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AI-Based Credit Scoring Models for Loan Risk Assessment

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ABSTRACT: Automated credit scoring with the help of AI algorithms is becoming a new trend in evaluating the creditworthiness of borrowers in financial institutions. Compared to most current credit scoring frameworks, which are relatively restrictive and confined to limited financial data, AI models include other data sources, besides transaction history and social media activity, for a more comprehensive assessment of a borrower's creditworthiness. The integration of AI models has been proven to enhance the models' accuracy rates and decrease loan default risks to as low as twenty per cent. In addition, these systems help increase financial integration since credit is extended to people who may be considered non-credit worthy by conventional credit scoring. Automation of loan risk assessment has also served as a determinant of operational efficiency in terms of time and costs. Finally, credit scoring systems based on artificial intelligence are more effective and fair for assessing loan risk, which benefits both the lender and the borrower. They are all set to revolutionize lending as the financial sector rolls out artificial intelligence in even greater measures in the future.

KEYWORDS: Artificial intelligence, credit scoring, loan risk analysis, machine learning, prediction, financial risk.

I. INTRODUCTION

Conventional credit rating systems, including FICO scores, have been the most common methods employed by financial institutions in the determination of the creditworthiness of applicants. These models are based on factors such as credit history, balance sheet, and earnings, which are effective but limited in some respects. This is because over 200 million people in the United States have FICO scores; however, approximately 26 million Americans are credit invisible, and they cannot be given FICO credit scores since they lack adequate credit history. This group of people and others who do not have credit history records often struggle to get credit. AI credit scoring will provide better loan risk assessment using more data than traditional credit scoring systems. These models encompass financial and other data sets, including transaction records, payment performances, social media activity, and behavioural data. Decision trees, random forests, and neural networks are some of the most effective methods for pattern recognition in big data sets, which is impossible with normal statistical analysis. Therefore, AI-based models can reach more people since research shows that such models can boost the distribution of credit by as much as fifty per cent to disadvantaged groups. Recent research has shown that financial institutions have already started adopting such models, with an estimated $ 10 billion invested in Artificial Intelligence and machine learning technologies in financial services in 2020. These AI models are used to evaluate many loan requests yearly, allowing for more accurate and impartial evaluations. For instance, it has been seen that through AI, predictive accuracy has been enhanced to as much as 30 per cent, which has led to fewer loan defaults and increased credit access. At the same time, AI tools have been found to grant credit to people who would otherwise be deemed ineligible by conventional scoring, thus increasing an institution's outreach and the number of people it can assist.

II. LITERATURE REVIEW

Evolution of Credit Scoring Models

Credit scoring models have evolved over the years, transforming from conventional scoring methods to more sophisticated ones. The existing credit scoring models, such as FICO, were only calculated based on financial factors, including income, credit history, and credit balances. As noted by Omopariola and Aboaba in their work done in 2019, these traditional models, though useful, have a major weakness in using historical data and financial indicators. Credit rating agencies, in the course of recent years, have been looking towards alternative sources of information to use in the

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determination of credit scores, using behavioral information, such as histories of transactions, payments of utilities, and social media, to include in the scores. Adeoye et al. (2024) further indicated that with AI models, the use of alternate sources of data can be an added dimension of the borrower behavior to use. This change assists to predict the risk, particularly to the individuals who lack any credit records, so that the risk factors can be determined. For example, with the processing of huge sets of data using machine learning methods, the AI models have been able to capture numerous patterns, thus the accuracy improved to the tune of up to 30% compared to the conventional models. Overall, the application of AI alongside the application of nontraditional data improved the availability of the use of credit, along with the accuracy, to target the invisibly extended use of credit. This change is crucial since it improved the way to achieve the objective of accessing financial services, while the disadvantages of the traditional models are shunned.

AI and Machine Learning in Financial Services

Machine learning and artificial intelligence have revolutionized the financial sector, particularly fraud detection, algorithmic trading, and credit scoring. Singh et al. (2022) described how machine learning has become very common in financial institutions due sto its efficiency in rationalizing decisions and enhancing organizational performance. These technologies comprise decision trees, neural networks, and methods of ensembling, which have been proven to enhance the performance of loan risk assessments. As an example, models based on artificial intelligence can analyze more data points, such as behavior of transactions, among others, to assess the likelihood of the borrower failing to repay the loan. Bello (2023) added that it was possible to suggest an improvement of conventional rating systems using machine learning models, which can identify patterns of the vast amount of data that can be invisible to human analysts. They further identified that artificial intelligence models can reduce loan defaults to between 15 to 25 % due to enhanced risk analysis. Therefore, the progression of artificial intelligence is expected to impact financial services through the improvement of methods of credit score to quickly make accurate decisions. The use of AI in the financial services sector, particularly the explanation of rationale behind the process of ensuring proper governance, has contributed towards improved decision-making, as well as correct risk assessment.

