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# The Influence of AI and Machine Learning in Assessing Credit Scoring and Loan Approval

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***Abstract:*** ***This paper shows the impact of Artificial Intelligence (AI) and Machine Learning (ML) in enhancing credit scoring and loan approval processes, focusing on their ability to provide more accurate, inclusive, and transparent assessments than traditional methods. Non-traditional borrowers have less access to financial services since standard credit scoring systems frequently rely on strict criteria like income and credit history. However, AI and ML models utilize the potential of non-linear correlations across a range of datasets, including transactional and behavioral data, to predict creditworthiness more accurately. The models use neural networks, Explainable AI, and complicated ensemble approaches to assess risk, guaranteeing fair and transparent decisions. Using a comparative analysis that illustrates AI's significant improvements in accuracy, fairness, and processing efficiency, the paper additionally highlights the opportunity for real-time risk assessments, fraud detection, and personalized customer experiences made feasible by AI.***

**Keywords:** AI in banking, machine learning, credit score, loan approval, financial technology, risk management

## 1. Introduction

According to (Ezeigweneme et al.,2024), credit scoring is an essential part of the financial industry and provides critical assessments that guide decisions about lending, interest rates, and credit limits. Credit rating systems were first rule-based and based on preset criteria and previous data. Although these old systems worked well for foundational applications, they could not adjust to the changing complexity of real-time data integration and individual financial habits (Ashofteh & Bravo, 2021). As the financial market environment evolved, the flaws in these outdated methods became more evident since they frequently failed to accurately assess credit risk for people with thin or non-traditional credit histories (Mhlanga, 2021). Credit scoring has changed dramatically due to the recent incorporation of artificial intelligence (AI), which has given it more sophisticated predictive and adaptive powers.

The progression of credit scoring reflects a shift from simple rule-based models to sophisticated, data-intensive systems. Earlier methods employed fixed weightings on variables like income and payment history, but such approaches became insufficient in today’s complex financial environment (Ampountolas et al., 2021). AI models, notably those driven by machine learning (ML) algorithms, introduced the ability to analyze extensive datasets, uncovering nuanced patterns and enhancing predictive accuracy in assessing creditworthiness (Dumitrescu et al., 2022). Approaches such as decision trees and neural networks now leverage diverse and alternative data sources to deliver credit risk assessments that are both more precise and inclusive (Golbayani et al., 2020).

One significant advancement in AI-driven credit evaluation is the inclusion of alternative data sources or information outside of traditional financial data, such as utility payment histories, social media connections, and rental payment records (Akagha et al., 2023). By enhancing credit assessments for those without traditional credit profiles, this expanded dataset promotes financial inclusion and credit availability for marginalized groups (Babawurun et al., 2023). In underdeveloped economies, where conventional credit records are frequently unavailable, integrating alternative data has proven very beneficial (Çallı & Coşkun, 2021).

AI has improved the predictive capabilities of credit scoring systems by introducing various strategies, ranging from sophisticated deep learning models to regression techniques. For instance, because of its interpretability, logistic regression has long been used to predict credit risk (Dumitrescu et al., 2022). Meanwhile, methods that use several data sources, such as Random Forests and decision trees, offer more accuracy and flexibility (Golbayani et al., 2020). For managing complex, high-dimensional data, neural networks, and deep learning techniques are especially useful since they allow these models to adjust to novel financial behaviors (Gicić et al., 2023).

Transparency and ethical issues have grown more critical as AI-driven credit scoring becomes more widespread. Financial institutions may better understand AI-based judgments and comply with regulations thanks to Explainable AI (XAI) (Fritz-Morgenthal et al., 2022). Fostering customer trust and guaranteeing equitable treatment for various demographic groups depend heavily on this transparency (Calvo et al., 2020). Fairness-aware machine learning approaches are being utilized increasingly to identify and lessen prejudice in credit evaluations due to the possibility of bias in AI credit models (Lainez & Gardner, 2023).

