The Prediction of Non-Performing Loans Using Artificial Intelligence - A literature Review

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Abstract

The profitability and stability of financial institutions are seriously threatened by Non-Performing Loans (NPLs), hence precise prediction of these loans is crucial for efficient risk control. This paper studies the development of prediction approaches, from statistical methods to Machine Learning (ML) and more recently, deep learning models in predicting Non-Performing Loans. Machine Learning models have shown more accurate results at spotting non-linear patterns than statistical methods, but they still struggle to analyze sequential or unstructured datasets efficiently. Results obtained by this paper showed that although machine learning methods such as Support Vector Machines and Decision Trees produced consistent results, deep learning techniques, especially Artificial Neural Networks (ANN), particularly show consistently better accuracy over a spectrum of applications. By evaluating recent prediction approaches, this study emphasizes the necessity of utilizing deep learning techniques to handle the changing complexities of credit risk assessment, particularly the prediction of Non-Performing Loans (NPLs) in financial institutions.

Keywords: Non-Performing Loans, Statistical Methods, Machine Learning, Deep Learning, Datasets.

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التنبؤ بالقروض المتعثرة باستخدام الذكاء الاصطناعي – مراجعة الأدبيات

الملخص

تتعرض ربحية واستقرار المؤسسات المالية لتهديد خطير بسبب القروض المتعثرة (NPLs)، وبالتالي فإن التنبؤ الدقيق بهذه القروض أمر بالغ الأهمية للسيطرة الفعالة على المخاطر. تدرس هذه الورقة تطوير مناهج التنبؤ، من الأساليب الإحصائية إلى التعلم الآلي (ML) ومؤخراً، نماذج التعلم العميق في التنبؤ بالقروض غير المؤدية. أظهرت نماذج التعلم الآلي نتائج أكثر دقة في اكتشاف الأنماط غير الخطية من الطرق الإحصائية، لكنها لا تزال تكافح لتحليل مجموعات البيانات المتسلسلة أو غير المنظمة بكفاءة. أظهرت النتائج التي حصلت عليها هذه الورقة أنه على الرغم من أن طرق التعلم الآلي مثل آلات ناقلات الدعم وأشجار القرار أنتجت نتائج متسقة، إلا أن تقنيات التعلم العميق، وخاصة الشبكات العصبية الاصطناعية (ANN)، تُظهر بشكل خاص دقة أفضل باستمرار على مجموعة من التطبيقات. ومن خلال تقييم النهج الحديثة للتنبؤ، تؤكد هذه الدراسة على ضرورة استخدام تقنيات التعلم العميق للتعامل مع التعقيدات المتغيرة لتقييم مخاطر الائتمان، ولا سيما التنبؤ بالقروض المتعثرة في المؤسسات المالية.

الكلمات الرئيسية: القروض المتعثرة، الطرق الإحصائية، التعلم الآلي، التعلم العميق، مجموعات البيانات.

Introduction

The process of loan prediction is a common concern that all financial organizations encounter during their lending operations. A loan approval process that is automated has the potential to increase the pace of service and save a significant amount of time for consumers. The reduction in operational costs and the increased levels of consumer satisfaction are both of importance to the financial sector. On the other hand, the advantages can only be realized if the bank has a reliable model that can accurately predict which loans from consumers should be approved and which should be rejected, thereby reducing the risk of Non-Performing Loans (NPLs).

Financial stability is threatened by large or rising stocks of non-performing loans in the banking industry. The question of how well future events may be accounted for is raised by the potentially dire effects of an accumulation of non-performing loans for the economy. This question is obviously significant for policymaking as well as academics. Machine learning techniques were implemented in numerous studies to assist financial institutions in resolving the issue of non-performing loans and loan faults. [1]

Nevertheless, the accuracy of the model is impacted by the challenge inherent in each technique applied to the dataset used. After the introduction of deep learning techniques in recent years, researchers began to employ them. In the past decade, there has been a significant focus on deep learning. To enhance machine learning techniques on numerous levels, numerous deep learning techniques have been developed. A deep learning algorithm is a particular type of neural network that represents the various levels. This means that higher levels of features are responsible for performing more aspects of abstract data. This research enhances the expanding literature on the utilization of deep learning in financial risk management. By illustrating the efficacy of Artificial Neural Networks (ANNs) in forecasting NPLs, it establishes a basis for subsequent study and practical use within the financial sector.

1. Literature Review

The literature examined in this paper focuses on the studies held from the years 2019 to 2024 and consists of a wide spectrum of scholarly publications offering fundamental understanding of the topic of non-performing loans (NPL) prediction and associated developments in artificial intelligence. Reputable journals including the Journal of Economic Studies, IEEE, International Research Journal of Modernization in Engineering Technology & Science, Indonesian Journal of Electrical Engineering and Computer Science, Indian Scientific Journal of Research in Engineering and Management, International Journal of Advanced Research in Science, Communication & Technology, Journal of Forecasting, and the International Journal of Machine Learning and Computing have provided the chosen works.

