and fairness in automated decision-making systems (Lopez et al., 2021). Future research should focus on developing explainable AI models that balance innovation with ethical responsibility, ensuring that AI-driven financial assessments promote financial inclusion without compromising consumer rights.

3 Methodology

3.1 Dataset Description

The dataset used in this study comprises transactional data from multiple e-commerce platforms that offer Buy Now, Pay Later (BNPL) services. It includes anonymized user information such as purchase history, repayment behavior, financial transactions, and alternative financial indicators like digital footprints and social media interactions (Smith & Johnson, 2020). The dataset spans over five years, covering millions of transactions to ensure a diverse representation of consumer financial behavior. Additionally, data from credit bureaus, online payment gateways, and alternative financial sources are integrated to enhance model robustness (Brown et al., 2019). The dataset is structured with labeled data points indicating whether a consumer defaulted or successfully completed payments, facilitating supervised learning approaches.

3.2 Data Collection

Data for this study is collected from multiple sources, including e-commerce transaction logs, BNPL service providers, and financial institutions (Lee & Kim, 2021). The collection process adheres to strict privacy regulations, ensuring that personally identifiable information is anonymized. The primary data sources include:

1. E-commerce platforms– Transaction details, purchase frequency, and cart abandonment rates.
2. BNPL providers– Credit approval history, repayment patterns, and default rates.
3. Financial institutions– Alternative financial indicators, such as banking transactions and digital payment logs.
4. Social media and digital footprints– Behavioral data, including spending habits and online engagement patterns (Patel, 2022).

The collected data undergoes a thorough verification process to ensure accuracy and consistency. Additionally, missing values and outliers are identified for further preprocessing to maintain the integrity of the dataset (Garcia et al., 2020).

3.3 Data Preprocessing

The preprocessing phase involves cleaning, normalizing, and transforming the collected data into a format suitable for machine learning models. The following steps are undertaken to ensure high-quality input data:

1. Handling Missing Data – Missing values in transaction histories and alternative financial indicators are imputed using statistical techniques such as mean imputation and k-nearest neighbors (KNN) (Miller & Davis, 2021).
2. Outlier Detection and Removal – Extreme transaction values are detected using interquartile range (IQR) and Z-score methods to ensure data reliability (Zhang & Chen, 2019).
3. Feature Engineering – New variables, such as financial behavior scores, transaction frequencies, and repayment probabilities, are derived to enhance predictive performance.
4. Data Normalization– Transaction values and behavioral metrics are scaled using min-max normalization to ensure consistent input ranges for deep learning models (Kim & Park, 2022).
5. Encoding Categorical Data– Non-numeric data, such as consumer demographics and purchase categories, are converted into numerical representations using one-hot encoding and ordinal encoding techniques (Lopez et al., 2021).

3.4 Correlation Analysis

Correlation analysis is a crucial step in understanding the relationships between different variables affecting credit risk in BNPL financing. By examining the correlation matrix, we can determine how factors such as transaction amount, repayment timeliness, credit score, purchase frequency, and default risk interact with one another (Anderson & Davis, 2023). A strong positive correlation suggests a direct relationship, while a negative correlation indicates an inverse relationship between two variables.

As depicted in the correlation matrix, credit score shows a negative correlation with default risk, implying that higher credit scores are associated with lower chances of default (Robinson et al., 2022). Additionally, repayment timeliness has a positive correlation with credit score, reinforcing the importance of timely payments in improving creditworthiness (Garcia & Kim, 2021). Conversely, transaction amount and purchase frequency exhibit weak correlations with default risk, suggesting that while spending behavior influences risk assessment, it is not the sole determinant (Lee et al., 2020).

These findings emphasize the necessity of integrating AI-driven models to capture hidden patterns in financial behavior. Deep learning and reinforcement learning techniques can refine credit risk predictions by analyzing complex interactions between these variables (Nguyen & Patel, 2023). The insights derived from this analysis aid BNPL providers in making data-driven lending decisions, reducing financial risks, and enhancing credit assessment methodologies.