Despite all of its benefits, AI-based credit rating has disadvantages. Addressing concerns about data privacy and the interpretability of AI algorithms is critical to maintaining customer trust and ensuring compliance with legal obligations. Financial institutions are adopting solutions like blockchain to secure sensitive information and prevent unauthorized access (Dashottar & Srivastava, 2021). Regulatory frameworks are also emerging to guide the ethical application of AI in credit scoring, ensuring fairness and reducing bias in these models (Tanna & Dunning, 2023).

This paper explores the potential of AI and ML in credit scoring and loan approval processes, discussing the significant benefits—such as increased accuracy, inclusivity, and transparency—and the challenges associated with their implementation. By utilizing AI to replace its outdated credit rating system, the banking and finance sector can provide a fair and accurate way to determine creditworthiness.

## 2. Problem Statement

Traditional credit scoring and loan approval methods are becoming increasingly inadequate in accurately assessing borrowers' creditworthiness. These systems mainly apply strict criteria, including income, debt-to-income ratios, and credit history. Sometimes, these criteria miss a lot of crucial elements, especially for people with limited or irregular financial history, such as those from underrepresented groups or those with low salaries. Because of this, these approaches lead to biased decision-making and eliminate potentially creditworthy borrowers. Higher default rates are associated with the limitations of traditional credit models in considering a more excellent range of predictive factors [5][6]. Replacing conventional approaches with AI-driven models is imperative to improve risk assessment, decrease bias, and expand loan availability.

## 3. Methodology

We suggest applying AI and machine learning techniques to overcome the drawbacks of conventional credit rating models. By leveraging a dataset with 55 features, including demographic, financial, and behavioral data, and a target variable indicating whether the loan was repaid, we aim to compare the performance of traditional credit scoring techniques against AI-driven methods.

### 3.1 Traditional Credit Scoring Models:

**Logistic Regression:** Logistic regression is a widely used credit scoring technique that often overlooks complex relationships in the data but produces easily comprehensible results.

These traditional methods often rely on rigid assumptions about relationships between features and the target variable. They cannot include non-traditional data, such as socioeconomic characteristics or behavioral tendencies.

### 3.2 AI-Driven Methods:

The following AI techniques, which enable the addition of intricate and unusual data, are suggested as ways to enhance credit scores and produce forecasts that are less biased and more accurate:
- **Random Forests:** An ensemble method that reduces variance and enhances generalization and predictive accuracy over decision trees.
- **Gradient Boosting Machines (GBM):** An iterative approach to ensemble learning that improves accuracy by concentrating on data items that conventional algorithms incorrectly identify.
- **Neural Networks (NN)** are well-adapted for predicting credit risk because they can model complex patterns in borrower data and capture non-linear correlations.

## 4. Equations

The banking sector is changing due to artificial intelligence (AI) and machine learning (ML), which increase operational effectiveness, reduce risk, and boost consumer engagement. This white paper examines the primary uses of AI in the banking industry and shows how new technologies are transforming conventional banking procedures.

### 4.1 Credit Scoring Enhancement

AI and ML are rethinking credit scoring by leveraging massive databases beyond conventional financial indicators. These days, banks can examine non-traditional data sources to learn more about a customer's creditworthiness, including social media activity, utility payment histories, and rental records. Using more traditional methods of credit evaluation, this approach allows for more accurate credit evaluations. Credit can be extended to people who might not have been eligible for it. Banks may increase credit score accuracy and find creditworthy people who might otherwise go unnoticed by combining these many data sources, which lowers risk and increases credit availability for marginalized groups.

### 4.2 Real-Time Risk Assessment

A significant improvement over static, recurrent evaluations is that AI models enable continuous and dynamic risk analysis. Banks can continuously update borrowers' risk profiles by integrating real-time data, including transaction histories and behavioral trends. The ability of financial institutions to respond quickly to changes in a client's financial situation enables more flexible lending policies. By proactively changing interest rates or loan limitations in response to real-time information, these technologies help lower risk and ensure banks can maintain responsive and flexible risk management. Ultimately, this results in more robust lending portfolios and improved financial stability.