From engineering, technology, and computational developments to economic and financial predictions, these publications together address a wide range of subjects. Starting from conventional statistical methods to machine learning and deep learning approaches, this overview emphasizes the development of approaches employed in NPL prediction by synthesizing results from several sources. This thorough investigation emphasizes the multidisciplinary character of the topic and its increasing importance in both theoretical and pragmatic spheres.

The prediction of non-performing loans, often known as NPLs, has emerged as an important subject of research due to the enormous implications it has for the management of institutional risk and the stability of the financial system. Non-performing loans, also known as non-performing loans, are loans for which the borrower is unable to meet their repayment commitments. These loans have the potential to affect the profitability and operational efficiency of financial institutions, which could ultimately lead to wider economic ramifications.

With the ability to accurately predict Non-Performing Loans (NPLs), lenders can reduce risks, maximize resource allocation, and remain in compliance with regulatory requirements. Over the course of the last twenty years, researchers have investigated a wide range of approaches to enhance the precision and dependability of NPL prediction. In the beginning, statistical models were the most prevalent in the industry, and they provided fundamental insights into credit risk assessment. Despite this, machine learning (ML) and deep learning approaches have emerged as revolutionary tools, capable of identifying complex patterns in borrower behavior and financial data. These techniques have emerged because of breakthroughs in computers and data science.

In this literature review paper, the focus is on the utilization of non-performing loans prediction, credit risk assessment, statistical models, machine learning, deep learning, artificial intelligence, borrower behavior, financial data analysis, and risk mitigation strategies. Additionally, an in-depth analysis of scholarly contributions from the years 2000 to 2019 is provided. The important themes and approaches that were covered throughout the review are generally reflected in these terms.

Kumbhar et al. (2024), The suggested methodology made use of a Random Forest Classifier Ensemble Learning model on a Two-wheeler Motorcycle Indian Dataset to improve credit risk assessment in a comprehensive manner, particularly for those who are the sole proprietors of their own businesses. To give loan amount estimations together with risk considerations, credit line forecasts that incorporate ensemble learning on random forest are being applied. This is accomplished by considering bank records or other pertinent financial data. This article examined credit scoring for self-employed individuals with a Random Forest Classifier Ensemble Learning model to improve credit risk evaluation. Although it may not directly pertain to non-performing loans, precise credit scoring can indirectly assist in forecasting such loans. Credit risk assessment accuracy reached 87%. In addition to improving credit risk assessment and loan amount predictions, it addresses the difficulties that individuals who are self-employed experience when attempting to demonstrate their capacity to repay loans.[2]

Meenakshi (2024), this study suggested the creation of a novel loan recommendation system that can be implemented. Loan recommendation systems that are both accurate and transparent are required in today's modern financial environment because of the landscape. There are typical constraints in terms of efficiency and transparency that are associated with conventional evaluation procedures, which can result in potential dangers for both lenders and borrowers. By utilizing the capabilities of machine learning (ML) and explainable artificial intelligence (XAI). This work focused on Explainable AI and machine learning loan recommendation systems. It underlines improving loan eligibility forecasts and openness by using several ML techniques and XAI approaches including LIME. However, certain limitations were highlighted including the lack of efficiency and transparency in conventional assessment procedures and that there is possibility of risk for both the lenders and the borrowers.[3]

Abhishek et al (2023), developed a Loan Prediction System (LPS) that uses machine learning to evaluate creditworthiness, which may be tailored for forecasting non-performing loans, Applicants for loans are evaluated using the Loan Prediction System, which is a sophisticated financial instrument that employs machine learning and data analytics to determine whether they are considered creditworthy. Through the examination of a wide range of data points, including applicant demographics, credit history, and sources of income, the LPS generates comprehensive profiles for the purpose of conducting comprehensive risk assessments. Through the process of continuously learning from previous data, the system can adjust to the ever-changing political and economic realities. Furthermore, the LPS makes use of AI models that are open to scrutiny, which helps to cultivate confidence between lenders and applicants while simultaneously simplifying the process of loan approval and contributing to a reduction in operational expenses for financial institutions.so improving risk assessment and supporting financial inclusion. The random forest algorithm attains the highest performance, as evidenced by experiments, with an F1 score of 87%, precision of 84%, recall of 90%, and random forest algorithm accuracy of 87%. The logistic regression model also exhibits satisfactory performance, with an F1 score of 84%, precision of 80%, recall of 89%, and accuracy of 84%.[4]