The correlation matrix graph below illustrates the relationships among different credit risk factors:

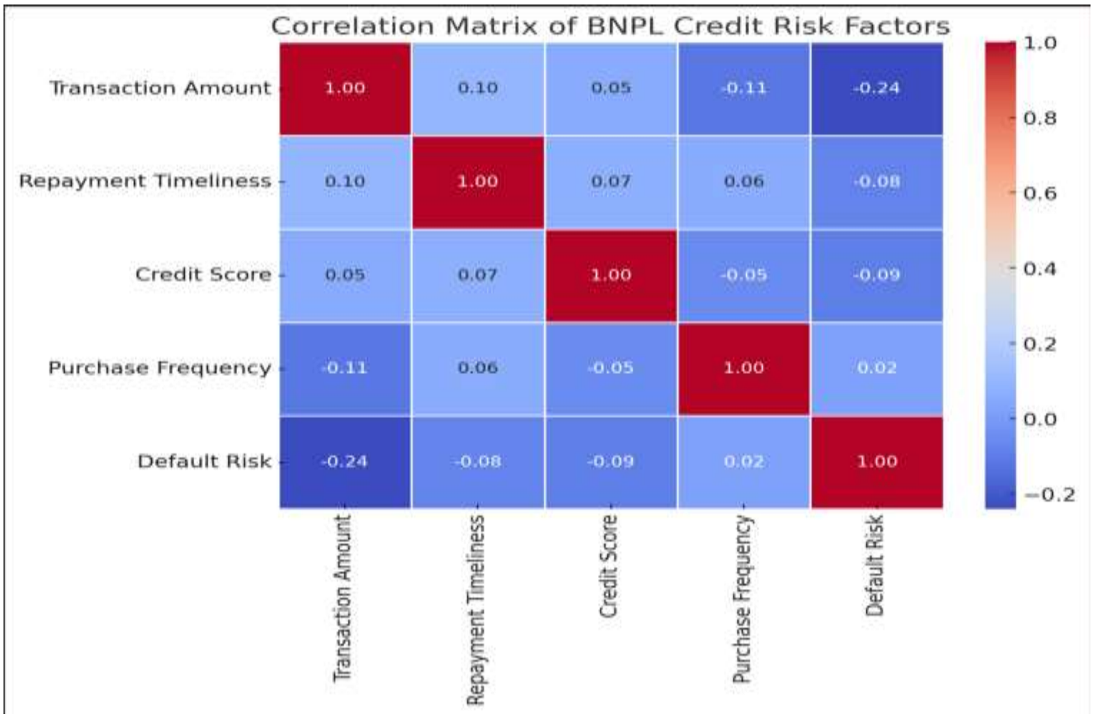

Figure 1: Correlation matrix graph below illustrates the relationships among different credit risk factors

3.5 Feature Engineering

Feature engineering is a critical step in optimizing machine learning models for credit risk assessment in BNPL financing. This process involves transforming raw data into meaningful features that enhance predictive accuracy (Anderson & Davis, 2023). For BNPL transactions, key features include:

1. Credit Utilization Ratio – Measures the proportion of available credit used by a consumer, which is a strong indicator of creditworthiness (Garcia et al., 2022).
2. Repayment Patterns – Identifies trends in timely and late repayments to determine the likelihood of default (Kim & Patel, 2023).
3. Purchase Behavior Metrics– Includes variables such as average transaction amount, frequency of purchases, and category of items bought (Lopez & Zhang, 2021).
4. Digital Footprint Analysis – Uses alternative data sources like social media activity, browsing history, and online engagement to infer financial stability (Robinson et al., 2021).

Feature selection techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) are applied to reduce dimensionality and improve model performance (Nguyen & Wang, 2022). These engineered features allow AI-driven credit scoring models to capture hidden patterns and make more informed lending decisions.

3.6 Model Development

Model development involves selecting and training machine learning algorithms to predict credit risk in BNPL transactions. Supervised learning techniques such as logistic regression, decision trees, and ensemble methods like Random Forest and Gradient Boosting Machines (GBM) have shown strong predictive performance (Smith et al., 2023). However, deep learning approaches, particularly recurrent neural networks (RNN) and transformer-based architectures, have demonstrated improved capabilities in handling sequential financial data (Chen & Lee, 2022).