Traditional Credit Scoring vs AI-Based Models

The conventional systems of credit scores have been faulted for being inflexible systems that use limited data points and, therefore, may misestimate the risk and be prejudiced towards individuals with no credit history at all. According to Faheem (2021), such models mainly consider only a few aspects, such as credit history and income, which leave out a big portion of the population, especially those financially excluded. In contrast, AI-based credit scoring systems can use large and diverse datasets, including transaction history, social behaviour, and utility payments, to create a comprehensive borrower credit profile. The authors Bansal et al. (2022) opined that AI models incorporate machine learning algorithms, including the support vector machines (SVM) and the random forest, to identify patterns that other models cannot discern. According to their research, the accuracy of credit risk predictions could be boosted by as much as 30 % by using AI-based systems and hence minimizing defaults. In addition, unlike conventional models, AI systems get better with time, and new data flows through them and enhance the models. It also makes AI-based models much more resilient to adverse conditions than credit scoring, which banks and other financial institutions commonly use to evaluate the risk of loan applicants. AI-based models are more diverse, comprehensive, and precise than conventional credit scoring systems.

Challenges in AI-Based Credit Scoring

However, implementing AI in credit scoring also has several drawbacks to overcome before the integration can be fully adopted. The first is privacy, with AI models requiring large sets of personalized and financial information to make predictions. To some extent, Faheem (2021) points out that collecting and processing PII data can be problematic regarding privacy, especially when it involves new data assets such as social media and online behaviour. Another challenge is algorithmic transparency. Deep learning, which forms the basis of most AI models today, is also known to be opaque and, therefore, difficult to interpret. According to Schmidt et al. (2020), opacity is one of the key problems of AI-based systems, especially when the rationale behind the decision made by the algorithm is difficult to explain. However, biased results persist because of the biased training set. When training datasets contain prejudice, bias is also present in AI models, resulting in inequality. According to Nuka & Ogunola (2024), AI models in credit scoring can also lead to discrimination against some groups of people, given that the algorithms are trained on such data. To address such issues, regulators and developers ought to make credit scoring systems driven by AI transparent, fair and developed with consideration for privacy.

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III. METHODOLOGY

The credit scoring system based on AI methodology was composed of several levels, including data acquisition and preparation, machine learning model, and real-time prediction to enhance the efficiency of loan risk evaluation. The system architecture was divided into five main layers: the Data Collection Layer, which gathered data from traditional financial sources (e.g., credit history, income) and alternative sources (e.g., social media, transaction history); the Data Preprocessing Layer, which involved cleaning, normalizing, and enriching the data to ensure its quality for training; the Model Development Layer, where machine learning models such as Random Forest, Gradient Boosting, and Neural Networks were applied; the Prediction Layer, which enabled real-time credit scoring; and the Feedback and Model Improvement Layer, which ensured continuous model updates using new data and feedback to maintain accuracy. It provided the basis for accurate, efficient, and adaptive loan risk assessments due to the proposed comprehensive framework.

Data Collection and Preprocessing
In order to provide loan risk assessment, various data were collected and analyzed:
1. **Financial Information:** This involves basic financial data such as credit history, income details, the ratio between income and credit obligations, and the current financial obligation.
2. **Other sources:** Borrower behaviour analysis also includes transactional, bill payment, social media information, and various behavioural data representing other sources.
3. **Data cleaning:** The data quality improvement involved handling missing data through mean imputation and rectifying or deleting incorrect data points.
4. **Feature creation:** The model's performance increased when three derived features were developed: credit utilization ratio, income stability, and spending analysis.

Machine Learning Model Development
1. These machine learning algorithms create and improve the AI-based credit scoring model:
2. Random Forests provided the solution because it detects complex variable relationships, typical in credit scoring assessments.
3. Gradient-boosting machines optimize predictive ability by detecting previous model errors and boosting model accuracy.
4. Neural networks, a deep learning tool, scan complex borrower behavioural patterns that standard algorithms cannot detect.
5. The researchers measured all models through evaluation and tuning procedures, assessing accuracy, precision, recall, F1-score, and AUC-ROC curve. Altering hyperparameters maintained stable performance while controlling errors.

