Artificial Intelligence & Machine Learning Models for Credit Scoring and Risk Management

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Abstract*—Credit risk management is an essential aspect of financial management for lenders and borrowers alike. This paper provides an overview of credit risk management, including its measurement and mitigation. The measurement of credit risk involves the use of proprietary risk rating tools and requires qualitative and quantitative techniques to rate the risk of business borrowers. Credit risk can be mitigated through credit structuring techniques, sensitivity analysis, and portfolio-level controls. Basel I, Basel II, and Basel III are rules made by the Basel Committee on Banking Supervision to ensure banks have enough money to cover any losses they might have. The traditional 5C model, the FICO scoring, VantageScore, decision trees, logistic regression, and neural networks are among the many of the credit scoring models addressed in the paper. Credit scores are calculated and risks are monitored using statistical models, credit scoring software, risk assessment tools, data visualization tools, and credit bureau reports. The combination of these analysis tools helps lenders and financial institutions identify patterns and trends, assess borrower creditworthiness, and mitigate credit risk. This paper highlights the importance of effective credit risk management in ensuring the financial stability of lenders and borrowers.*

Keywords – *Credit Scoring, Financial Risk, Artificial Intelligence (AI), Machine Learning (ML), Algorithm, Models.*

INTRODUCTION

Lenders use credit scoring as a tool to assess borrowers' creditworthiness. The term "credit" is used to describe a sum of money that a financial institution lends to a customer and that must be repaid, with interest, over time (Hand and Henley 2007). Based on information from your credit reports, a credit score predicts your credit behaviour, such as how likely you are to repay a loan on time. To assess a borrower's likelihood of timely debt repayment, numerous elements are examined, including credit history, payment history, income, and other financial data. Risk management is the procedure for identifying, evaluating, and minimizing any hazards connected to lending. In doing so, it is necessary to consider both the risks involved in lending to a specific borrower or group of borrowers as well as the larger economic and market risks that might have an effect on a lender's portfolio.

As one of the primary instruments used in the risk management process, credit scoring and risk management are closely related. By assessing a borrower's creditworthiness, lenders can more accurately gauge the risks involved in lending to that borrower and decide whether and under what conditions to give credit. For lenders to reduce their vulnerability to possible losses and keep a healthy loan portfolio, effective risk management is essential.

The use of quantitative modeling techniques in finance has become increasingly important in recent years, particularly in the wake of the 2008 financial crisis. However, it is important for financial institutions to be transparent about the assumptions and limitations of their models, in order to avoid false comfort about their accuracy. In addition, the rise of AI and machine learning methods in the industry has led to concerns about the lack of transparency and the "black box" effect of these techniques. Despite the potential benefits of AI in reducing model risk and improving predictive power, the lack of explainability remains a practical and ethical issue. The World Economic Forum has called for the development of minimum criteria for governance and control of AI in the banking and insurance sectors, including reliability of algorithms, models' explainability, and interactions between humans and intelligent algorithms. Overall, understanding and explaining the output of machine learning is becoming a top priority for banks and regulators in order to ensure transparency and reliability in financial modeling.

Therefore, traditional financial service companies and banks have begun to understand the importance of user experiences to build customer loyalty and improve their market share; thus, some of them have started acquiring or cooperating with fin-tech firms. The trend of using artificial intelligence and machine learning techniques by Fin-Tech firms has helped reshape customer relations, like customer contact, from traditional face-to-face contact to interactive contact using web systems where no human intervention is involved. Indeed, there are more use cases of artificial intelligence and machine learning in finance than ever before, from detecting client risk profiles or solvency to providing warning signals to traders about position risk in financial markets, and more.