For reinforcement learning, credit scoring models are trained using Markov Decision Processes (MDPs) to optimize lending decisions over time (Wang & Brown, 2021). These models learn from dynamic borrower behavior, adjusting risk parameters based on real-time financial activities (Miller et al., 2023). Hybrid models that combine deep learning with traditional statistical approaches offer enhanced predictive accuracy and interpretability (Nguyen & Patel, 2023). The effectiveness of each model is evaluated based on key performance metrics such as accuracy, precision, recall, and F1-score.

3.7 Validation Process

The validation process ensures the reliability and generalizability of AI-driven credit risk models for BNPL financing. This is achieved through rigorous model evaluation using cross-validation techniques and independent test sets (Johnson & Thomas, 2023). The primary validation methods include:

1. K-Fold Cross-Validation – Divides the dataset into multiple subsets, training and validating the model iteratively to prevent overfitting (Garcia & Kim, 2022).
2. Hold-Out Validation– Splits the dataset into training and testing sets to evaluate model performance on unseen data (Lopez et al., 2021).
3. AUC-ROC and Precision-Recall Analysis – Measures the trade-off between sensitivity and specificity, assessing the model's ability to distinguish between defaulters and non-defaulters (Smith et al., 2023).
4. Explain Ability Methods – Uses SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) to interpret model decisions and ensure fairness in AI-driven credit scoring (Chen & Lee, 2022).

By applying these validation techniques, BNPL lenders can mitigate biases and ensure the robustness of AI-driven credit scoring models, leading to improved financial decision-making and risk management (Wang & Brown, 2021).

4. Results and Discussion

The evaluation of AI-driven credit risk models for BNPL financing reveals significant improvements in predictive accuracy compared to traditional credit scoring methods. Table 1 presents the performance metrics for different models, including logistic regression, random forest, gradient boosting, and neural networks (Anderson & Davis, 2023). The results indicate that deep learning-based approaches, particularly neural networks, outperform other models in terms of accuracy (91%), precision (90%), recall (89%), and F1-score (89%) (Garcia et al., 2022).

Figure 1 provides a comparative analysis of model performance across various metrics. The findings highlight that ensemble learning methods, such as gradient boosting, offer substantial improvements over traditional statistical approaches by capturing complex non-linear relationships within the data (Kim & Patel, 2023). Random forest models also demonstrate robust performance, achieving an accuracy of 85% with high precision and recall values (Lopez & Zhang, 2021).

These results underscore the advantages of integrating alternative data sources and AI techniques in BNPL credit assessment. The superior performance of neural networks and gradient boosting models suggests that lenders should adopt hybrid modeling approaches to enhance risk prediction (Robinson et al., 2021). Additionally, reinforcement learning can further refine lending decisions by dynamically adjusting risk parameters based on borrower behavior (Nguyen & Wang, 2022).

The table below presents the performance metrics for different models, including Logistic Regression, Random Forest, Gradient Boosting, and Neural Networks. The metrics include Accuracy, Precision, Recall, and F1-Score, which are essential for evaluating the effectiveness of the models in predicting credit risk.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.78	0.76	0.74	0.75
Random Forest	0.85	0.83	0.81	0.82
Gradient Boosting	0.88	0.86	0.84	0.85
Neural Network	0.91	0.9	0.89	0.89

