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A Review on Loan Approval Prediction Based on Machine Learning Techniques

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Abstract

The banking industry has also benefited greatly from technological advancements. An increasing number of individuals are submitting loan applications on a daily basis. When deciding which loan applicants to approve, the bank must take certain rules into account. The bank needs to choose the best one for approval based on certain characteristics. The process of carefully verifying every person and recommending them for loan approval is laborious and fraught with danger. Currently, machine learning is extremely popular. In today's technologically advanced society, there are machine algorithms for learning govern and manage almost all applications. After forecast whether a loan application will be approved or not, several ML models, often used for classification algorithms, are developed and evaluated in different tasks. This review investigates the key combination of machine learning approaches with loan approval prediction in the banking sector. The study uses supervised and unsupervised machine learning methods to create a prediction model based on a dataset of previous customers of banks. The study also thoroughly investigates the components of loan eligibility, the sorts of risks encountered in the banking industry, and the numerous classification methods used. This detailed analysis adds to a better understanding of the complex interactions between machine learning and loan processes within the banking sector.

Keywords: Loan approval, banking sector machine learning, classification methods

INTRODUCTION

A bank's main activity is making loans. Profit is mostly generated by interest on loans [1, 2]. On the one hand, before approving a loan, banks determine whether the consumer is a defaulter or not. However, personal loans are offered to dependable clients as well, but in general, consumers refuse these loans, as seen in our dataset samples [3]. The banking sector has a significant challenge in predicting which customers would approve the personal loan because of this issue.

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Loan Forecasting is quite helpful for applicants as well as bank employees. This project aims to provide a simple, rapid method for selecting eligible applicants. All loan kinds are handled by Housing Financing Corporation. They can be found in every metropolitan, semi-urban, and rural area. After applying for a loan, the user's eligibility is verified by the bank or company. An organisation or bank wants to automate the loan qualifying process using data that customers provide on registration forms. Other information is provided, such as credit score, loan term, number of dependents, gender, family status, occupation, and income. According to a set of criteria, loans were approved for this project using data from previous bank customers. Because of this, the machine learning model, which is predicated on the random forest technique, learns from that record how to provide accurate results. Since the primary goal of this study is to forecast loan safety, the data is first processed to remove any inaccurate values from the information set before the algorithm is trained. Statistical and prospective methods produced by various machine learning algorithms may be used to make decisions [4].

The banking sector needs more precise predictive modelling systems for a number of issues [5]. Bank employees can create the models by hand, but it will take a lot of man-hours and time. These days, machine learning (ML) methods are quite helpful for making predictions when working with large volumes of data. Therefore, by using ML approaches, such models may be applied to the financial sector. Following that prediction model, if they can use machine learning to anticipate which customers would accept bank offers for personal loans, the loan approval procedure will be automated, saving banks a tonne of man-hours and enhancing customer service [6].

Teaching computers to learn without the need for predetermined, explicit rules is the goal of the AI subfield of ML. In contrast to rule-based systems that follow predetermined, explicit rules to accomplish any activity, ML systems learn from experience. More data exposed to the system means better performance. It picks up new skills and changes its approach on its own. Our project's main objective is to assess current customers' information using a few ML methods. Then, they will utilise this analysis to forecast which future loan applications will be accepted [7]. The following paper is organized as: "*Overview of Loans In Banking Industry*" and "*Factors Affecting Bank Loan*" provide the overview of loans in banking industry, types, risk, and Factors Affecting Bank Loan, next "*Machine Learning Algorithms*" provides the ML algorithms types for loan forecasting, The "*Classification Algorithms*" provide the classification techniques for a loan approval forecasting, after this "*Literature Review*" provides the literature review on loan approval prediction utilizing ML, and lastly, the "*Conclusion*" provides the conclusion of this paper and future work.

OVERVIEW OF LOANS IN BANKING INDUSTRY

The banking sector is a crucial component of any economy. Banks serve as intermediaries between savers and borrowers and are responsible for providing financial services to individuals, businesses, and governments. When it comes to banking services, loans are among the most crucial. Loans are essential for the growth of the economy. They give the people and small businesses the ability to invest in new ideas, buy houses and cars, and make other purchases that they would not be able to afford to make without borrowing. Businesses can choose to pursue their goals, hire workers, and develop the economy by relying on loans. Apart from the role that banks play in the provision of credit, banks are also crucial as far as risk management is concerned. The banks, performing thorough reviews of loan applications, will decide on which borrower to lend the money and how risky the loan is [8]. They can decrease the risk of default due to the fact that they provide loans to the borrowers with a higher likelihood for repaying these loans. Banks create lending policies, and according to such regulations, loans are approved based on the status of the applicant. Loan applications are reviewed in accordance with the standing of the applicant under the lending policies established by banks. Loans are frequently only approved by banks after a thorough evaluation of the applicant's condition, either through methodically examining submitted documents or through direct asset verification. Having said that, it is by no means certain that the chosen applicant is the most qualified [9].