LITERATURE REVIEW

Financial Technology industry funding has already reached new highs globally in 2018, with an increase of nearly 12 times from 2010 to 2018. In 2018, venture funding for African fintech startups increased by 51%, reaching $195 million, according to a report from Disrupt Africa (KPMG 2018). AI and ML have also increased efficiency and reduced the cost of labor in the financial industry. Automation of production processes has enabled companies to increase

their total output, and the use of robots has eliminated the need for breaks and refreshment, unlike human capital (He et al. 2018). For credit scoring, a crucial financial activity, both statistical and Artificial Intelligence (AI) algorithms have been investigated. Recent research indicates that integrating many classifiers, or ensemble learning, may have a superior performance, while there is no consensus on which is preferable (Wang et al. 2010). AI is transforming the financial services industry by generating and utilizing insights from data, leading to new business models and reshaping competitive environments. It enhances efficiency, reduces biases and errors, and improves management information. As algorithms and data volume increase, regulation becomes integral to managing risks and instilling trust in consumers. The future of machine learning in the banking and financial industry is well recognised, and it is expected that the field of risk management will also seek to apply machine learning techniques to enhance their capabilities (Leo, Sharma, and Maddulety 2019). The experimental results and statistical tests from (Marqués, García, and Sánchez 2012) show that the decision tree constitutes the best solution for most ensemble methods. Over the years, despite the innovations in the financial services sector credit risk still remains the most prominent reason for bank failure. For this reason, "more than 80% of the bank's balance sheet commonly relates to this aspect of risk management". The ultimate objective of credit risk management is to intensify the risk-adjusted rate of return by controlling and standardizing credit risk exposure (Oino 2016). Banks earn revenue through their primary lending business, and it is important for them to prioritize managing credit risk as it directly impacts their profitability. The Basel Committee on Banking Supervision (2001) defines credit risk as the probability of incurring losses, either in full or in part, due to risky loans. Banking companies also assess their business activities undertaken to know their profitability performance. CAMEL (Capital Adequacy, Asset Quality, Management, Earning and Liquidity) analysis is used by the banks to analyse financial performance. Banks adopt CAMEL model analysis to assess various kinds of risks and manage them effectively. Financial ratios have been long practiced by the researchers to evaluate the bank's financial performance. Banks use CAMEL ratings for examining their financial health and performance (Rostami 2015). In consumer credit risk modeling, a variety of prediction tasks occur. As per Basel II Capital accord, it is necessary for banks and other financial institutions to estimate: i) probability of default (PD); ii) exposure at default (EAD); and, iii) loss given default (LGD) (Trivedi 2020). (Bandyopadhyay 2006) concluded that by using „Z' score model banks and investors in emerging markets like India can get early warning signals about the firm's solvency status and reassess the magnitude of default premium they require on low grade securities.

DIFFERENT PERSPECTIVES OF CREDIT SCORING AND RISK MANAGEMENT

Credit risk management involves two main categories: measurement and mitigation.

Measurement:

Credit risk is measured by lenders using proprietary risk rating tools that vary by firm or jurisdiction. For personal lending, creditors assess the borrower's financial situation, including assets, liabilities, income, and credit history. Commercial lending is more complex and requires qualitative and quantitative techniques to rate the risk of business borrowers.

Mitigation:

Credit risk can be mitigated through credit structuring techniques such as collateral security, loan-to-value ratios, loan covenants, and amortization periods. Sensitivity analysis is also performed by changing variables in the proposed credit structure to assess the impact on credit risk. Additionally, portfolio-level controls such as monitoring credit types and risk scores of borrowers can be employed by financial institutions and non- bank lenders to mitigate credit risk.

(Oino 2016) In 2002, the Reserve Bank of India (RBI) released a directive on credit risk management, which was in line with international regulations. The implementation of Basel I was crucial in strengthening the financial system by addressing issues such as weak incentives and inadequate risk management practices. In light of this, Basel II was introduced to assess banks' inherent risk exposure and ability to adapt to financial innovations like securitization.

Basel I, Basel II, and Basel III are rules made by a group called the Basel Committee on Banking Supervision to make sure that banks have enough money to cover any losses they might have.

- ***Basel I,*** which was created in 1988 and required banks to have enough money to cover at least 8% of the risks they take on.
- ***Basel II,*** introduced in 2004, made the rules more complex and required banks to have enough money to cover all the different types of risks they face.
- ***Basel III,*** which was introduced in 2010, made the rules even stricter and required banks to have even more money set aside to cover risks. The goal was to make the banking system more stable and able to handle any big problems that might come up.

Credit Scoring Models: Most statistical credit scoring models employed today follow a similar pattern, combining quantifiable financial indicators of a company's performance with a small number of additional variables intended to capture qualitative aspects of the credit evaluation process.

