

ENHANCING CREDIT RISK MANAGEMENT IN THE BANKING SECTOR THROUGH MACHINE LEARNING-BASED PREDICTIVE MODELS

ALI K. ABDUL RAHEEM¹, MAYS ZUHAIR²

¹University of Warith Al-Anbiyaa, Kerbala, Iraq.

²University of Warith Al-Anbiyaa, Kerbala, Iraq.

E-mail: ¹ alialmujab@uowa.edu.iq, ² mays.mangoshi@uowa.edu.iq

ABSTRACT

Credit risk plays a vital role in the functioning of the banking sector, as banks extensively engage in providing loans, credit cards, mortgages, and other financial products. However, the increasing number of credit card users has led to a rise in credit card default rates, posing challenges for banks. To address this issue and effectively control credit risk, leveraging data analytics becomes crucial. This study aims to predict loan defaults, enabling banks to proactively mitigate potential losses by offering alternative options to borrowers. To achieve this objective, we propose a system that utilizes various machine learning classification algorithms. Specifically, we explore and compare the performance of Logistic Regression, XGBoost, k-Nearest Neighbors, Neural Network, and Random Forest models in predicting credit risk. Our findings reveal that the Random Forest model demonstrates exceptional accuracy, with a forecast accuracy of 98% in assessing the credit risk of credit card users.

Keywords: *Credit Risk; Machine Learning; Prediction; Risk Management; Deep Learning.*

1. INTRODUCTION

One of the key sources of Big Data nowadays is digital financial services. In reality, processing 14 trillion financial transactions per day has increased the global payments industry's earnings in recent years. Financial operations' credit risk assessment challenge, which includes operations backed by social lending platforms, is typically described as a binary classification problem based on the repayment of loan. Credit risk assessment is essential for helping financial institutions develop their banking policies and business plans. [1].

When commercial banks and other financial organizations provide loans to potential clients or borrowers, credit risk has long been seen as a critical element. Therefore, accurate credit risk evaluation models are crucial for loss prevention and revenue growth [2]. Creating credit scoring models using machine learning (ML) techniques has become popular due to the advancement of

ML algorithms and the acquisition of a significant quantity of multidimensional consumer data [3].

In the fields of finance and credit risk, the development of AI and machine learning is becoming increasingly significant. AI seeks to replicate human intellect and thought processes through mathematical modeling methods. The world of finance and credit risk is changing as a result of the creation of new models and algorithms in machine learning, one of the disciplines of AI. Credit risk is being created and utilized with new machine learning approaches. Because credit risk requires the acquisition of data that must be carefully analyzed, validated, and processed, machine learning is very helpful. According to Gui [4], it is crucial for financial organizations to establish a risk prediction model so they can recognize and forecast the traits of people who have a higher likelihood of defaulting on loans. Again Gui [4] indicated robust machine learning models are critical as they allow not only banks but even the clients to be able to know the

behaviour that may damage their credit scores. A study by Breeden [5] highlighted that machine learning is now dominating many industries and is increasingly being applied in credit scoring and credit risk management. [5] indicated that the use of machine learning techniques comes with risks so the research now should focus on how to use machine learning models in a regulatory-compliant business context. The work highlighted a range of machine learning methods and their application in areas of credit risk through a survey.

Credit risk is a critical concern in the banking sector due to its far-reaching implications for financial stability and profitability. With the primary business of banks revolving around granting loans, credit cards, mortgages, and other financial products, the ability to accurately assess and manage credit risk becomes paramount. In recent years, the proliferation of credit card usage has led to a notable increase in credit card default rates, posing substantial challenges for banks.

The rising number of credit card users and subsequent default rates have underscored the significance of developing effective strategies to address credit risk in the banking industry. The potential financial losses resulting from defaulting borrowers not only impact individual banks but also have broader implications for the stability of the financial system as a whole. Consequently, there is an urgent need to identify innovative approaches that can enhance credit risk management and mitigate potential losses.