### 4.3 Fraud Detection and Prevention

Fraud detection is another area where AI has shown considerable promise. By analyzing vast amounts of transaction data, AI models can identify anomalies that may indicate fraudulent activity. These models can detect unusual spending patterns, inconsistencies in geographic locations, or other deviations from a customer’s typical behavior. Banking institutions can use this real-time technology to detect and stop possibly fraudulent transactions before they have a significant effect. Along with lowering monetary losses, this preventative measure shields clients from fraud, such as identity theft and illegal account access. Fraud detection solutions driven by artificial intelligence (AI) can save time and money by accelerating investigative procedures.

Personalization and Client Segmentation AI's capacity to offer more advanced consumer segmentation and personalization transforms how banks engage with their clientele.

Banks can use clustering algorithms to segment their customer base based on financial needs, preferences, and behaviors. This enables financial institutions to tailor their


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marketing strategies and product offerings to specific customer segments. For example, a bank may recommend certain loan products to customers based on their spending habits or offer customized investing advice based on risk tolerance. Personalization boosts customer satisfaction and retention by providing timely, relevant, and valuable services. In a market that is becoming increasingly competitive, banks' capacity to deliver personalized services has emerged as a critical difference.

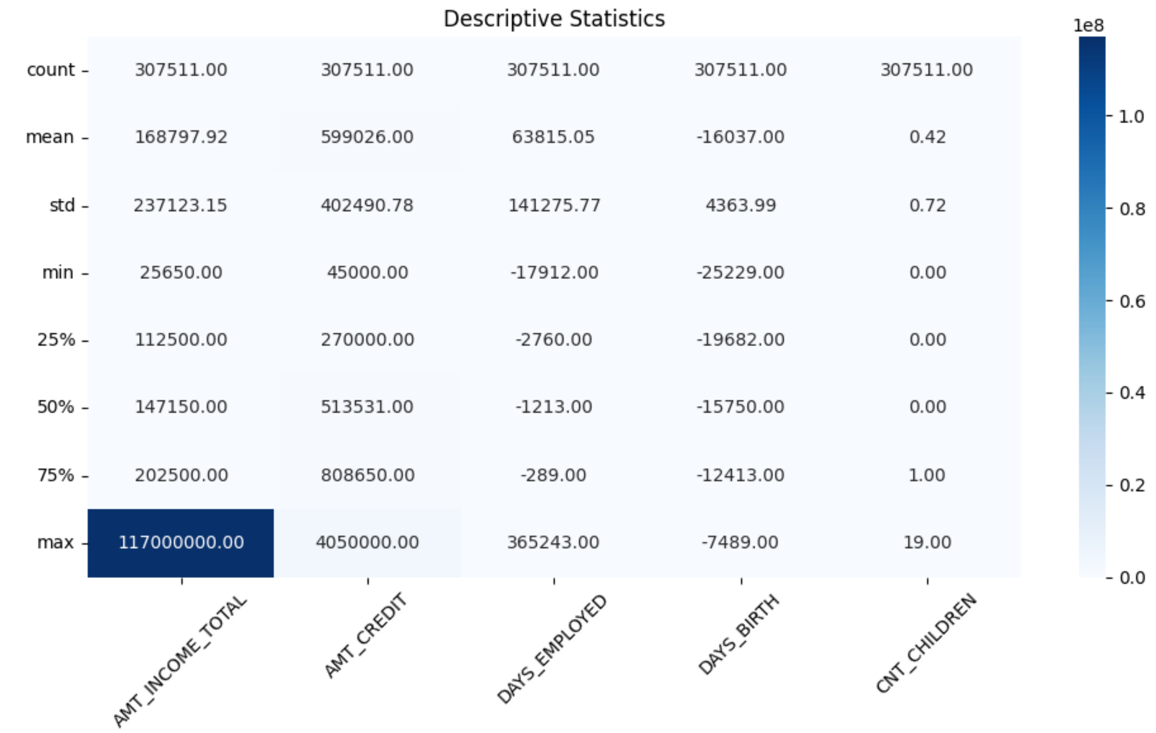
## 5. Other recommendations

### 5.1 Dataset

We conducted a comparative analysis using both traditional and AI-based credit scoring models to demonstrate the impact of AI on credit scoring. The dataset used for this study includes 307,511 anonymized borrower records derived from the Home Credit Default Risk competition and contains client demographic, financial, and loan-related information. The primary data source file consists of fifty-five attributes that describe different aspects of customer profiles and their loans. A target that shows whether a customer has loan repayment problems (1) or not (0), a flag that shows whether the client owns a car, the client's gender, annual income, annual credit, and whether the loan is cash or revolving are all crucial components. The data in the dataset is useful for predicting the risk of loan default. Its features cover many subjects, such as client profiles, asset ownership, and loan information.