Mohamed et al (2023), this research made use of several machine learning approaches. It is possible to exert control over nonperforming loans, which play a significant part in the overall performance of financial institutions, by making predictions about the likelihood of nonperforming loans occurring. To anticipate the amount of bank nonperforming loans that will be placed on the financial institutions in emerging countries, The paper showed that advanced machine learning methods, especially the random forest model, effectively forecast nonperformance loans in banks from emerging nations with 76.10% accuracy. In predicting, it stresses bank-specific factors, particularly diversification, above macroeconomic ones. restricted to the financial institutions of developing countries of the world. In the process of predicting nonperforming loans, macro factors contribute less significantly.[5]

Suraya et al (2023), The purpose of this work was to give an empirical evaluation of a variety of Machine Learning (ML) algorithms for forecasting Non-Performing Loans (NPLs). NPLs, which stands for non-performing loans, are a serious challenge that is being confronted by financial institutions all over the world. This challenge is also known as the problem of non-performing loans. Corruption, which has been linked to the issue of non-performing loans (NPLs), has emerged as one of the issues that has been identified as a contributing cause. Considering the limited amount of study that has been carried out on the application of machine learning techniques to investigate the connection between corruption and Non-Performing Loans (NPLs), this solution has been implemented. This research contained an analysis of the value of machine learning characteristics in addition to comparisons of machine learning performance. The purpose of this research is to justify the effect of corruption factors on the various machine learning algorithms for forecasting Non-Performing Loans (NPLs). The study assessed multiple machine learning algorithms for forecasting Non-Performing Loans (NPLs), revealing that the majority attain an accuracy exceeding 70%. The random forest algorithm surpassed others, however, the corruption index exerted no influence on model performance. Limitations therefore include that the corruption index has a negligible impact on the way machine learning works. Hence, more research is required on the various machine learning algorithms.[6]

Hazar, Altinbas and Hanişoğlu (2023), In Turkey, there has been a growing trend in the amount of non-performing loans in recent years, which has caused stress in both the real estate and financial sectors since the beginning of this year. Increasing volumes of loans that are non-performing are a sign that there are problems in certain industries or in the economy. There is also a strong connection between it and the stability of the banking system. Since this is the case, it is essential for regulatory and supervisory institutions, as well as banks, to possess the capability to accurately forecast problematic loan levels, as this will facilitate improved policymaking and management. This research predicted non-performing loans in Turkey by machine learning techniques, particularly random forests and boosted trees, utilized data from 2003 to 2019. It integrated macroeconomic, bank-specific, and uncertainty variables to analyze their correlations with non-performing loans. Results showed partial dependencies and positive link between inflation, interest rate and capital adequacy ratios, negative relationship with credit to gross domestic product ratio and non-performance loans.[7]

Yash et al (2023), Within the context of banking systems, banks offer a wide variety of items for sale; nonetheless, the credit line is the primary source of revenue for any bank. As a result, they can generate income from the interest on the loans that they credit. When it comes to loans, whether a bank makes a profit, or a loss is to a significant measure determined by whether the customers are paying back the loan or defaulting on it. A reduction in the bank's Non-Performing Assets can be achieved through the process of forecasting loan defaulters. As a result, the investigation of this phenomenon is of utmost significance. It has been demonstrated by previous research conducted in this age that there is a great deal of approaches to investigating the issue of controlling loan default. However, because accurate forecasts are of utmost significance for the purpose of maximizing profits, it is of the utmost importance to investigate the nature of the various methodologies and investigate how they compare them to one another. One of the most significant methods in the field of predictive analytics is the Logistic regression model, which is utilized in the investigation of the problem of predicting loan defaulters. For the purposes of analysis and forecasting, the data is gathered through the Kaggle platform. The research explored forecasting loan defaulters with machine learning, specifically logistic regression, which examines a variety of consumer factors. Banks can reduce non-performing assets and make more informed lending decisions by precisely identifying probable non-performing loans. The optimal precision achieved on the initial dataset is 0.811. The conclusions indicate that candidates with the lowest credit scores are unlikely to receive loan approval due to a heightened risk of defaulting on repayment. [8]

Chioma et al (2023), The research investigated non-performing loan prediction utilizing explainable ensemble and deep neural network techniques, highlighting many factors that influence loan performance. Ensemble algorithms can learn complex nonlinear correlations in huge datasets, which results in higher predicted accuracies than the approaches that are traditionally used. Since they require explanation, practitioners and regulators have demonstrated a significant amount of reluctance in implementing them in the field of credit risk management. They evaluated indicators to forecast asset quality deterioration in a consumer loan dataset by utilizing five ensemble learning approaches and a one-dimensional convolutional neural network.