Traditional model: The 5C model is a method used to evaluate the risk and creditworthiness of potential borrowers. It considers five main factors, referred to as the 5 C's: character, capacity, capital, collateral, and conditions (Treece and Tarver 2021).

→ Character refers to the borrower's reputation and credit history

→ Capacity evaluates their ability to repay the loan.

→ Capital refers to the borrower's financial resources

→ Collateral considers any assets that can be used as security for the loan.

→ Conditions evaluate the overall economic and industry climate that could affect the borrower's ability to repay the loan. Together, these factors are used to determine a borrower's creditworthiness and risk level.

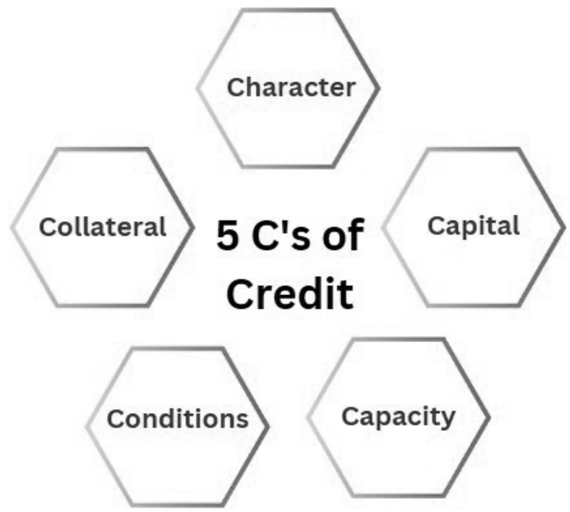

Fig. 1
5 C's of the credit scoring system

Although the 5C's model is a helpful framework for assessing a borrower's creditworthiness and risk, it is not a credit scoring model on its own. Nowadays, more complex credit scoring models that incorporate a greater range of data and variables have become more prevalent and are widely used by lenders and financial institutions. These models have largely replaced the 5C's model, but some lenders may still utilize certain elements of it, particularly when evaluating larger or more complicated loans. Advances in technology and the collection and analysis of data have led to the increased sophistication and prevalence of credit-scoring models in recent years.

➢ *The FICO Score* (FDIC, 2007) is a credit scoring model developed by the Fair Isaac Corporation and widely used to evaluate creditworthiness. It considers several factors such as payment history, credit utilization, credit history length, credit types used, and recent credit inquiries.

➢ *Vantage Score,* on the other hand, is a credit scoring model developed by Equifax, Experian, and

TransUnion. It uses machine learning algorithms to analyze a wide range of data, including payment history, credit utilization, credit age and mix, and recent credit behaviour. (FDIC, 2007)

- *Decision Trees* are a type of machine learning algorithm that evaluates creditworthiness based on factors such as income, employment status, credit history, and loan purpose, using a tree-like model.
- *Logistic Regression* is a statistical modeling technique that is often used for credit scoring. It identifies the relationship between factors such as income, credit history, loan amount, and the likelihood of default or delinquency.
- *Neural Networks* are another type of machine learning algorithm that analyzes large amounts of data using a complex network of nodes and connections to identify patterns and trends that can be used to predict credit risk.

  Factors that do impact your FICO Score fall into one of the following five categories. (Black 2022)

  → Payment History: 35%

  → Amounts Owed: 30%

  → Length of Credit History: 15%

  → New Credit: 10%

  → Credit Mix: 10%

EXPLORING THE TECHNOLOGIES WHICH ARE HELPFUL IN CREDIT SCORING AND RISK MANAGEMENT

The calculation of credit scores and risk management involves the utilization of various analytical tools, including statistical models, credit scoring software, risk assessment tools, data visualization tools, and credit bureau reports.

- Statistical models like logistic regression, decision trees, and neural networks are commonly employed to develop credit scoring models that predict the probability of a borrower defaulting on a loan or credit card.
- Credit scoring software, such as FICO score open access, Zoot, ScoreNet, etc., automates the credit scoring and risk management process by utilizing diverse data sources to calculate credit scores and assess risk.
- Risk assessment tools, such as Value at Risk (VaR) and Monte Carlo simulations, aid in identifying and evaluating risks in a borrower's financial profile, estimating potential losses in a portfolio or investment based on specific risk levels.
- Data visualization tools, such as Tableau, Power BI, and QlikView, facilitate the analysis and presentation of complex data in visual formats, allowing for the identification of patterns and trends in borrower data.
- Credit bureau reports collect and maintain data on borrowers' credit histories, such as payment records, credit utilization rates, and account balances, providing lenders and other institutions with vital information to assess a borrower's creditworthiness and manage risk.