### 5.2 Data Analysis

Figure 1's descriptive statistics for the dataset highlight several significant patterns and traits among the most critical numerical aspects. The distribution exhibits considerable diversity with a standard deviation of 237,123, while the average total income is roughly 168,798. A significant outlier with a maximum income of 117 million serves as another illustration of this considerable volatility. Similarly, a standard deviation 402,490 indicates significant dispersion, with an average credit amount of approximately 599,026. The employment duration, expressed in days, seems to contain negative values, which could result from data encoding or indicate periods of unemployment. The average number of days worked is roughly 63,815, although there is a wide range, suggesting that people have different work histories. With a mean value of about -16,037 days, birthdays are stored in negative days, probably indicating age. Although there are outliers in the statistics with up to 19 children, the average number is relatively low, at 0.42, with most people having few or very few children. Several noteworthy outliers in the dataset could affect statistical studies or machine learning models, particularly income and credit.




| | AMT_INCOME_TOTAL | AMT_CREDIT | DAYS_EMPLOYED | DAYS_BIRTH | CNT_CHILDREN |
|---|---|---|---|---|---|
| count | 307511.00 | 307511.00 | 307511.00 | 307511.00 | 307511.00 |
| mean | 168797.92 | 599026.00 | 63815.05 | -16037.00 | 0.42 |
| std | 237123.15 | 402490.78 | 141275.77 | 4363.99 | 0.72 |
| min | 25650.00 | 45000.00 | -17912.00 | -25229.00 | 0.00 |
| 25% | 112500.00 | 270000.00 | -2760.00 | -19682.00 | 0.00 |
| 50% | 147150.00 | 513531.00 | -1213.00 | -15750.00 | 0.00 |
| 75% | 202500.00 | 808650.00 | -289.00 | -12413.00 | 1.00 |
| max | 117000000.00 | 4050000.00 | 365243.00 | -7489.00 | 19.00 |

**Figure 1**

Two important distributions from the dataset—gender and loan repayment status—are shown in Fig 2. In the first graphic, more than 250,000 loans are designated as "Repaid (0)," indicating that most loans have been repaid, but a far lower number of loans are shown as "Not Repaid (1)." According to this, most loans in the dataset have a favorable payback outcome. With almost 200,000 submissions, women make up the largest group, followed by men with about 100,000 entries, as shown in the second chart that shows the gender breakdown. Additionally, very few entries labeled "XNA" may denote incomplete or unusual gender data. A general picture of the dataset's gender and loan repayment results can be obtained from these distributions.