They utilized the SHAP framework to ensure explainability of the models' ranking of features relevance. These approaches improved forecast accuracy and provided insights into the factors influencing loan defaults in financial institutions. The SHAP framework solved the problems of how to rank aggregate features and performance evaluation metrics when using different machine learning methods on the same dataset.[9]

Ramaraju et al (2023), One of the most important factors that determines whether a bank makes a profit, or a loss is regarding loans, specifically whether the clients of the bank are paying back the loan or defaulting on it. The bank can lower the amount of non-performing assets by assessing the amount of loans that are past due.
Because of this, this study is of utmost significance regarding this issue. Several studies that have been conducted in this era have demonstrated that there are a great number of approaches to the problem that may be utilized to manage the default rate on loans. As a result of the fact that accurate predictions are of utmost significance to maximize the goods, it is of utmost importance to investigate the nature and structure of the various approaches and to compare them. To gain a better understanding of the challenges associated with identifying loan defaulters, two significant advancements in predictive analytics have been implemented: (i) the collection of data; (ii) the cleaning of data; and (iii) the evaluation of performance. This research emphasized the need of accurate predictions to reduce loan defaults, the research explores employing machine learning techniques forecasting non-performance loans. It shows how better the Naïve Bayes model forecasts loan delinquency than other techniques Among the features that were utilized as inputs for the model that was developed were features such as the applicant's gender, marital

status, qualifications, information regarding dependents, annual income, loan amount, and credit history.[10]

Binh and Thuan (2022), One of the most significant items that banks and other financial organizations offer is loans. Every single institution is working hard to discover efficient business tactics that will encourage a greater number of customers to submit loan applications. However, due to circumstances beyond their control, certain clients are unable to repay the loan after it has been accepted. When deciding whether to grant a loan, numerous financial organizations and banks have taken into consideration several cases. This paper predicted loan repayment using machine learning techniques more especially, Logistic Regression, Decision Tree, and Artificial Neural Networks were discussed in this article [11]. The dataset utilized in this study was sourced from www.lendingclub.com. The dataset comprises 37,066 loans recorded from January 2018 to September 2020. This paper addresses the issue of selecting predictor variables in classification tasks. Logistic regression, decision trees, and genetic algorithms are some of the methods that are utilized in this approach. The method also comprises the phases of data collecting, data preprocessing, data analysis, and model construction. It shows how complicated it is to ascertain borrower repayment capacity and use an ensemble learning model to get an accuracy of 84.68%.

Lin Zhu et al. (2019), P2P online lending platforms have recently offered opportunities to businesspeople because of the advancement of electronic commerce and big data technology. However, at the same time, these platforms are also confronted with the risk of user loan default, which is related to the development of platforms in a way that is both sustainable and healthy. Since this is the case, the purpose of this article is to construct a loan default prediction model using the Random Forest method, taking into consideration the actual loan data that is available on Lending Club. To address the issue of an imbalanced class in the dataset, the SMOTE approach is utilized. Following this, several operations, including data cleaning and dimensionality reduction, are carried out. This paper used the Random Forest Algorithm to build a model for predicting loan default. For the first quarter of 2019, the Lending Club provided the dataset that was utilized. It includes around 115,000 original loan records from users with 15 different qualities. According to Lin Zhu et al., random forests have substantially higher accuracy (98%) than other techniques such as support vector machines (75%), decision trees (95%), and logistic regression (73%). To attain the state-of-the-art performance of the model, studies on larger data sets or adjusting the model in future research is recommended.[12]

Supporting the agriculture industry and markets requires giving out agricultural loans to private citizens. The idea of credit risk is one of the most significant hazards influencing the banking industry. For banks to reduce credit risk and make the best choices, predicting an individual's likelihood of non-performing loans is an essential and advantageous function. These choices are based on customer demographic information, loan payment history, and credit analysis that comply with generally accepted standards. An ensemble-based model was proposed in this paper to improve classification accuracy. Elnaggar et al. (2020) predicted non-performing loans using an Egyptian credit dataset comprising 112,907 occurrences and 17 variables. In this study, classification techniques like logistic regression (LR), k-Nearest Neighbours (KNN), support vector machines (SVM), decision trees (DT), and meta classifiers have been applied to the dataset for training and testing purposes. The results show that the accuracy of the ensemble approach is preferable to all other methods [13]

Credit risk estimation and the risk evaluation of credit portfolios are crucial to financial institutions which provide loans to businesses and individuals. Non-performing Loan (NPL) is a loan type in which the customer has a delinquency; because they have not made the scheduled payments for a time period. NPL prediction has been widely studied in both finance and data science. In addition, most banks and financial institutions are empowering their business models with the advancements of machine learning algorithms and analytical big data technologies.Serengil et al. (2022) used a customer portfolio from a Turkish private bank to deploy a variety of machine learning methods to create NPL prediction models, dealt with a class imbalance problem using class weights Several performance measures, including precision, recall, F1 score, imbalance accuracy (IAM), and specificity, have been assessed using a sizable dataset of 181,276 samples. The results show that, for the dataset, the light gradient boosting machine (LightGBM) outperformed the logistic regression, support vector machine (SVM), random forest (RF), bagging classifier, eXtreme gradient boosting (XGBoost), and long short-term memory (LSTM) [14]