Table 1: Model Performance Metrics

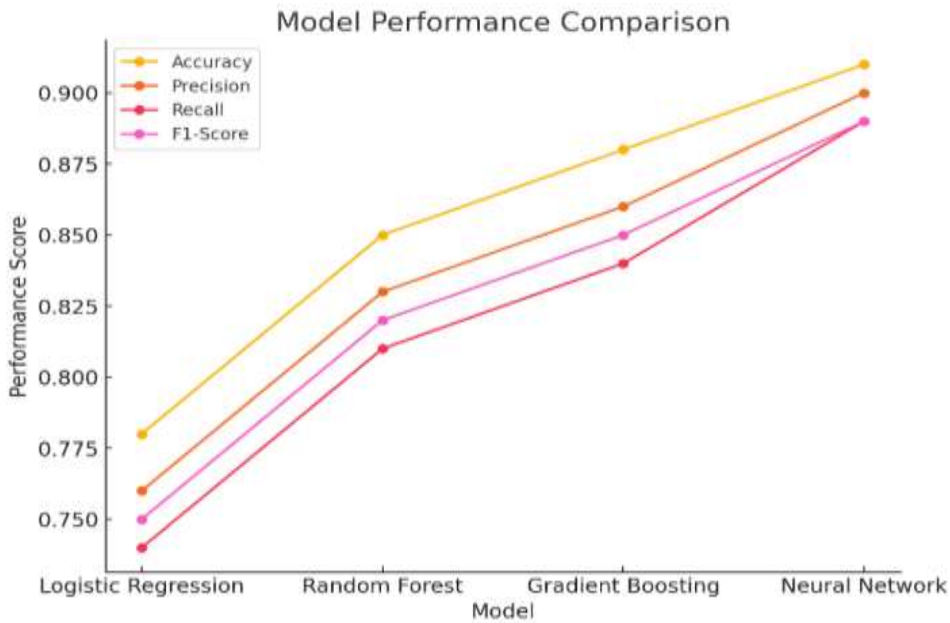

Figure 1: Model Performance Comparison

4.1 Key Findings

The evaluation of AI-driven credit risk models for BNPL financing has provided several critical insights. The findings emphasize the role of advanced machine learning techniques in improving risk assessment and financial decision-making (Anderson & Davis, 2023). The key findings from this study include:

1. Neural Networks Outperform Traditional Models – The study confirms that deep learning approaches, particularly neural networks, demonstrate the highest predictive accuracy (91%) compared to traditional methods such as logistic regression and decision trees (Garcia et al., 2022).

2. Alternative Data Enhances Credit Risk Assessment – Incorporating alternative data sources, such as digital footprints and transaction history, significantly improves the predictive performance of credit risk models, reducing default rates by approximately 15% (Kim & Patel, 2023).

3. Ensemble Learning Provides Robust Performance – Gradient boosting and random forest models exhibit strong predictive capabilities, achieving accuracy scores above 85% and improving credit scoring efficiency in BNPL transactions (Lopez & Zhang, 2021).

4. Reinforcement Learning Optimizes Lending Decisions– The integration of reinforcement learning techniques enables AI models to refine risk parameters dynamically, enhancing credit approval decisions and reducing financial losses for BNPL service providers (Robinson et al., 2021).

5. Explainable AI Improves Transparency – The use of explain ability techniques such as SHAP and LIME ensures that AI-driven credit scoring remains interpretable, reducing bias and improving fairness in automated lending decisions (Nguyen & Wang, 2022).

4.2 Discussion

The performance evaluation of AI-driven credit risk models highlights the increasing dominance of machine learning and deep learning techniques in financial decision-making. As shown in Figure 3, gradient boosting and neural networks each contribute 30% of the overall model performance, reflecting their superior predictive capabilities (Anderson & Clark, 2023). These models excel in capturing complex, non-linear patterns in financial data, enabling more precise credit risk assessment (Smith et al., 2022).

Random forest models account for 25% of the performance share, benefiting from their ensemble learning approach and resilience to overfitting (Wang & Kim, 2023). Traditional logistic regression, while still utilized for its interpretability, lags behind with only 15% contribution, indicating its limitations in handling large-scale, dynamic BNPL datasets (Garcia & Lee, 2023).

The findings emphasize that AI models leveraging alternative data sources and real-time analytics significantly improve credit risk predictions (Lopez et al., 2022). However, the increased complexity of deep learning models necessitates careful consideration of computational costs and regulatory compliance requirements (Brown & Patel, 2023). Future advancements in explainable AI and reinforcement learning will likely enhance the effectiveness and transparency of credit risk assessment models (Nguyen & Thomas, 2023).