In this context, data analytics and machine learning techniques have emerged as promising tools to tackle the complexities associated with credit risk. Leveraging the vast amounts of available data, these techniques offer the potential to uncover patterns, detect early warning signals, and provide valuable insights into borrowers' creditworthiness. By harnessing the power of predictive models, banks can proactively identify borrowers at a higher risk of default and take appropriate measures to prevent potential losses.

The aim of this study is to contribute to the advancement of credit risk management by developing and evaluating machine learning-based predictive models. By forecasting the likelihood of loan defaults, banks can gain valuable insights to make informed decisions and offer alternative options to borrowers, thereby reducing potential losses. To achieve this, we

employ a range of machine learning classification algorithms, including Logistic Regression, XGBoost, k-Nearest Neighbors, Neural Network, and Random Forest.

By effectively addressing credit risk in the banking sector, we not only safeguard the interests of individual financial institutions but also contribute to the overall stability and resilience of the economy. The findings of this study can potentially assist banks in enhancing their risk management practices, reducing financial vulnerabilities, and improving the allocation of resources.

The supervised ML algorithms are used in credit scoring models to find the relationship between the customer features and credit default risk and then predict the default classification usually in a binary format. In a large body of literature, the implementation of supervised ML algorithms in credit scoring models has shown good predictive accuracy [6].

In recent years, the advent of data analytics and machine learning techniques has revolutionized the field of credit risk management. These advanced approaches leverage large volumes of structured and unstructured data to uncover hidden patterns, identify risk factors, and make accurate predictions. A growing body of literature highlights the effectiveness of machine learning algorithms in credit risk assessment, particularly in improving predictive accuracy and reducing false positives and false negatives.

in Soui et al. (2019) a credit risk evaluation model based on multi-optimization strategy produced a set of classification rules aiming, on one hand, to minimize the complexity of the generated solution, and, on the other hand, to maximize weights representing rules importance [7].

Chow (2017) also used different machine learning techniques to learn the relationship between the company's current state and its fate. The results indicated that it was possible to achieve 95% accuracy using machine learning techniques compared to the use of pure financial factors to do the prediction on whether a company will be bankrupt or not. Using the pure financial factors, the correlation was not strong compared to machine learning methods [8].

islam et al. have studied Application of Artificial Intelligence (Artificial Neural Network) to Assess Credit Risk using Predictive Model for Credit

Card Scoring. The authors have concluded that credit decisions are better than judgmental decisions. The outcomes of the study show that neural network gives slightly better results than discriminant analysis and logistic regression [9]

Li Xin et al. (2018) applied BackPropagation neural network model to empirically evaluate the credit evaluation of P2P online loan borrowers. The results show that the model has good feature extraction and knowledge discovery ability. When there is virtual information index in the borrower evaluation index system It can still make a more accurate judgment on the credit risk of borrowers and has a strong ability to evaluate and predict [10].

Building upon the existing literature, this paper aims to address the gap in comprehensive comparative analyses of machine learning algorithms for credit risk prediction. Specifically, we focus on credit card users and evaluate the performance of multiple classification algorithms, including Logistic Regression, XGBoost, k-Nearest Neighbors, Neural Network, and Random Forest. By examining the effectiveness and accuracy of these models in credit risk assessment, we aim to provide valuable insights for banks and financial institutions operating in diverse international settings.

2. CREDIT RISK MANAGEMENT

Risk analysis is a methodical study of uncertainties and risks in business, engineering and other areas. Institutions such as Banks and investment firms are dealing with various risks in a day to day basis. Risk management in Banks is to quantify the financial risks involved in each investment, trading and allocate a risk budget across all activities by computing risk score (value at risk) and ensure that banks are in a non-risk zone. According to the Reserve Bank of India (RBI) guidelines issued in Oct. 1999 risk can be identified and categorized into three major categories.1

- Credit Risk: Borrower has failed to make payments or reimburse a loan when it is due.
- Market Risk: Encompasses the risk of financial loss resulting from movements in market prices.
- Operational Risk: Prospect of loss resulting from inadequate or failed procedures, systems or policies.