By a significant margin, the most important activity in retail banking is lending. While most loans are repaid in full and within the allotted period, there are some loans that are defaulted on because the borrower does not adhere to the repayment plan. These latter loans, which are usually referred to as Non-Performing Loans (NPLs), have been the focus of concern for European authorities in recent years. This is because many banks continue to struggle with the situation of disposing of those debts that emerged on their balance sheets during the financial crisis. Banks are encouraged by authorities to pool their non-performing loans (NPLs) and sell them to specialist investors, such as debt collection agencies, to reduce the risk of impairment losses and worries over the soundness of the financial system. Bellotti et al. (2019) examine the outcomes of a wide range of regression techniques and machine learning algorithms for predicting recovery rates on nonperforming loans using a proprietary database from a European debt collection company. The outcomes demonstrate that rule-based algorithms outperform alternative strategies by a large margin, including cubist, boosted trees, and random forests. Besides the specificities of loan contracts, the indicators related to the bank recovery procedure before the transfer of portfolios to debt collectors were also shown to significantly improve forecasting performance. [15]

Bhargav and Sashirekha (2023) compared machine learning techniques for loan approval prediction using unique Random Forest classifiers. For accuracy and loss testing, loan prediction datasets from the Kaggle library were used. In a sample of 20 cases, the RF technique outperformed the standard Decision Tree with 67.28% precision and 32.71% loss, achieving 79.44% precision and 21.03% loss. A p-value of 0.33 from statistical analysis using an independent sample T-test indicates that, with a level of certainty of 95%, there are no significant differences between the methodologies. According to this study, RF outperformed Decision Trees in predicting loan acceptance. One of the limitations of the model that has been proposed is that it is mostly classified based on a limited number of attributes, which is utilized for generating the loan approval prediction. Both the employees of the bank and the applicants stand to benefit from the ability to predict loan amounts. It is the responsibility of the loan risk system to automatically identify the weight of each loan processing characteristic, and the same characteristics are processed on new test data. [16]

For the success of financial institutions, nonperforming loans, often known as NPLs, are of the utmost importance. Being able to effectively estimate them is vital since they can have a substantial impact on the profitability and stability of a bank. It is emphasized in this study that good forecasting methodologies are required to better manage non-performing loans and reduce financial risk. Abdullah et al. (2023) used a variety of machine learning approaches to forecast nonperforming loans in financial institutions in developing nations. Advanced machine learning models, particularly random forest, outperformed linear techniques with 76.10% accuracy while analysing data from 322 banks in 15 different countries. When it came to predicting nonperforming loans, bank diversification prevailed over macroeconomic conditions as the primary predictor. The result is highly reliable across a variety of performance parameters. The variable importance analysis finds that the most important factor in determining whether a bank will have further nonperforming loans in the future is the bank's level of diversity.[17]

The measurement of credit risk and the risk assessment of credit portfolios are extremely important for financial organizations that offer loans to consumers and businesses. Non-performing loans, also known as NPLs, are a type of loan in which the borrower has a delinquent. This is because they have not made the payments that were planned for a certain amount of time. In both the field of finance and the field of data science, NPL prediction has been the subject of extensive research. Furthermore, the majority of banks and other financial institutions are enhancing their business models by utilizing the latest developments in machine learning algorithms and analytical big data technology. Sefik et al (2022) predicted non-performing loans (NPL) with artificial intelligence, employing machine learning algorithms such as LightGBM, XGBoost, and LSTM to evaluate customer data, tackle class imbalance, and improve prediction accuracy using metrics like Precision, Recall, and F1 Score, combined with explainability tools like SHAP and LIME. Additional research will be conducted on these benchmarked algorithms using other sampling techniques on which in some cases might yield improved results.[18]

In the lending industry, it can be challenging to generate reliable estimates of loan defaults. The lending companies suffer a considerable loss because of the large amounts of money that are owed as loans. Using a model that can categorize a loan instance as either defaulted or completely paid, the paper investigates the phenomenon of loan default in the context of online peer-to-peer lending. Ebenezer et al (2022) presented a Deep Neural Network model for online peer-to-peer lending loan default prediction. They used Adaptive Synthetic Sampling (ADASYN) to balance the dataset, it attains a prediction accuracy of 94.1%. However, the study only took into consideration the categories of completely paid and default loans; it did not take into consideration risky loans. The result implied that the models we utilized are effective in boosting the accuracy of their forecast of loan default. Therefore, additional research about the latter category is required to be carried out to evaluate its behavior.[19]