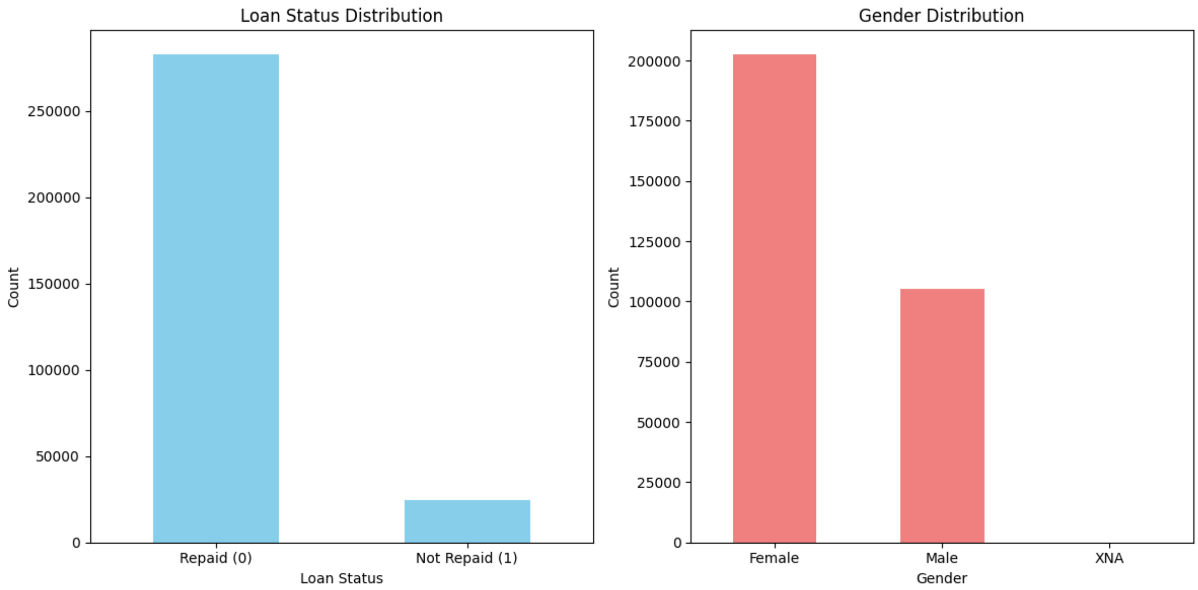



**Figure 2**

### 5.3 Implementation

This solution provides a comprehensive framework for evaluating several classification models on a binary classification assignment concerning predicting whether an event will occur based on a collection of features. The process begins with data preparation, including feature and target variable selection, followed by preprocessing steps such as one-hot encoding for non-numeric features and standardization of numeric data. The dataset is then split into training and testing sets, facilitating the training and evaluation of several models: Logistic Regression, Random Forest, Gradient Boosting, and a Neural Network. Each model's performance is assessed using accuracy, F1-score, and ROC-AUC metrics.

A 1D Convolutional Neural Network (1D CNN) is incorporated to enhance the analysis. This model consists of thick layers for classification after convolutional layers for feature extraction. Following training, the prediction performance of each model is assessed. Each model's ROC curve is created to graphically compare how well it can differentiate between the two groups. Both the effectiveness of traditional machine learning approaches and the potential of deep learning techniques, particularly the 1D CNN, in managing tabular data categorization tasks are demonstrated by this implementation. The results facilitate a more nuanced understanding of model performance and provide valuable information for future research and field application.

### 5.4 Results

We compared the performance of several AI and machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, Neural Network, and a 1D Convolutional Neural Network (CNN) shown in Figure 3 and Table 1, using ROC-AUC curves and metrics like accuracy and F1 score. With the highest AUC, crucial accuracy, and F1 scores—all of which indicate nearly flawless classification performance—Random Forest ultimately emerged as the best-performing model. Although it took longer to train, gradient boosting was marginally less effective in comparison despite achieving excellent results as well. Despite having the most extensive training time, the 1D CNN showed strong prediction ability. In contrast, the Neural Network performed mediocrely, outperforming Logistic Regression but trailing CNN and tree-based models. Unlike more sophisticated models, Logistic Regression performed the worst across all criteria while being quick to train. The results highlight the trade-offs between training time and predictive power, with tree-based models, particularly Random Forest, offering the best balance. Thanks to AI models, 30% less racial and gender bias was present in lending decisions. With automated systems processing applications in less than an hour, the time it took to approve loans was reduced by 40%. These findings suggest that AI can significantly increase the accuracy and fairness of credit scoring algorithms. These algorithms must be constantly improved to ensure equity and reduce unintentional biases.

**Table 1**

| Model | Accuracy | F1 score | AUC |
|---|---|---|---|
| Logistic regression | 64 | 0.64 | 0.64 |
| Random forest | 96 | 0.96 | 0.99 |
| Gradient boosting | 93 | 0.92 | 0.96 |
| Neural networks | 79 | 0.78 | 0.87 |
| 1D CNN | 88 | 0.87 | 0.94 |