Components of Loan Eligibility

There are many components that describe in loan eligibility:

- *Principal:* Here they have the initial sum that was borrowed by a bank.
- Loan Term: The period of time that the borrower has to pay back the loan.
- *Interest Rate:* The common way to express the rate of increase in the total amount due is the annual percentage rate, or APR.
- *Loan Payments:* The amount that must be paid weekly or monthly to pay off the debt, based on the loan's principal, interest rate, and repayment term. If they want a loan, borrowers need to prove they can pay it back and have good money management skills.

- *Income:* To ensure that borrowers would not have trouble making payments on bigger loans, banks may establish a minimum income requirement. Particularly for mortgages, a steady income for a number of years could be required.
- *Credit Score:* An individual's creditworthiness may be quantified by their credit score, which is derived from their payment history [10]. The credit score of an individual might take a major hit in the event of bankruptcy or missed payments.
- *Dept-To-Income Ratio:* When deciding how many loans they have available at any one time, lenders consider both the borrower's income and their credit history. A high debt-to-income ratio indicates that the borrower would have problems making their loan payments.

Types of Risks in Banking

Credit risk, market risk, and operational risk are the three main categories into which the Reserve Bank of India classified the bank's hazards [11]. There are two types of risks: financial and non-financial. Among the financial risks are those associated with credit and the market, whereas operational risks are considered to be non-financial. The three primary categories of risk classification are shown in Figure 1. Examples of credit risk include risks associated with counterparties or borrowers, as well as risks associated with the industry, portfolios, or concentrations. Market risk encompasses a wide range of potential negative outcomes, such as fluctuations in interest rates, liquidity, hedging strategies, and different currencies. Risks that do not involve money include strategic risk, legal risk, political risk, and funding risk.

Credit Risk

Credit Risk believes that banks primarily generate profits via the production of loans [12]. This implies that banks lend money with the expectation of making a profit, even when they are indirectly taking on risk. Credit activities may generate financial turmoil, hence credit-risk management is crucial to banks' development and survival.

Counterparty/Borrower Risk

Borrower risk, also called counterparty risk, is a possibility that one of the contracting parties may fail to fulfil their obligations under the agreement. When parties are about to sign a contract, it is important to keep the potential impact of counterparty risk in mind.

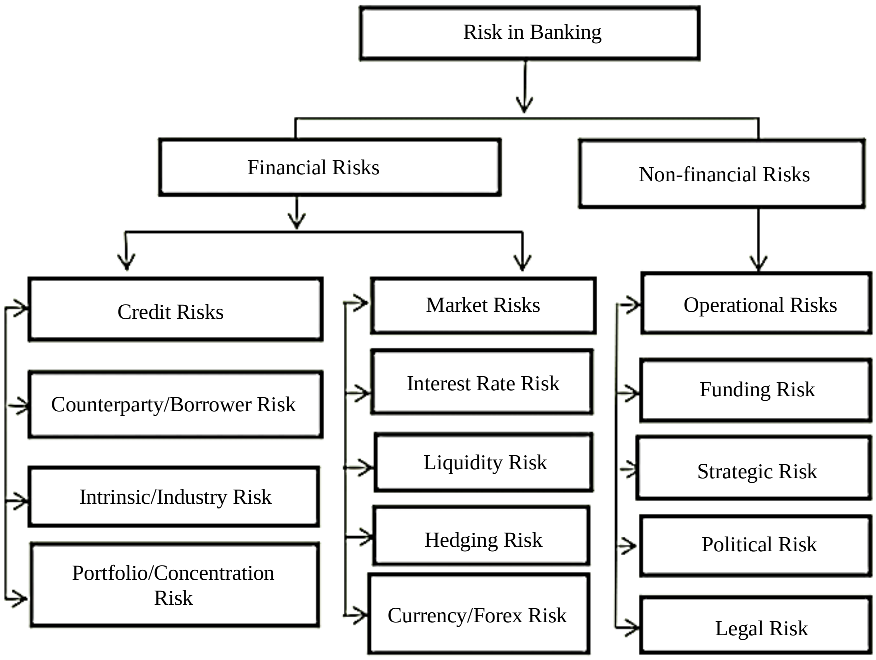

Figure 1. Types of risk in banking.