In response to the growing significance of non-performing loans (NPLs) in the secondary market, the European Institution decided to regulate transactions, which revealed some characteristics that are distinct from those of the main market for NPLs. A new regulatory framework might be able to address the issue of doing adequate due diligence to support investment options in non-performing loan portfolios. In the context of secured Non-Performing Loans (NPLs), due diligence can have a critical impact on the profitability of a firm, beginning with the sale of the NPLs on the secondary market and continuing through the dispute resolution process for recovery action. Carannante et al (2024) used a random forest regressor to forecast recovery rates and alleviate informational asymmetry. The study investigates the use of machine learning to evaluate the profitability of Non-Performing Loans (NPLs) in the secondary market. The goal of the paper is to improve the transaction price for secured NPLs. By valuing the dangerous component of informational asymmetry between better-informed banks and possible investors for higher quality, collateralized NPLs, evaluation method employed helps to lower the "lemon discount".[20]

Ankur and Rao (2023), emphasized on the significant role that the banking sector plays in India's financial system, with particular attention paid to the significance of the industry in terms of money transactions, credit distribution, and payment habits. Having a robust financial system is necessary for both the expansion and maintenance of the economy. The research study made the observation that although the banking industry has witnessed an increase in the number of loans and advances, there has also been a notable decrease in key performance measures such as Net Profits, Return on Assets (ROA), and Return on Equity (ROE) as a result of the increasing number of nonperforming assets (NPAs).This paper used machine learning techniques including Naïve Bayes, Support Vector Classification, and Random Forest to forecast credit risk, the study examines non-performing assets (NPAs) in Indian banking sectors from 2008 to 2019, obtaining accuracy of 86%, 97%, and 100%, respectively. Secondary research was the primary method of data gathering. This study was based on financial performance data that was available in the public domain, such as Annual studies, Analysts Presentations, and/or any other research studies on prominent banks that were available to the public. [21]

Banks and other types of financial institutions compete with one another for consumers by offering a diverse selection of products and services. Most banks, on the other hand, derive the vast majority of their revenue from their credit portfolio. Borrowers who accept loans may be subject to interest charges on those loans. The loan portfolio, and the repayment patterns of clients in particular, can have a significant impact on the bottom line of a financial institution. It is possible for the financial institution to lower its Non-Performing Assets if it is able to precisely identify which borrowers are most likely to default on their loans. Consequently, there is a significant amount of academic value in investigating the prediction of loan endorsement. Lavanya et al (2022) asserted that it is possible for machine learning to effectively anticipate non-performing loans by examining the characteristics of borrowers and their repayment histories. This can assist financial institutions in reducing their Non-Performing Assets. Because of this predictive power, risk assessment is improved, and the processes for loan approval are made more efficient, which ultimately benefits both banks and borrowers. For predicting loan recognition, machine learning was utilized. Preprocessing the data, completing the missing values, and doing a preliminary analysis of the data are the first steps in the prediction procedure.[22]

Alvi, Jahanzaib et al (2024), The purpose of this study was to provide a comprehensive analysis of a considerable corpus of high-quality research articles on Default Prediction Models (DPM) that were published between the years 2015 and 2024. A wide spectrum of techniques, such as Textual Models, Systematic Review Studies, Hybrid Models, Intelligent Models, and Statistical Models, were all included in this complete analysis of DPM. This study was prompted by the urgent requirement to reduce and get a better understanding of the credit default risk, which is a substantial danger to the integrity of the global financial system. With the help of a methodologically rigorous approach and an evidence-based approach, this research provides a critical analysis of the gaps, efficacy, and evolution in the DPM approaches that are now in use. It was conducted as there is a crucial need to minimize and comprehend the credit default risk that poses a substantial danger to financial stability all over the world, it discussed the intelligent model used for default prediction, which only includes Machine Learning and Deep Learning (ML and DL). Intelligent models used for financial predictions include Artificial Neural Networks (ANN) and Deep Learning models, which are popular and have high accuracy estimates. (75 to 85% and 80 to 90%, respectively). Machine Learning, Random Forest, and Support Vector Machine (SVM) approaches achieve high accuracies within ranges (e.g., SVMs at 78-86%). Gradient Boosting achieves an astonishing 85-95% accuracy. Validation techniques like ROC Curve Analysis and Area Under Curve (AUC) Analysis confirm the great performance of deep learning models, with ROC analysis suggesting accuracy of up to 95%. [23]