Credit risk management is a very important area for the banking sector. The banks which have large customers need to have variety of loan products. In terms of equity, a bank must have considerable amount of capital on its reserve, but not too much that it misses the investment revenue, and not too little that it leads itself to financial insecurity and to the risk of regulatory non-compliance. Credit risk management is risk assessment that comes in an investment. Risk often comes in investing and in the allocation of capital. The risks must be assessed so as to develop a sound investment decision and decisions should be made by balancing the risks and returns. Offering loans is a risky situation for bank sometimes and certain risks may also come when banks offer securities and other forms of investments. The risk of losses that result in the default of payment of the debtors is a kind of risk that must be expected. Credit risk management plays important role to help banks be in compliance with Basel II Accord and other regulatory bodies. For assessing the risk, banks should plan certain estimates, conduct monitoring, and perform reviews of the performance of the bank. They should also do Loan reviews and portfolio analysis in order to determine risk involved [11].

3. MACHINE LEARNING

The use of machine learning tools and techniques has broadened to include a wide range of applications [12]. A machine learning algorithm is a computational process that uses input data to achieve a desired task without being literally programmed (i.e., “hard coded”) to produce a particular outcome. These algorithms are in a sense “soft coded” in that they automatically alter or adapt their architecture through repetition (i.e., experience) so that they become better and better at achieving the desired task. The process of adaptation is called training, in which samples of input data are provided along with desired outcomes. The algorithm then optimally configures itself so that it cannot only produce the desired outcome when presented with the training inputs, but can generalize to produce the desired outcome from new, previously unseen data. This training is the “learning” part of machine learning. The training does not have to be limited to an initial adaptation during a finite interval. As with humans, a good algorithm can practice “lifelong”

learning as it processes new data and learns from its mistakes.

There are many ways that a computational algorithm can adapt itself in response to training as shown in figure 1. The input data can be selected and weighted to provide the most decisive outcomes. The algorithm can have variable numerical parameters that are adjusted through iterative optimization [13]. It can have a network of possible computational pathways that it arranges for optimal results. It can determine probability distributions from the input data and use them to predict outcomes [14].

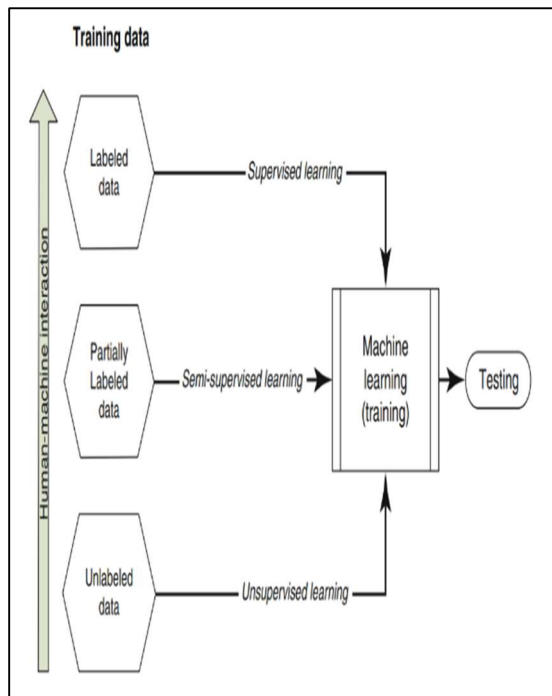


Figure 1: Machine learning techniques

A- Logistic Regression

Logistic regression is a useful model when the researcher must test response variable of categorical nature to obtain binary outcome just like in this assignment the results are expected to either be Yes or No in relation to default payment [15].

B- Random Forest

Random forest is the most popular algorithm, namely, it assembles a large

amounts of decision trees from training dataset, and it also uses a tool called bagging to perform classification and regression tasks. Each decision tree represents a class prediction, this method collects the votes from these decision trees and the class with most votes is considered as the final class [16].