Overall, a combination of these analysis tools is used to evaluate a borrower's creditworthiness and manage risk, with the specific tools used depending on the lender or institution and the data available.

Artificial intelligence (AI) and machine learning (ML) have transformed the financial industry in several ways. AI and ML have provided businesses with the ability to process large amounts of data, analyze market trends, and make informed decisions. One of the major breakthroughs in AI has been natural language processing and vision recognition, which has enabled companies to automate production processes and provide highly accurate computations and reports automatically.

AI and ML have been instrumental in helping businesses gain a competitive edge through cost reduction and increased efficiency. AI software can quickly analyze web data and provide feedback. Machine learning has also found applications in fintech, such as personalized investment plans, fraud detection, and risk management. Machine learning is the mathematical aspect of AI that enables machines to learn and improve from data without explicit programming. Data scientists manually identify and test data, and human decision-making guides the application of the information provided.

Machine learning is a growing field that utilizes data, computers, and algorithms to learn and make predictions. There are two main types of machine learning:

- Supervised: In supervised learning, input data is used to predict a well-defined output.

- Unsupervised: In unsupervised learning, the goal is to extract useful information or trends from input data.

A newer type of machine learning called **reinforcement learning** combines elements of both. Supervised learning is further divided into two categories:

- Regression, which involves predicting quantitative variables. In credit scoring, historical data is used with regression algorithms to establish a relationship between input features (e.g. credit history, income, employment status) and the likelihood of loan default. The regression model uses this relationship to predict the probability of future loan default.
- Classification, which involves predicting qualitative variables with class values. In Credit scoring, classification means predicting whether a customer is likely to default on a loan or not based on their financial history, credit score, and other relevant features.

Examples of classification problems include credit risk assessment and predicting churn or attrition rate. Understanding the different types of machine learning can aid in selecting the appropriate algorithm for a given problem, as machine learning is a powerful tool for data analysis and prediction.

In credit scoring, banks use credit scores to assess a customer's creditworthiness based on numerical scores. However, some banks still rely on outdated statistical models, which may not be as accurate or adaptable. Regression algorithms have been commonly used due to their interpretability, but the limitations of using a single model like logistic regression are becoming apparent with the emergence of new machine learning algorithms.

MACHINE LEARNING ALGORITHMS USED FOR CREDIT RISK MANAGEMENT

Logistic Regression:

A classification algorithm used to predict the probability of a binary outcome. Commonly used in credit risk modeling to predict loan default likelihood based on credit history and financial data. (Tyagi 2022)

Decision Tree:

A tree-like model used for classification and regression. It splits the dataset based on significant features to determine the outcome. Commonly used in marketing to identify target audience based on demographic data. (Trivedi 2020)

Linear Discriminant Analysis (LDA):

A statistical model for classification with multiple classes. Reduces dimensionality of dataset to maximize separation between classes. Commonly used in image classification. (Tyagi 2022)

Quadratic Discriminant Analysis (QDA):

Similar to LDA, but allows for non-linear decision boundaries. Captures complex relationships between features and classes. Commonly used in medical research for disease diagnosis based on patient data. (Trivedi, 2020)

Random Forest (RF):

Creates multiple decision trees in the forest, and the prediction for an unseen sample is obtained by averaging the predictions from all the trained individual decision trees on that sample. By creating multiple estimators, the influence of over-fitting is reduced. (Trivedi 2020)

Neural Network (NN):

It is a mathematical model of how the brain functions. It receives external information in the first layer, and neurons in the input layer send signals to the hidden layer. By adding more hidden layers, the number of layers can increase. NNs have been used in many financial prediction studies since the 1990s and have higher accuracy than conventional statistical techniques like LDA, QDA, logistic regression, etc. (Tyagi 2022)

Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. Each decision tree is trained on a random subset of the training data and a random subset of features. The final prediction is made by aggregating the predictions of all the decision trees. Random Forest is a highly scalable algorithm and can handle large datasets with high dimensionality. It is also robust to noisy data and missing values.