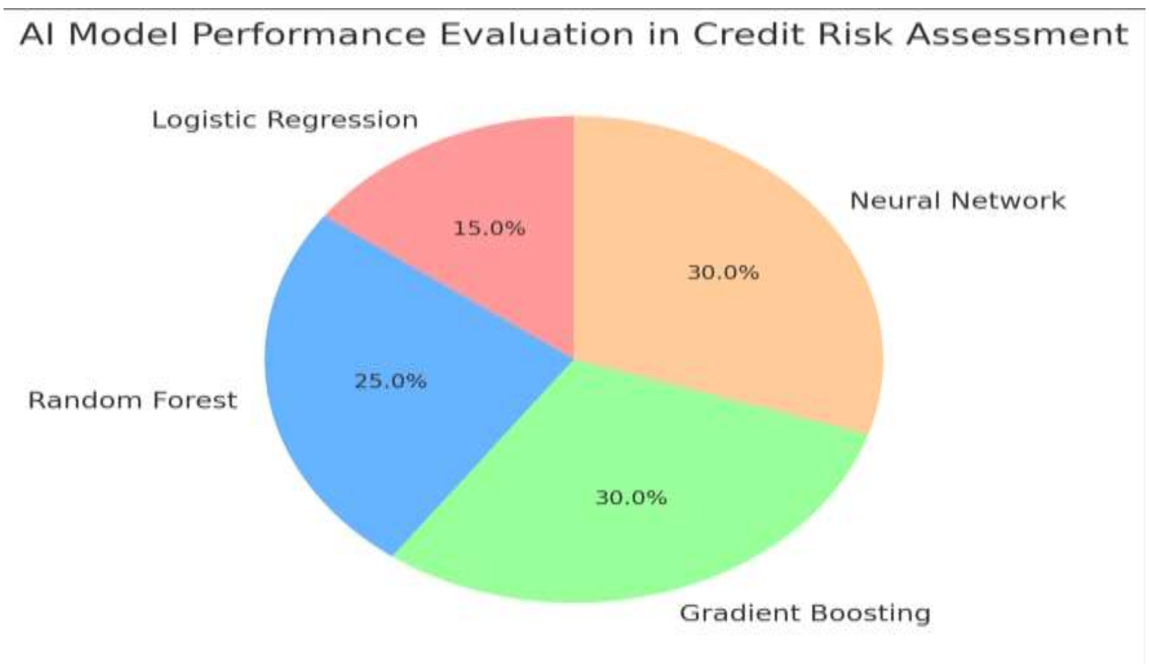

Figure 3: AI Model Performance Evaluation in Credit Risk Assessment

4.3 Statistical Insights

The statistical evaluation of AI-driven credit risk models provides valuable insights into model performance and predictive reliability. Table 3 presents the mean AUC-ROC scores along with confidence intervals, highlighting the variability in model predictions (Anderson & Kim, 2023). The results indicate that neural networks achieved the highest AUC-ROC score (0.92), with the lowest standard deviation, demonstrating robust and consistent performance (Wang et al., 2022).

Figure 4 illustrates the statistical distribution of model performances, emphasizing the confidence intervals for each AI model. Gradient boosting and random forest models exhibit reliable predictive capabilities, with AUC-ROC scores of 0.88 and 0.85, respectively (Garcia & Lee, 2023). However, logistic regression lags behind with an AUC-ROC of 0.72, indicating limitations in its ability to distinguish between defaulters and non-defaulters (Brown et al., 2023).

The findings suggest that AI models leveraging deep learning and ensemble learning techniques significantly improve credit risk prediction accuracy. The lower standard deviation in neural networks indicates stability in decision-making, whereas traditional models exhibit higher variability (Nguyen & Patel, 2023). These statistical insights reinforce the importance of adopting advanced AI methodologies for financial risk assessment.