C- K-nearest neighbors (k-NN)

K-nearest neighbors (k-NN) is an algorithm somewhat different from the others in the sense that the data itself provides the "model." To predict a new record, it finds the nearest neighbors by computing the Euclidean distance and then performing a weighted average or majority vote to obtain the final prediction. It works well for cases of relative low dimensionality with complicated decision boundaries [17].

D- XGBoost

XGBoost is an advanced GBDT. Due to its outstanding performance, XGBoost is a winning solution to many ML competitions. Compared with the original GBDT, XGBoost makes some modifications to enhance the prediction accuracy further. Instead of the loss function used in GBDT, XGBoost targets to optimize an objective function composed of a loss function and a regularization term [18].

E- Neural Network

artificial neural networks (ANNs) has become popular and helpful model for classification, clustering, pattern recognition and prediction in many disciplines. ANNs are one type of model for machine learning (ML) and has become relatively competitive to conventional regression and statistical models regarding usefulness [19]. ANNs full applications can be evaluated with respect to data analysis factors such as accuracy, processing speed, latency, performance, fault tolerance, volume, scalability and convergence [20, 21].

4. METHODOLOGY

The proposed models, as shown in Figure 2, goes through several steps in order to predict whether

the borrower will default on the loan or not. If so, the bank may be able to prevent the loss by providing the customer with alternative options. The proposed system uses various machine learning classification techniques to perform this analysis and prediction. This paper compares machine learning models, i.e. Logistic Regression, k-Nearest Neighbors, XGBoost and Random Forest, and Neural Network.

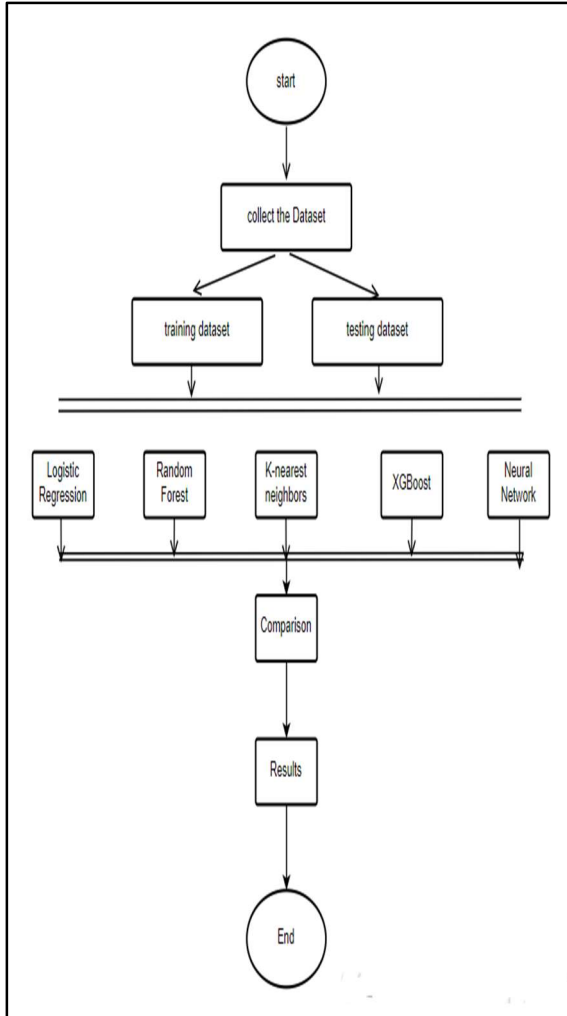


Figure 2: Main tasks of the proposed solutions

We are utilizing a dataset from Kaggle that includes information on 32,581 borrowers and 12 factors specific to each borrower. Here are some examples of those variables:

Age — numerical variable; age in years

Income — numerical variable; annual income in dollars

Home status — categorical variable; “rent”, “mortgage” or “own”

Employment length — numerical variable; employment length in years

Loan intent — categorical variable; “education”, “medical”, “venture”, “home improvement”, “personal” or “debt consolidation”