Intrinsic/Industry Risk

There are two primary sources of credit risk: default risk and portfolio risk. Concentration risks and inherent risks make up the portfolio. Both internal and external variables might contribute to the risk of default in a bank's loan portfolio. Economic policies, trade restrictions, interest rates, currency exchange rates, stock price fluctuations, government regulations, and economic sanctions are all examples of external variables. Several inherent factors contribute to the problem, including ineffective loan policies and administration, unclear lending limits for credit committees and officers, flawed appraisals, an over-reliance on collateral and low-risk pricing, no system to review loans, and no post-disbursement monitoring.

Portfolio/Concentration Risk

A bank's concentration risk is the ratio of its total outstanding loans to the total number of borrowers. They use a concentration ratio to quantify concentration risk. Each bank loan's share of the total accounts is shown there. The default rate will be too high for the bank to handle if the economy slows down in a certain sector where the majority of its assets are located. Therefore, it is smart to lend to many parts of the economy to spread out the risk.

Market Risk

Position losses due to changes in market prices are known as market risk. Due to changes in the market price, an investment might be subject to market risk. The potential decline in the investment's value is the danger here. Systematic risk is another name for this, and it may also apply to a particular commodity or currency.

Liquidity Risk

To be considered liquid, a financial organisation must be able to pay its bills when they come due. The term "liquidity" refers to a bank's capacity to meet its short-term obligations, such as accepting deposits and other forms of liability, making loans, and paying off claims that do not appear on the balance sheet. Uncertainty over the availability of funds is known as liquidity risk. A refinancing risk or rollover occurs when long-term assets are funded with short-term obligations.

Hedging Risk

Consider hedging as insurance coverage if you want a clear explanation. If you decide to hedge, it is like buying insurance against bad things happening. While hedging cannot guarantee that a negative event will not happen, it may lessen its effect if it does. Companies, portfolio managers, and individual investors all utilise hedging strategies to lessen the impact of potential losses. A yearly premium payment to an insurance provider is only the beginning of what is involved in financial market hedging.

Interest-rate Risks

A potential threat to a bank's bottom line caused by unfavourable changes in interest rates is known as interest rate risk. The term refers to the gap between the interest that is generated on loans and the interest that is paid on deposits. Financial losses associated with asset and obligation management due to changes in market interest rates constitute this form of risk.

Operational Risk

The definition of operational risk is " the possibility of suffering a loss, either directly or indirectly, as a result of problems with internal processes, personnel, or systems, or with outside forces". Operational risk can be defined as failures in the reporting system, information systems, internal monitoring policies, and processes that are meant to address issues promptly or ensure adherence to the internal risk policy.

Legal and Regulatory Risk

As part of their routine business operations, financial institutions often engage into a plethora of contractual agreements. Consequently, legal issues with counterparties might ensnare banks on

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occasion. There is a substantial possibility that the company's operations may be severely impacted by litigation brought about by dissatisfied employees, customers, careless actions, inadequate paperwork, workplace restrictions, or environmental damage.

Strategic Risk

This danger might occur if an unsuccessful business concept is pursued. Strategic risk may result, for example, from management's inability to appropriately react to changes in the business environment, insufficient allocation of resources, and bad decision execution.

Funding Risk

It is the potential for financial loss due to either insufficient cash or increased financing expenses. Inadequate finances to run the firm are the consequence of a project's cash flow being strained due to a high cost of capital [13].

FACTORS AFFECTING BANK LOAN

Lending funds are sourced from capital, deposits, and reserves. A variety of variables may impact each of these sources, which in turn would affect lending. Bank management should promptly pay attention to, analyse, and act upon internal and external issues that impact or restrict lending, as lending is the primary purpose of the banking business. Without lending, banks would see a significant decline in their revenue, particularly interest income, which might impact their viability. Since nonperforming loans (NPLs) are an indication of low asset quality, it follows that the variables affecting banks' lending decisions also affect NPLs. Thus, the following variables that affect bank loans may also have an effect on non-performing loans (NPLs):

Capital Position

Bank capital acts as a rule to safeguard the money of depositors. A bank's ability to absorb risk is influenced by its capital to deposit ratio. Longer maturities and higher credit risk might be associated with loans with comparatively large capital structures.