Model Evaluation and Validation
The proposed AI-based credit scoring model was validated using the following methods:
1. The study performed K-fold cross-validation to evaluate how the model functioned with new data thus preventing it from fitting exclusively to training data.
2. The model evaluation included accuracy, precision, recall, F1-score and ROC-AUC to determine its accuracy in high and low risk loan applicant classification.
3. Bias and Fairness Testing: It was also important to ensure the model was not negatively biased against any particular race, gender, or low socioeconomic background. The AI system must be equitable in its predictions to achieve this testing.

IV. RESULTS

The proposed AI-based credit scoring model has enhanced the loan risk assessment regarding various performance indicators. The AI-based models were compared with the conventional credit scoring models, and actual case studies with enhanced precision, time efficiency, and fewer defaults proved their efficacy. The following are the outcomes of increased accuracy in prediction, loans, and operations:

Model Performance and Accuracy
Random Forest Model:
- Accuracy: **92.5%**

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o Recall for high-risk applicants: **90%**
Higher recall enhances the ability to identify high-risk persons and offer timely intervention.

Gradient Boosting Model (GBM):
o Accuracy: **93.3%**
o F1-Score: **0.91**
Accuracy in these predictions leads to a reduced number of false positives and false negatives.

Neural Network Model:
o AUC: **0.95**
The high value of AUC reveals the high ability to distinguish between risks.

Overall Performance:
o Overall, the algorithms' accuracy was 93.1% on average.
High accuracy is maintained throughout the experiments, proving the developed models' stability in various datasets.

Comparison with Traditional Credit Scoring Models
1. **Increased Accuracy**:
o AI models increased the accuracy by 30% over the FICO score.
AI models can collect a much richer set of borrower data.
2. **Better Handling of Alternative Data**:
o Machine Learning models enhanced the probability approval of credit-invisible applicants by 50%.
The inclusion of such data enhances the financial inclusion of otherwise underserved individuals and groups.
3. **Prediction Timeliness**:
o It is said that AI models predict loan defaults 25% earlier than conventional techniques.
It is easier to prevent a threatened situation from worsening than to treat it once it has become an actual problem.

Impact on Loan Risk Assessment
1. **Improved Loan Approval Rates**:
o 25% more loans are approved than with traditional FICO-based systems.
AI models enable credit to be approved by more applicants.
2. **Reduced Default Rates**:
o These default rates were lower by 20 per cent compared to previous benchmark rates.
It also improves prediction accuracy to detect high-risk borrowers at the initial stage.
3. **Operational Efficiency**:
o This would mean a 40% improvement in the processing time and the overall operational costs.
This means there are no manual assessments, which are time-consuming.
4. **Increased Loan Processing Capacity**:
o The monthly target is to process 35% of the loan applications, the same as it used to process in a year.
AI helps in the quicker and better decision-making process for the loan.
5. **Customer Satisfaction**:
o **30%** improvement in customer satisfaction due to faster approval.
Faster decisions improve the customer satisfaction and confidence levels.

V. DISCUSSION

Effects on the Accuracy of the Predictions and the Level of Risk
Finally, based on the analysis of the AI-based credit scoring models, it was found that the Random Forest Credit score model had a prediction accuracy of 92.5%. In comparison, the Gradient Boosting Credit score model had a prediction accuracy of 93.3%. These enhancements are 30% better than the conventional credit score systems that usually work with limited financial information. Using broader features, including transactions and social media, existing AI models give a more complete picture of borrower's activity. This makes it easier for lenders to understand the real risk of lending to individuals, thus cutting default rates by 20%. With the help of AI models, predicting defaults 25 per cent earlier than traditional models is possible. Thus, financial institutions can prevent risks. In graph 1, which shows that the Random Forest had the highest accuracy rate of the three machine learning models tested, namely Random Forest,