Technique Used	Count of Research Papers	Estimated Accuracy	Evaluation/Validation Technique	Estimated Accuracy
Artificial Neural Networks (ANN)	12	75–85 %	Cross-Validation	Varies with model
Deep Learning	15	80–90 %	ROC Curve Analysis	80–95 %
Machine Learning	10	70–85 %	Confusion Matrix	Varies with model
Random Forest	8	80–88 %	Precision-Recall Analysis	75–90 %
Support Vector Machine (SVM)	11	78–86 %	Area Under Curve (AUC) Analysis	85–95 %
Logistic Regression	9	70–80 %	Holdout Method	70–85 %
Decision Trees	10	72–82 %	Bootstrapping	75–90 %
Gradient Boosting	10	85–95 %	K-Fold Cross-Validation	80–90 %
Ensemble Learning	9	77–87 %	Leave-One-Out Cross-Validation	Varies with model
Deep Belief Networks	10	83–93 %	F1 Score Analysis	78–88 %

Table 1: Intelligent Model [24]

Danovi et al,(2022).The purpose of this study project, which consisted of four phases, was to determine whether or not a loan screening application that was based on machine learning (5D) could identify bad loans. The outcomes with a sensitivity of 0.91, a prevalence of 0.0253, and a positive predictive value of 0.19, 5D were able to accurately identify 1,461 defective loans out of a total of 1,613 exposures. Additionally, it was able to correctly classify 55,866 exposures out of the remaining 62,150 exposures with a specificity of 0.90 and a negative predictive value of 0.997. Explanation of terms Our first findings lend credence to the concept that applications based on artificial intelligence that utilize Big Data and Advanced Analytics have the potential to reduce bias and enhance consumer protection throughout the loan screening process, all without compromising the efficiency of the credit risk assessment.[24]

Karmakar A (2023), The purpose of this research was to investigate, analyze, and build a machine learning model that is capable of accurately determining whether an individual is likely to default on a loan based on specific characteristics. This kind of use of machine learning algorithms can be of assistance to banks and other financial institutions in identifying financial features of prospective borrowers. These qualities may signal that the borrower is at risk of defaulting on their loan and failing to repay it within the allotted amount of time. The first step in this prediction process is data cleaning and processing, which includes filling in missing values and doing experimental analysis of the dataset. Next comes model development, which is followed by evaluation of the models that have been constructed throughout this phase. The Random Forest Classifier achieves the highest level of accuracy for our dataset, which is almost 92%. This is followed by the Support Vector Machine, which achieves 89%, the Decision Tree, which achieves 85%, and Logistic Regression, which achieves 83%.[25]

Authors Names	Data set	Techniques	Results
Lin Zhu et al. (2019),	Cases=115,000	Random Forest	Accuracy= 98%
		Support Vector Machine	Accuracy= 75%
		Decision Trees	Accuracy= 95%
		Logistic Regression	Accuracy= 73%
Elnaggar et al. (2020)	Cases=112,907 Variables=17	Decision Tree	Accuracy= 80.4%
		Support Vector Machine	Accuracy= 87.9%
		Logistic Regression	Accuracy= 87.9%
		Majority Voting	Accuracy= 88%
		K-Nearest Neighbors	Accuracy= 87.4%
		Bagging	Accuracy= 88%
Binh and Thuan (2022)	Cases= 37,066	Ensemble Learning Model	Accuracy= 84.68%
Danovi et al. (2022)	Cases= 63,763	5D Ml System	Accuracy=90%
Karmakar A (2023)	Cases=3,000,000 Features=11	Random Forest Classifier	92%
		Support Vector Machine	89%
		Decision Tree	85%
		Logistic Regression	83%
Abdullah et al. (2023)	322 banks from 15 emerging countries	Random forest model	Accuracy= 76.10%
Serengil etal. (2021)	Cases=181,276 samples	LightGBM	AUC=0.85
		Logistic Regression	AUC=0.7
		Random forest	AUC=0.87
		Support Vector Machine	AUC=0.73
		Bagging Classifier	AUC=0.81
		Xtreme gradient boosting	AUC=0.84

		Long short-term memory	AUC=0.83

Table 2: Survey for the Comparison between literature Reviews.

2. Research Gap & Discussion

The literature review of Artificial Intelligence (AI) in the process of predicting Non-Performing Loans (NPLs) results in the emergence of significant discoveries within the domain of financial risk management. The purpose of this paper is to highlight major themes, consequences, and prospects for future research by synthesizing findings from a variety of scientific works. Initially, the review highlights the significant role that artificial intelligence plays in improving the accuracy and efficiency of non-performing loan prediction models. Solutions that are powered by artificial intelligence offer scalability, versatility, and the capacity to handle massive volumes of financial and behavioral data. This enables financial institutions to perform risk assessments that are more effective and informed. Research highlights the ways in which artificial intelligence technologies, like Machine Learning (ML) and deep learning, offer tools that enable the identification of loans that are at risk in real time, hence facilitating proactive intervention measures.