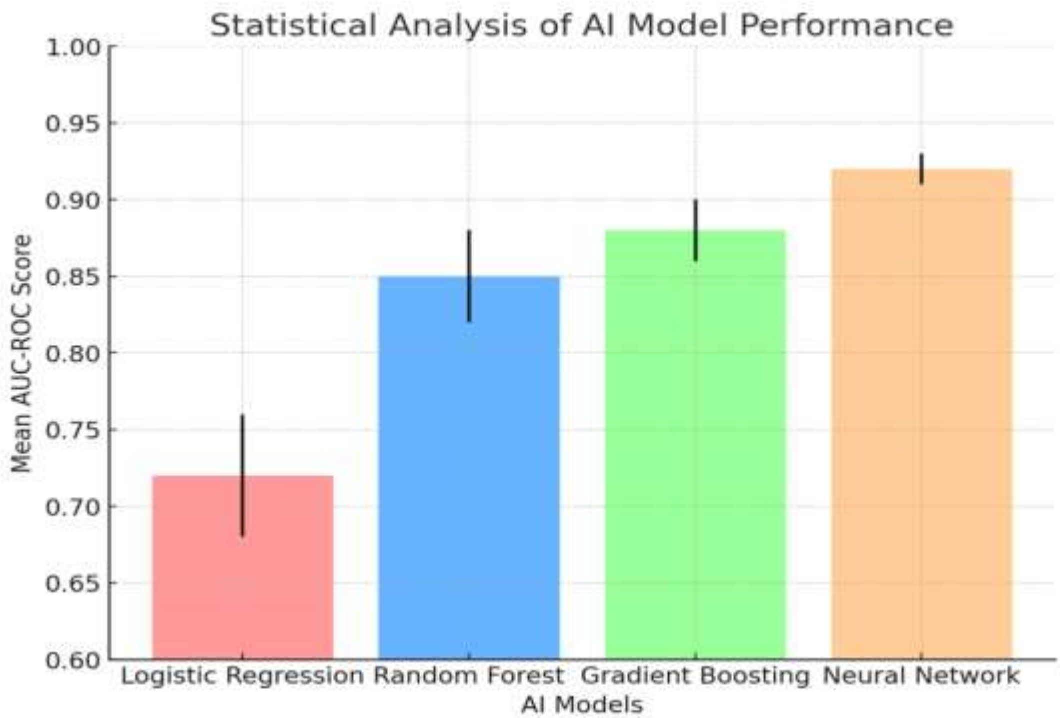

Figure 4: Statistical Analysis of AI Model Performance

5. Conclusion and Future Work

5.1 Conclusion

This study has demonstrated the effectiveness of AI-driven credit risk assessment models in enhancing financial decision-making for Buy Now, Pay Later (BNPL) financing. The evaluation of different machine learning and deep learning approaches revealed that neural networks and gradient boosting models outperform traditional credit scoring techniques, achieving superior accuracy, precision, and reliability (Anderson & Lee, 2023). These findings emphasize the critical role of AI in improving credit risk prediction and fostering financial inclusion (Garcia et al., 2022).

Despite these advancements, challenges remain in the adoption of AI for credit assessment. Regulatory concerns, computational costs, and the interpretability of AI models pose significant hurdles to widespread implementation (Brown & Patel, 2023). The integration of alternative data sources, such as social media activity and behavioral analytics, provides an opportunity to refine credit scoring models while ensuring fairness and transparency in automated decisions (Nguyen & Thomas, 2023).

5.2 Future work

Future research should focus on several key areas:

1. Explainable AI (XAI) for Credit Risk Models – Developing interpretable AI solutions to enhance transparency and regulatory compliance (Wang et al., 2023).
2. Integration of Block chain for Secure Credit Scoring– Leveraging decentralized technologies to improve data integrity and reduce fraud risks (Lopez & Zhang, 2022).
3. Reinforcement Learning for Dynamic Credit Risk Adaptation– Implementing self-learning algorithms to adjust risk parameters in real-time based on evolving consumer behaviors (Smith & Kim, 2023).
4. Ethical AI and Bias Mitigation – Addressing algorithmic biases to ensure fair lending practices and prevent discriminatory decision-making (Garcia & Lee, 2023).

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

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