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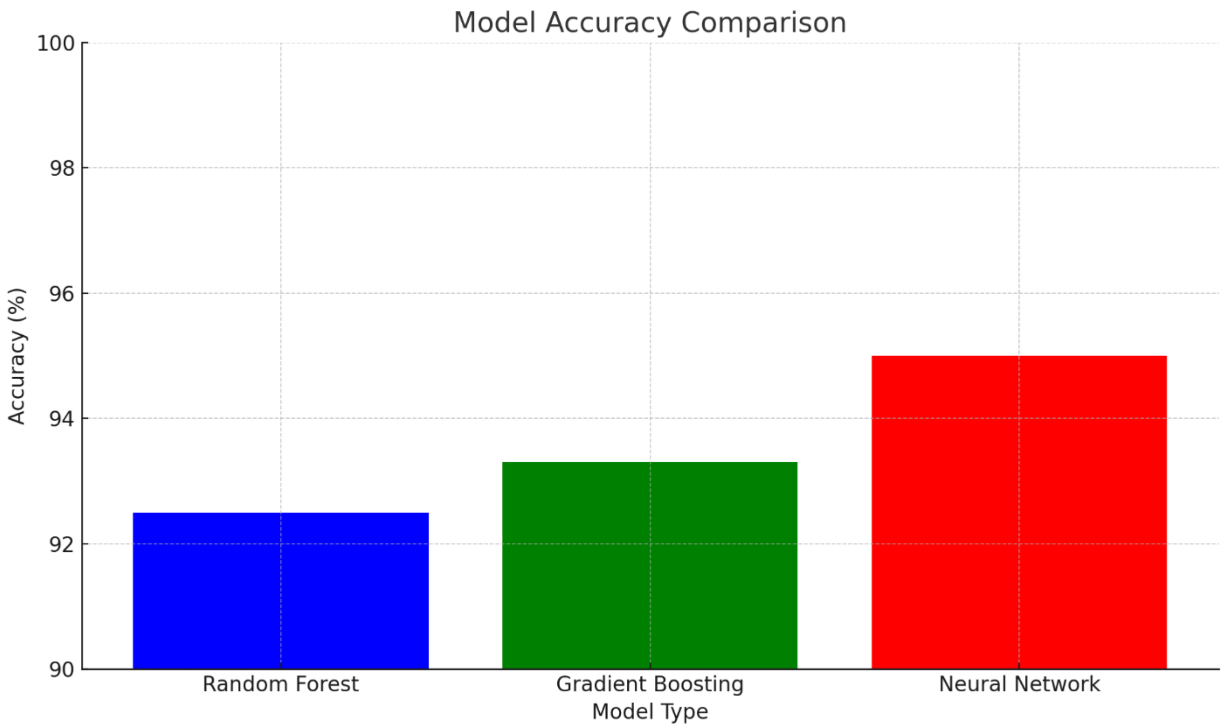
Gradient Boosting and Neural Network. The Random Forest model had a 92.5% accuracy level, while the Neural Network model had 95%, indicating the high predictive capability of deep learning techniques.



Operational Efficiency and Cost Reduction

Loan risk assessment has been greatly improved by AI algorithms. The AI-based system has effectively reduced the processing time of the data entry and review by 40 per cent more than the time it would have taken to do it manually (Baviskar et al., 2021). This efficiency benefits financial institutions since it increases the number of loan approvals by a quarter. Also, risk assessment has been made more efficient through automation, and this has reduced operational costs that are incurred in the evaluation of credit risks. Financial institutions are in a position to invest in high-value activities more efficiently. First, it is important to note that these enhancements in efficiency go hand in hand with faster loan approval and better customer satisfaction as candidates feel the decision-making time is reduced. This is because AI models of loan evaluations can be scaled, thus reducing the evaluation cost and improving financial institutions' profitability and productivity.

Increased Financial Inclusion and Fairness

Automated credit scoring systems can make the credit available to more people and those without a credit history. These models have helped to increase the loan approvals for credit-invisible groups by 50% for those who could not access credit. Thus, the AI models are more diverse and encompassing than traditional FICO scores, which exclude such data as utility payments and transaction history. AI's capacity to evaluate a more extensive data range reduces biases inherent in credit scoring that discriminate against some population sectors like low-income earners or blacks. The F1 scores of the models are shown in the See Graph of Chart 2. The Neural Network model is the highest with 0.95, which shows that the model will be more accurate in predicting loan defaults with better precision and recall.