Profitability

Certain banks could prioritise making more money than others. Banks that are under more pressure to make money may use more aggressive lending practices. Consumer loans, which are often given at higher interest rates than short-term loans, might be called in response to an aggressive programme.

Stability of Deposits

It is necessary to take into account the deposit type and fluctuations. The bank can only start lending after making sufficient reserves preparations. Even yet, since uncertain demand forces banks to take deposit stability into account when determining lending policy, these reserves are meant to handle known swings in deposits and loan needs.

Economic Conditions

A liberal credit policy works better in a stable economy than one that is prone to cyclical and seasonal fluctuations. The deposit of a famine economy is more erratic than that of an economy recognised for its steadiness. The national economy has to be taken into account. If a factor has a significant negative impact on the country as a whole, it may ultimately have an impact on local situations.

Influence of Monetary and Fiscal Policies

The availability of reserves to the commercial banking system boosts banks' capacity to lend money when monetary and fiscal policies are broad and robust. Banks are allowed to have more lenient lending standards under these rules.

Ability and Experience of Bank Personnel

The formulation of bank loan policy is not unaffected by the knowledge of lending professionals. There was likely a shortage of qualified workers, which is why banks were hesitant to go into consumer lending.

Credit Needs of the Area Served

Mortgage real estate loans are only one example of the many sorts of loans that banks specialise in. One of the main purposes of chartered banks is to provide the community's credit requirements. Borrowers with reasonable and economically viable loan requests should be granted credit by banks. Banks' lending and investment decisions are influenced by other variables as well.

The Interest Rate

It symbolises the potential rates of return from several alternative investments and financing endeavours. Maintaining an appropriate ratio of return to risk is a fundamental challenge for bank management.

The Liquidity of Fund

The term refers to the total value of liquid assets that are invested or loaned out. A bank's ability to keep its cash on hand depends on its vigilant defence against unsustainable losses in lending and investment. A bank runs the risk of having its asset value fall below its liability value if it makes too many poor loans.

Tax

Bank loans are impacted by corporate income tax rates in several ways. One way is that banks may reduce their tax liability by lowering interest rates on deposits or by raising lending rates and fees. Another thing to consider is that the rate of corporate income tax affects both the production and the substitution of inputs. A lower level of output in the integrated sectors is the result of a higher CIT rate, according to the output substitution effect. A decrease in the demand for loans occurs here, as does the input substitution effect, which shows how equity is being replaced with other inputs, like debt. One aspect of banking industry taxation is the fact that banks are able to decrease their tax burden via strategic portfolio allocation. By increasing fees and interest spreads, the bank may pass the burden of taxes on to its customers. One straightforward way to affect the number of non-performing loans is to increase the lending rate on loans and decrease the interest rate on deposits, so transferring the tax burden to consumers. Furthermore, because of the presence of double taxation, corporate organisations transfer their tax liability to other taxpayers.

MACHINE LEARNING ALGORITHMS

ML is an algorithmic technique that allows software programmes to learn and improve their predictive abilities over time without human intervention. Part of AI is based on the idea that machines can learn from data, see patterns, and make judgements to find the best solutions with little to no human input. In the field of ML, two types of algorithms exist: supervised and unsupervised. There are primarily two types of ML approaches. Among them are [14]:

Supervised Learning

The goal or result variable is the fundamental component of this method. In order to forecast other elements, the target variable is used in conjunction with a set of independent variables. Furthermore, a function is defined that, by use of the target variable, converts inputs into the intended outputs. When the model achieves the desired level of accuracy using the training data, the training process terminates. There is a wide variety of classification and regression algorithms and methodologies used in supervised learning approaches, including decision trees, ensemble methods, generalised linear regression, discriminant analysis, SVMs, and non-linear regression.

Unsupervised Learning

To forecast or estimate anything in unsupervised learning, you do not have a goal or outcome variable. The primary use of this algorithm is to categorise things into distinct categories for targeted interventions. Some algorithms that do not need supervision to learn include Apriori and K-means. The research generally agrees that classification algorithms work best with labelled data. This study makes use of a labelled data set, which is ideal for classification analysis. The techniques used to forecast a bank customer's creditworthiness, measured by their capacity to repay their credit or not within a certain time period, are derived from MATLAB §R and the Python scikit-learn package, respectively.