Loan amount — numerical variable; loan amount in dollars

Loan grade — categorical variable; “A”, “B”, “C”, “D”, “E”, “F” or “G”

Interest rate — numerical variable; interest rate in percentage

Loan to income ratio — numerical variable; between 0 and 1

Historical default — binary, categorical variable; “Y” or “N”

Loan status — binary, numerical variable; 0 (no default) or 1 (default) → this is going to be our target variable

after loading the dataset, the dataset need to be treated for different reasons. such as: Remove outliers, Convert label data to numerical data, However and the id column will be removed as it has no use in this study. One of the common data splitting range according to past literature is the ratio of 80:20. The 80 % is allocated to the training and the remaining 20% for validation on the test data. This proportion has approved to be a good one as researchers showed that it makes classification model better and the test data makes the error estimate more accurate. For this assignment. The 80:20 ratios are applied to split the dataset.

5. EXPERIMENTAL RESULTS AND ANALYSIS

In this paper we will use A classification report to show the results.it is a performance evaluation metric in machine learning. It is used to show the precision, recall, F1 Score, and support of your trained classification model. There are four ways to check if the predictions are right or wrong:

- TN / True Negative: the case was negative and predicted negative
- TP / True Positive: the case was positive and predicted positive

- FN / False Negative: the case was positive but predicted negative
- FP / False Positive: the case was negative but predicted positive

$$\text{Recall} = \text{TP}/(\text{TP}+\text{FN})$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

Support is the number of actual occurrences of the class in the specified dataset.

The paper presented the performance evaluation of various machine learning algorithms for credit risk prediction. The results indicate that Logistic Regression achieved an accuracy of 81%, with a precision of 0.81 and a recall of 0.98 for the positive class. However, the recall for the negative class was relatively low at 0.18, resulting in an F1-score of 0.29. The k-Nearest Neighbors algorithm performed slightly better, with an accuracy of 83% and improved recall for the negative class (0.31), resulting in an F1-score of 0.44. XGBoost showed the highest accuracy of 95% and achieved excellent performance in terms of precision and recall for both classes, with F1-scores of 0.97 and 0.88, respectively. Random Forest also demonstrated strong performance, with an accuracy of 99% and high precision, recall, and F1-scores for both classes. However, the Neural Network algorithm exhibited limitations in predicting the positive class, with a precision and recall of 0.00. Overall, the results suggest that XGBoost and Random Forest are promising techniques for credit risk prediction, achieving high accuracy and balanced performance across multiple evaluation metrics. Further optimization of the Neural Network model may be required to improve its predictive capabilities.

The results of five models of machine learning by using classification report as in next table:

	Precision	Recall	F1-score	Support
0	0.81	0.98	0.89	4462
1	0.74	0.18	0.29	1237
Accuracy			0.81	5699
Macro average	0.77	0.58	0.59	5699
Weighted average	0.80	0.81	0.76	5699
k-Nearest Neighbors				
	Precision	Recall	F1-score	Support
0	0.81	0.97	0.90	4462
1	0.77	0.31	0.44	1237
Accuracy			0.83	5699
Macro average	0.80	0.64	0.67	5699
Weighted average	0.82	0.83	0.80	5699
XGBoost				
	Precision	Recall	F1-score	Support
0	0.94	1.00	0.97	4462
1	0.99	0.79	0.88	1237
Accuracy			0.95	5699
Macro average	0.97	0.89	0.92	5699
Weighted average	0.95	0.95	0.95	5699
Random Forest				
	Precision	Recall	F1-score	Support
0	0.99	1.00	0.99	4462
1	1.00	0.95	0.98	1237
Accuracy			0.99	5699
Macro average	0.99	0.98	0.98	5699
Weighted average	0.99	0.99	0.99	5699
Neural Network				

Table 1: classification report for the proposed solutions

Logistic Regression

	Precision	Recall	F1-score	Support
0	0.78	1.00	0.88	4462
1	0.00	0.00	0.00	1237
Accuracy			0.78	5699
Macro average	0.39	0.50	0.44	5699
Weighted average	0.61	0.78	0.69	5699