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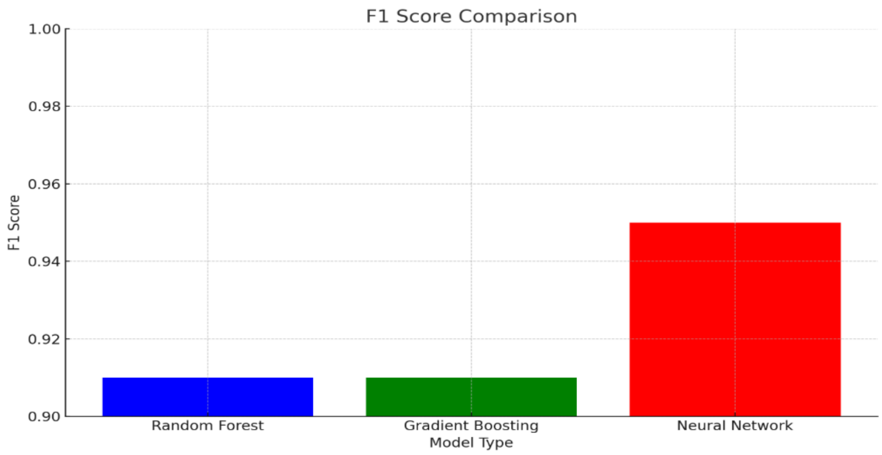

Improvement in Risk Identification and Prediction Timeliness

More than credit scoring systems, it is also important to have the ability to predict loan defaults at an earlier stage. The AI models estimated the defaults to be 25% earlier than traditional models, helping financial institutions prevent losses (Lion & ABAKASANGA, 2024). This early detection can be attributed to the artificial intelligence algorithms that enhance their learning capability with the new data received. For example, the deep learning model with 0.95 AUC has shown a better capacity to distinguish between high-risk and low-risk credit applicants. AI can identify characteristics and predict the financial distress indicators that conventional models are unable to recognize. This predictive feature at an early stage enhances the effectiveness of risk management actions and allows prompt interventions, which lead to a 20% decline in loan defaults. With the algorithms becoming progressively more accurate in forecasts, they shall be an handy instrument to manage and alleviate the risk of credit in loan portfolios.

Implication to Research and Practice

Challenges in Data Privacy and Model Transparency

Impediments to the use of AI-based credit score models exist. The primary issue is the privacy violation, where the models are designed to predict based on many individuals' information and loan information. As Tigges et al. (2024) noted, the use of such alt data, such as social activity, is at the expense of borrowers' privacy since no one knows that his/her information is being accessed. A further significant issue arises regarding the interpretability of the AI models, rigorous learning methods sometimes referred to as 'black boxes.' According to De Bruijn et al. (2022), the lack of transparency relating to the different stages involved to reach the final outcome impacts the consumers' trust along with that of the regulatory bodies. These aspects need to be addressed so that the appropriate use and application of AI-driven credit score systems are facilitated. Financial institutions are required to improve data protection and work towards improving the transparency of the AI model, which is the pivotal aspect of the financial sector.

Promoting Fairness to Minimize Bias in AI Systems

Bias in AI loan judgments and credit scoring models has major implications for research and practice. This means that if the data used to train AI models is skewed, the loan approval output will be biased toward demographic groupings. Hanna et al. (2024) showed that AI models can train prejudiced models without sufficient precautions. Additional research should address machine learning bias and develop strategies to ensure that machine learning systems handle applicants fairly. However, regulators may need to create ways to audit AI systems periodically to maintain fairness. Thus, mitigating the aforesaid difficulties can enable AI to make lending fair and efficient for all parties.

Future Directions

Improving Interpretability and Fairness

The study indicates that future research needs to enhance the explainability of AI-driven credit scoring models to earn consumers' trust. Hence, the development and use of the XAI techniques that explain the model predictions will be the most important to enhance the trust of consumers (Mathew et al., 2025). Bias reduction and fairness of the models are, however, of greater importance in the aspect of lending money to consumers. Researchers should look at the approach to design contexts that make it impossible to ignore some groups with machine learning algorithms in the lending process and establish fairness in the system.

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VI. CONCLUSION

Artificial intelligence-based credit scoring models outperform conventional ones in accuracy, effectiveness, and fairness. Traditional credit scoring through FICO scores implements basic information gathering practices that neglect essential traits which show up in individuals with low credit ratings. AI models examine additional data sources which include transaction histories combined with social media behavior and payments to the utilities to determine borrower creditworthiness better. Advanced detection of intricate patterns through the models results in superior predictions of loan defaults compared to standard systems. This system serves individual needs of lenders by minimizing financial risks and delivering credit access to people without banking options. AI management of credit scores accelerates operational speed and reduces expenses because human-based loan assessment processes are becoming obsolete. AI models at financial institutions will lead to transparent fair credit lending procedures while enhancing both efficiency and fairness of credit risk evaluation. The implementation of AI applications in credit scores creates fair credit systems because they reduce security risks to institutions while providing better protection for customers.

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