CLASSIFICATION ALGORITHMS

A data point may be "learned" to belong to the most appropriate classification using labelled observations; this is how classification algorithms make predictions. In its "learning" process, it makes use of a collection of input characteristics. Classification algorithms find widespread use in machine learning tasks due to their ability to efficiently arrange previously unseen data into their respective categories. Below is a quick discussion of a few of the popular classification methods employed in this study:

Neural Networks

Neural networks are great for investigating classification problems because they can run both classification and regression procedures.

Discriminant Analysis

The fundamental premise of discriminant analysis is that distinct classes of data are produced by means of distinct Gaussian distributions. Linear and quadratic discriminant algorithms are the most common kinds used for classification.

Naive Bayes

Since this method of classification relies on Bayes' theorem, which states that predictors are independent of one another, they may say that a feature's existence in one class indicates that it is independent of another feature in another class. Determining the probability or probability density of characteristics X given class Y is the basis of Naive Bayes classification.

K-Nearest Neighbour

Both regression and classification issues find applications in the KNN technique. Nevertheless, this research will use KNN for classification and prediction analysis as it is more often utilised in business for such tasks. The KNN is an easy-to-understand technique that records previous occurrences and then classifies new ones by means of a majority vote among its k-neighbours. The most common of the class KNN is the one that goes into the allocation process, as determined by a distance function. The most popular distance functions are the Minkowski, Hamming, Manhattan, and Euclidean distances.

Linear Regression

Estimating real values from continuous variable(s) is the main usage of it. By fitting the optimal line, independent and dependent variables are linked in linear regression. A linear equation Y=an X+b, with Y as the dependent variable, an as the slope, X as the independent variable, and b as the intercept, represents this best-fit line, which is called a regression line. Finding the minimum of the sum of squared differences of the distances between the data points and the regression line is the basis for deriving coefficients a and b.

Ensemble Learning/Method

"Bagging" refers to bootstrap aggregation, and the TreeBagger is an example of an ensemble learning approach. The input data used to construct each tree in the ensemble is randomly selected. For regression, TreeBagger averages the predictions of individual trees; for classification, it gets votes from individual trees; and finally, it calculates the ensemble prediction. Bagging is one example of an ensemble method that takes several poor learners and turns them into a strong one.

Decision Trees

A decision tree may be either a classification tree or a regression tree. In a decision tree, which looks like a flowchart, each node represents an attribute test, each branch represents the result of the test, and each leaf node represents the option or response given once all the characteristics have been discussed.

LITERATURE REVIEW

Predictions about the future are known as forecasts. Guesses are made all the time. Others, however, are based on solid scientific research, while others are merely speculation. Data mining, statistics, modelling, ML, and AI are all part of predictive analytics, a subfield of advanced analytics that uses historical data to generate predictions as shown in Table 1.

Table 1. Comparative analysis of existing work.

Research	Algorithms Used	Highest Accuracy	Notable Findings	Research Gaps	Future Work Suggestions
[15]	RF, Naive Bayes, Decision Tree, KNN	83.73% (Naive Bayes)	Ensemble learning approach, Naive Bayes with 83.73% accuracy.	Lack of model interpretability exploration and get only 83% accuracy.	Investigate model interpretability and explainability.
[16]	Decision Tree	82%	Quick, easy, and efficient method, Decision Tree with the highest accuracy.	Limited discussion on scalability and real-world implementation challenges. DTs not perform well with 82% accuracy.	Explore scalability and real-world implementation challenges.
[17]	RF, Gradient Boost, Decision Tree, SVM, KNN, Logistic Regression	95.55% (RF), 80% (Logistic Regression)	High-performance accuracy, RF with the highest score.	LRs not perform well with 80% accuracy.	Investigate potential biases and ethical considerations in loan eligibility prediction models.
[18]	RF	91%	Predicts health loan eligibility with 91% accuracy.	Used only single model of machine leaning.	Assess the generalizability of the model across diverse demographic groups.
[19]	Various ML Algorithms	95.55% (Random Forest)	Random Forest displayed the most accuracy.	The effect of unbalanced datasets on the accuracy of the models is not addressed.	Examine how model performance is affected by datasets that are not balanced.
[20]	RF, XGBoost, GBM, Neural Network	>90% (RF superior)	Predicting Chinese P2P loan default, RF model superior with over 90% accuracy.	Limited discussion on external validation and robustness of the models.	Validate models externally to ensure robustness.
[21]	Ensemble techniques (Bagging, Boosting)	83.97%	Outperformed state-of-the-art models, high accuracy, and model interpretation.	No mention of the computational complexity of ensemble techniques.	Evaluate the computational complexity of ensemble techniques.
[3]	Neural Network, NB, KNN, DT, Ensemble learning	80 to 76%	Predicting creditworthiness, models' accuracy ranged from 80% to 76%.	Does not address the potential integration of explainable AI techniques.	Explore the integration of explainable AI techniques.