On the other hand, ***Neural Networks*** are a set of algorithms that are modeled after the structure of the human brain. They consist of an input layer, one or more hidden layers, and an output layer. Each layer contains a set of neurons that perform a specific function. Neural Networks are highly flexible and can learn complex patterns in the data. They are widely used for image recognition, natural language processing, and speech recognition.

Compared to Random Forest, Neural Networks can handle more complex data structures and can learn more complex relationships between the features and the target variable. However, they require a lot of computational resources and can be difficult to train. In addition, Neural Networks are more prone to over fitting, which can lead to poor generalization performance on new data.

ISSUES AND CHALLENGES

Credit risk assessments are critical for banks to avoid losses. Adopting AI and ML models can help banks improve risk management and credit value chain. These technologies enable efficient analysis of large data sets, dynamic risk profile adjustments, and improved accuracy over time through machine learning. These models can also present only the final insights, reducing the need for manual data analysis and minimizing human expertise requirements. Starting from the initial underwriting process to risk measurement and analysis, until deciding on the final maximum exposure. Some of the key use cases that would be addressed are:

Fig. 2
Credit Risk assessment processes

Assessing Risk for Individual Customers

Traditional analytical models may not accurately predict loan defaults due to the over- representation of non-defaulters in the data. Machine learning models like Artificial Neural Networks can address this by creating diverse datasets that reflect the actual distribution of good and bad customers. This allows for more accurate predictions of default likelihood, helping banks make better lending decisions.

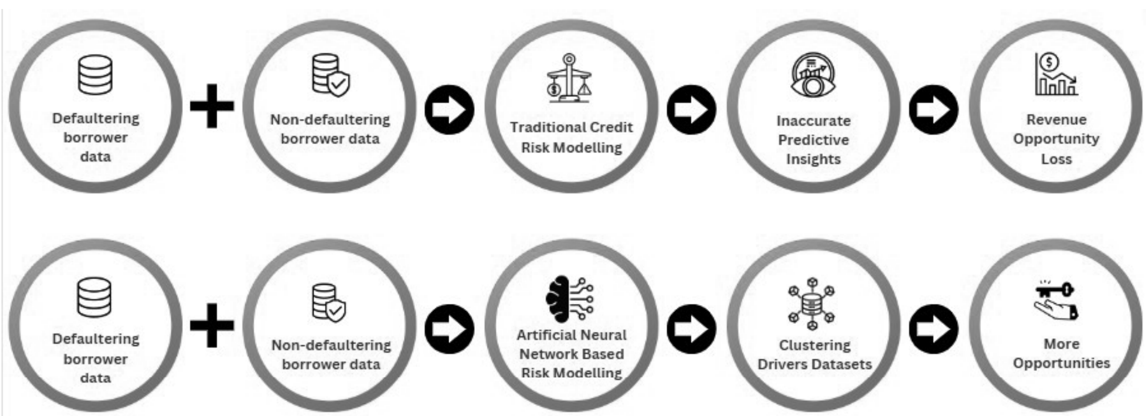

Fig. 3
How machine learning models lead to better revenue opportunities

Machine learning techniques, such as AI and ML, can reshape credit risk analysis by providing advantages over conventional statistical models. ML models can adapt and learn from data,

rather than relying on predefined instructions, which makes them more flexible and accurate. The ML model continuously analyzes new data to extract insights and generate predictions on fresh datasets, leading to a cyclical process that improves the accuracy of credit analysis over time.

CONCLUSION

The fintech industry has witnessed tremendous growth in recent years, largely due to increased funding and advancements in AI and ML technologies. The use of these technologies has revolutionized credit scoring, leading to increased efficiency and reduced costs. However, there is no one-size-fits-all approach, and traditional credit scoring models still coexist with AI and ML approaches. As these technologies continue to evolve, regulatory considerations and managing risks will be critical. Future research should focus on examining the impact of variables on credit scoring, exploring more advanced statistical models, and reducing the black box nature of AI and ML models to enhance reliability. Overall, the future of AI and ML in banking and finance is promising, but it will require further research and innovation to advance credit risk management practices in the industry.

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