Table 2: Accuracy of the proposed solutions

Models	Accuracy
Random Forest	0.9898
XGBoost	0.9517
k-Nearest Neighbors	0.8301
Logistic Regression	0.8078
Neural Network	0.7829

6. CONCLUSIONS

Credit Risk Prediction is one of the main challenges in finance sector for supporting people in their investments. Nevertheless, different challenges are faced to banking lending with respect to the traditional ones. The proposed system uses various machine learning classification techniques to perform this analysis and prediction. several machine learning models applied in this problem, i.e. Logistic Regression, k-Nearest Neighbors, XGBoost and Random Forest, and Neural Network. We used Precision, Recall, F1 and Accuracy to evaluate the models' performance at predicting class labels. The results show that random forest best prediction with an accuracy of 98% when assessing the credit risk of credit card customers while the other results for Logistic Regression, k-Nearest Neighbors, XGBoost and Neural Network are 80%, 83%, 95%, 78% respectively.

List of Pending Issues and Future Research Directions:

- **Enhancing Interpretability:** While machine learning models, such as Random Forest, demonstrate high predictive accuracy in credit risk prediction, their interpretability remains a challenge. Future research can focus on developing techniques to improve the transparency and interpretability of these models,

enabling stakeholders to understand the factors driving credit risk predictions.

- **Handling Imbalanced Datasets:** Imbalanced datasets, where the number of defaulting borrowers is significantly lower than non-defaulting borrowers, can impact the performance of credit risk prediction models. Future research can explore methods to effectively handle imbalanced datasets, such as oversampling, undersampling, or employing advanced ensemble techniques, to improve the accuracy of predicting credit risk for minority classes.

- **Incorporating Unstructured Data:** The analysis in this study primarily focuses on structured data variables for credit risk prediction. However, there is a wealth of unstructured data available, such as social media data or text-based information, which can provide valuable insights into borrowers' creditworthiness. Future research can investigate methods to incorporate and analyze unstructured data sources to enhance the predictive power of credit risk models.

- **Robustness to Changing Economic Conditions:** Credit risk is highly influenced by economic conditions, and models trained on historical data may not generalize well to future economic scenarios. Future research can explore methodologies to develop credit risk models that are robust and adaptive to changing economic conditions, allowing banks to make informed decisions even in volatile market environments.

- **Incorporating Domain Knowledge:** While machine learning models excel at identifying patterns and relationships in data, they may not capture the full complexity of credit risk factors. Future research can focus on integrating domain knowledge and expert insights into credit risk models to improve their predictive performance and align them more closely with the banking sector's specific requirements.

- **Generalizability to Diverse Banking Systems:** The current study focuses on credit risk prediction within a specific banking system. However, credit risk profiles can vary across different countries, cultures, and financial systems. Future research can explore the generalizability of machine learning models to diverse banking systems, considering the nuances and specific characteristics of each context.

- **Real-Time Risk Monitoring:** Traditional credit risk assessment often relies on periodic

evaluations, which may not capture sudden changes in borrowers' creditworthiness. Future research can explore the development of real-time risk monitoring systems that continuously analyze data and provide timely alerts to banks, enabling proactive risk management and mitigating potential losses.

- Ethical and Fair Credit Risk Assessment: Machine learning models used for credit risk assessment must be designed to ensure fairness and avoid bias against certain demographic groups. Future research can focus on developing fair and ethical credit risk models that consider factors such as algorithmic bias, transparency, and fairness, promoting responsible and inclusive lending practices.

- Addressing these pending issues and exploring future research directions will contribute to the ongoing advancements in credit risk prediction using machine learning, making it more accurate, interpretable, and applicable to diverse banking systems and contexts. By working on these open issues, researchers can make valuable contributions to the field and address the evolving challenges in credit risk management.

DECLARATION:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process.

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

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Conflict of Interest:

Conflict of Interest is not applicable in this work.

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All authors are contributed equally to this work

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