This article by Viswanatha *et al*. suggests using ensemble learning techniques in conjunction with ML models to determine the likelihood of approving certain loan requests [15]. The accuracy of the loan approval status for the applied individual was predicted using four distinct algorithms: RF, Naive Bayes, DT, and KNN. With the Naïve Bayes algorithm being the best, they were able to get an improved accuracy of 83.73% by using these.

Tejaswini *et al*. proposed a vigorous predictive approach to decide whether an applicant should be accepted or rejected [16]. The purpose of this study was to recommend a rapid, convenient, and effective approach for choosing eligible applications. The present study employed three machine learning algorithms for the purpose of predicting loan approval for customers. The Decision Tree algorithm has achieved highest accuracy among all models with the result of 82%.

This paper by Orji *et al*. illustrates a collection of six(6) machine learning algorithms: LR, RF, GB, DT, SVM, and KNN, for giving credit eligibility prediction [17]. They use the 'Loan Eligible Dataset', a historic dataset that is available on Kaggle and is licensed under the DbCL v1.0, for training. The findings of our study show the highest level of accuracy among the methods assessed. Logistic regression performed the worst scoring 80%, while the Random forest method performed the best getting 95.55%.

In study by Meenaakumari *et al*., an ML model that can be used to process the data provided by the user and evaluate, based on that data, if the user is qualified for a health loan [18]. Through retrieving the dataset from the Kaggle, this procedure starts with hiring specified parameters for loan application. Since the results of the analysis show that, RF algorithm is better than the others in two aspects; accuracy and error. Typically, the RF algorithm has an error value that is less than the other algorithms and a 91% accuracy rate for predicting the loan eligibility.

Park *et al*. compared six different machine-learning algorithms based on precision, recall, and accuracy [19]. The goal of this work is to forecast if a loan will be approved or not. Random Forest displayed the most accuracy in their study, at 95.55%, whereas LR displayed the lowest accuracy.

Xu *et al*. assessed the RF, XGBoost, GBM, and Neural Network ML models' ability to forecast Chinese P2P loan defaults [20]. All four of their models were more accurate than 90%, but RF was the best. While both studies make use of similar methodologies and algorithms, the focus of the two studies is different: one attempts to forecast P2P loan default while the other attempts to forecast whether or not a consumer would be eligible for a loan.

In the article, by Hossam, several ensemble ML methods, including Boosting and Bagging, have been implemented [21]. The prediction model for loan approval has an accuracy of 83.97% according to our study, which is around 25% higher than the majority of other modern loan forecasting models published in the literature. Trust in prediction was also supported by the excellent accuracy of the constructed models, and this study was able to interpret those models to explain a few crucial scenarios that bank decision makers may confront.

The research by Aphale and Shinde analysed real-life bank credit data to assist in the development of an automated risk assessment system by predicting consumers' capacity to repay loans [3]. Ensemble learning techniques, neural networks, decision trees, KNNs, and naive Bayes were among the ML algorithms they used. Their model accuracy was lower than ours as well, ranging from 76 to 80%.

CONCLUSION

Banks make the majority of their revenues through loans. Loan approval is an extremely crucial process for financial institutions. Easy prediction of loan repayment by customers is not possible owing to higher frequency of loan defaults, and banking authorities are finding it more and more difficult to appropriately assess loan applications and risks of people defaulting on loans. In conclusion, this review concludes that machine learning methods play a vital role in transforming the process of banks loan approval. Study of supervised and unsupervised learning algorithms, and key features determining loan eligibility, provides useful discoveries for both banking professionals and data scientists. Financial companies can benefit from automating loan qualification, such as the ability to increase efficiency, reduce processing times, and provide better customer service. A systematic study of different classification algorithms, including their uses and complexities, leads to better understanding of their applicability in predicting creditworthiness. The financial landscape continues to undergo significant changes, hence machine learning integration into loan approval procedures is no longer only a tool for risk management, but also a strategy for staying relevant in a dynamic market.

In the future, more research should be done to increase the efficiency of loan approval systems through the use of advanced machine learning models, the implementation of Explainable AI for clarification and exploring alternative data sources. Achieving ethical and effective machine learning-based loan approval systems, longitudinal research and real-world implementation is essential to test scalability and user acceptability.

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