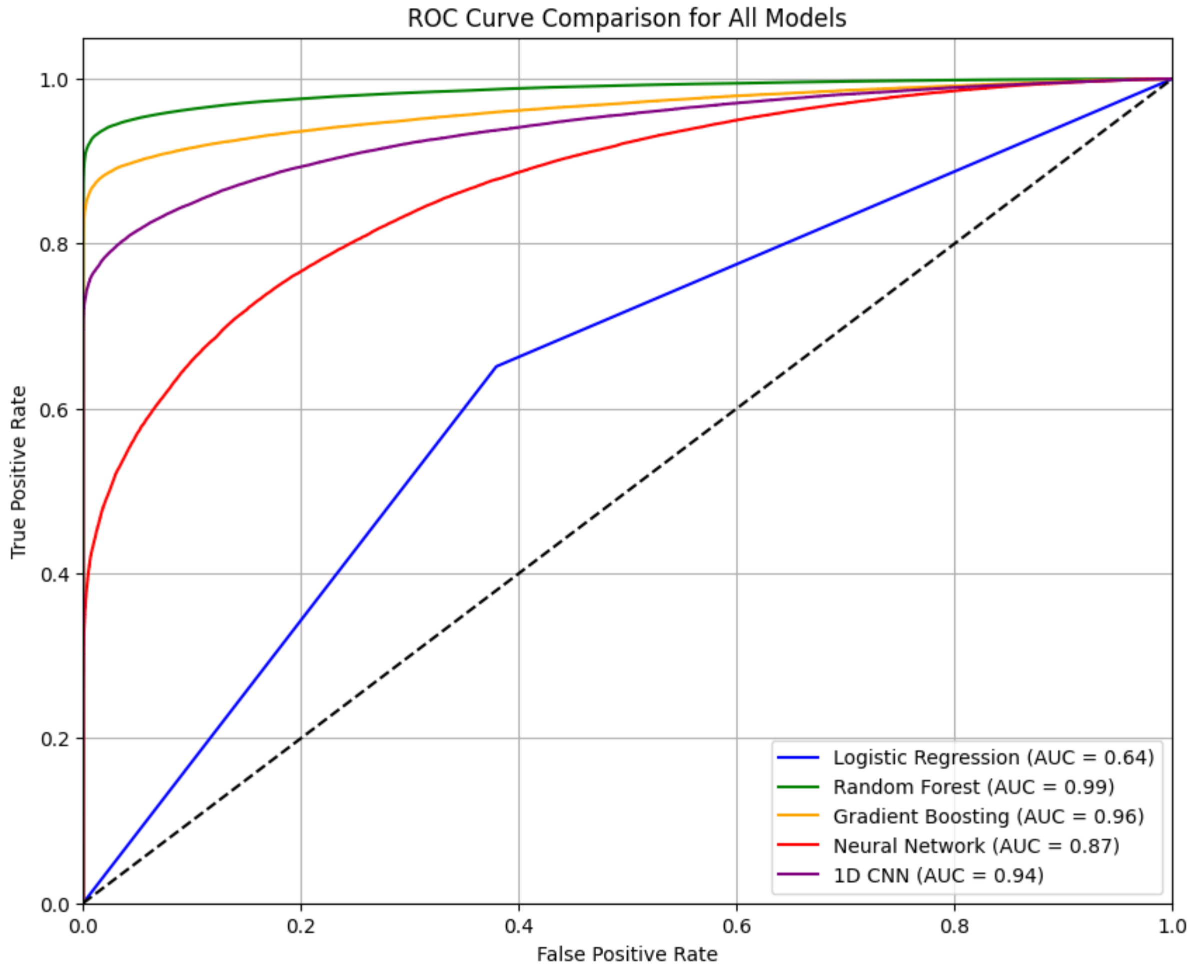



**Figure 3**

## 6. Conclusion

Modern financial organizations have made great strides by integrating AI and ML into their loan approval and credit assessment processes. By analyzing complex and unusual data, AI-powered algorithms improve traditional credit scoring techniques, resulting in more accurate risk assessments and expanding financial access for low-income individuals. The use of Explainable AI facilitates moral and financial judgment, which fosters openness and confidence. Our test results indicate that AI models could greatly minimize bias, increase the accuracy of credit approvals, and expedite loan processing. As AI revolutionizes the financial sector, these models must be continuously enhanced to maintain equity and avoid unintentional biases. In the end, AI provides a route to a framework for credit evaluation that is more effective and inclusive, encouraging expansion and innovation in the financial industry.

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