The limitations of classic Machine Learning (ML) techniques have been addressed by the development of Deep Learning Models, which have quickly become a powerful tool for predicting Non-Performing Loans (NPLs). The extraction of meaningful patterns from financial data is a process that can be labor-intensive and prone to oversight. Machine learning algorithms such as logistic regression or decision trees sometimes rely on considerable feature engineering to accomplish this. The ability of artificial neural networks (ANNs) for instance to handle raw, high-dimensional datasets and automatically understand complicated correlations between variables is a strength of these network types. A major improvement in predicted accuracy is brought about by their capacity to simulate complex and non-linear connections between borrower variables, loan features, and repayment patterns. Through the utilization of Artificial Neural Networks (ANNs), researchers and financial institutions can improve their ability to recognize early warning indications of loan default, thereby opening the way for more efficient risk management measures.

The ability of Artificial Neural Networks (ANNs) to extract meaningful characteristics directly from raw data is one of the most significant advantages of employing ANNs for NPL prediction. Financial datasets frequently include a variety of data kinds, including numerical values, category labels, and even textual information. Conventional machine learning algorithms have difficulty processing these datasets in their totality because of the mixed data types. Artificial neural networks (ANNs), and Deep Neural Networks (DNNs) in particular, can process these various data types without any problems, thereby revealing underlying patterns that have the potential to be overlooked by traditional methods. The application of specialized artificial neural network architectures, such as Convolutional Neural Networks (CNNs) for image-based borrower documentation or Natural Language Processing (NLP) techniques for analyzing textual financial records, could be the focus of future research. This would allow for a more comprehensive understanding of borrower profiles.

3. Future Work

Financial datasets frequently include sequential information, which is essential for predicting Non-Performing Loans (NPLs). Examples of this type of information include previous repayment records or borrower transaction histories. In most cases, traditional machine learning models only examine static snapshots of data, which means they overlook important temporal correlations. When it comes to Non-Performing Loans (NPL) prediction, one of the most persistent challenges is the inherent class imbalance in datasets. This occurs when the number of performing loans significantly exceeds the number of non-performing loans. Due to this imbalance, traditional machine learning models may make biased predictions since they may give priority to the class that is in the majority. Artificial Neural Networks (ANNs) offer robust methods to overcome this issue. Some examples of these mechanisms include cost-sensitive learning, synthetic data generation using GANs (Generative Adversarial Networks), and data augmentation approaches. Artificial Neural Networks (ANNs) make use of these technologies to guarantee that minority classes, such as non-performing loan situations, are accurately forecasted and effectively represented. It is possible that future research may concentrate on enhancing these methodologies to create balanced and trustworthy risk evaluations in financial datasets that are currently uneven.

Moreover, Traditional machine learning techniques may have difficulty scaling efficiently due to the enormous size of financial datasets, which present computational problems those techniques face. Artificial neural networks (ANNs), which are designed to process vast amounts of data in an effective manner, can harness the computational power of modern hardware such as Graphics Processing Units (GPUs) and Tetrahedral Processing Units (TPUs) to train models on extensive datasets. The scalability of this system is especially advantageous for financial institutions that operate in many locations, as the evaluation of borrower risk requires a wide variety of data in large quantities. For handling such large-scale predictions in a smooth manner, future study might place an emphasis on the development of distributed artificial neural network frameworks and cloud-based neural network implementations.

Conclusion

Traditional statistical approaches were the primary means by which financial firms initially evaluated the credit risk of their customers. A firm basis was provided by these methods, such as logistic regression and linear discriminant analysis, for the purpose of assessing structured data and gaining insights into the likelihood of loan default. Machine learning (ML) has emerged as a game-changing weapon in the field of Non-Performing Loan (NPL) prediction because of developments in technology and the availability of data. With the use of ML, the accuracy of credit risk models was greatly enhanced, which allowed financial institutions to identify possible non-performing loans with more precision. Nevertheless, machine learning models continue to rely significantly on structured data, and they frequently struggle with unstructured or high-dimensional data.

Deep learning and Artificial Neural Networks (ANNs) have become increasingly useful in recent years as a means of addressing the difficulties that have been presented. Instead of the usual machine learning techniques, Artificial Neural Networks (ANNs) are designed to handle high-dimensional, complicated data with minimal preprocessing. Deep learning models can automatically learn hierarchical representations of data because they are able to imitate the neuronal structure of the human brain. This allows them to recognize detailed patterns and correlations. As a result of this skill, they are very well adapted for non-performing loan prediction, which involves the complex and dynamic interaction of borrower behavior, loan attributes, and macroeconomic variables.

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