Machine Learning Innovations in Credit Card Approval: A Comparative Study of Algorithms

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Abstract: In the ever-changing financial services industry, credit card approval is increasingly reliant on innovative creditworthiness assessment algorithms. Traditional evaluation techniques, which examine applicants' demographic and financial information, are no longer adequate because of the amount and complexity of information accessible. By using machine learning (ML) models—specifically, logistic regression, random forests, decision trees, and support vector machines—to increase predictive accuracy over traditional credit scoring systems, this study seeks to improve the credit card acceptance process. By employing accurate experimental methodologies, the efficiency of these models is compared to traditional credit scoring techniques, revealing significant enhancements in credit card approval precision, reducing errors and improving fraud detection capabilities, especially in developing countries. This study provides significant insights for financial organizations looking to improve their methods for managing credit risk and address issues such as integrity, interpretation, and dynamic risk evaluation in credit card acceptance processes.

1 INTRODUCTION

Traditionally, credit card approval involves analyzing applicants based on a variety of financial and social factors, such as employment status, earnings, and credit history. The integrity of the financial system is preserved by this process, which lowers credit risk and guarantees that only eligible applicants are given finance (Pristyanto et al., 2019). However, traditional ways have grown less successful as data volume and complexity have expanded, leading financial institutions to investigate more advanced alternatives (Bhatore et al., 2020). In this regard, machine learning has become a powerful instrument for examining big datasets and locating patterns that are frequently challenging to find using traditional methods. Recent research have proved the predictive efficacy of machine learning models, particularly Support Vector Machines (SVM) and Artificial Neural Networks (ANN), in anticipating credit card acceptance outcomes (Pristyanto et al., 2019). By using feature selection approaches including information gain, gain ratio, and correlation-based feature selection (CBFS), these models can increase their prediction accuracy, leading to a more reliable and effective credit card acceptance process (Fan et al., 2020).

This paper examines the use of machine learning in credit card acceptance in the context of internet financing(Karthiban et al., 2019). It provides a thorough analysis of the growth of credit risk management by comparing methods with recently developed machine learning algorithms. This paper measures how different machine learning algorithms work in assessing credit and determines which machine learning algorithms are related to credit card approval methods(Gupta and Goyal, 2018). It advices banks how to use machine learning(ML) to optimize their processes and fix mistakes, especially in developing countries. This paper's main objective is to act as a guide for improving credit risk management practices and financial performance.(Sutedja et al., 2024)

The rising rate of digital payments and credit card fraud (CCF) highlights the urgent need for effective fraud detection and credit approval techniques (Alarfaj et al., 2022).The present study examines the literature on deep learning (DL) and machine learning (ML) models in relation to these systems.In order to address issues including class imbalance, human error, and controlling financial risks in a cashless economy, the study aims to analyze recent developments in these areas, highlighting the insights learnt from various approaches(Bansal and Punjabi, 2021).

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The goal of this paper is to examine how machine learning algorithms are used in the credit card approval process(Awoyemi et al., 2017), handling current issues including unbalanced datasets and changing fraudulent activity. This work aims to provide a comprehensive evaluation of various machine learning-based models and their ability to predict credit card acceptance outcomes(Arora et al., 2022).The results of this study are meant to provide clarity on and improve understanding of a credit card acceptance mechanism, with major implications for financial groups and guidance for future research in this quickly evolving field.

2 EVALUATING CRITERIA FOR CREDIT CARD APPROVAL

Banks usually use several critical methodologies for credit card approval, each including different models and cycles. The following are three different ways banks endorse credit card applications:

2.1 Credit Score-Based Approval:

Credit card approval typically relies on loan scores, especially credit scores or VantageScores, that are basic indicators of a person's financial stability. These record scores are numerical representations that help banks coordinate their underwriting choices. Banks could disperse (Fan et al., 2020) small score advantages for certain Visa items, favoring emerging applicants who surpass these limits and overlooking those who fall short. Furthermore, financial evaluations have a significant impact on the terms anticipated for credit card offers, such as initial expenses, credit restrictions, and associated fees. Higher scores typically translate into better terms, which is consistent with the chance-based assessment rule.

2.2 Income and Business Verification:

Verification plays a crucial role in the credit card approval process. Banks assess applicants' income to determine their ability to meet credit card repayment obligations. This is often done by reviewing pay stubs, expense reports , or other financial documents for confirmation (Karthiban et al., 2019). Additionally, applicants with stable employment histories and higher incomes are generally considered lower-risk borrowers, increasing their chances of approval. This evaluation of job stability and income level contributes significantly to the overall assessment of an applicant's financial reliability.

2.3 Debt-to-Pay Extent (DTI):

Debt-to-income ratio (DTI) is pivotal in credit card approval. Banks figure DTI by looking at a candidate's month-to-month commitment portions (contracts, vehicle propels, existing Visa commitment) (Gupta and Goyal, 2018) to their gross month-to-month pay. A lower DTI implies more optional income, exhibiting better financial capacity to manage additional charge card commitments and further developing support prospects. DTI is a basic bet assessment metric banks use to evaluate candidates monetary prosperity and choose monetary sufficiency.

3 MACHINE LEARNING APPROACHES IN CREDIT CARD APPROVAL

Machine learning has reformed different businesses, and its application in credit card approval process is no exception. By harnessing the force of information-driven calculations, monetary organizations can dissect immense measures of client data to go with additional precise and productive choices regarding credit card approval. These methods collectively enhance the effectiveness and reliability of credit card approval decisions.

3.1 Credit Risk Assessment

In this framework, machine learning algorithms are entirely prepared based on authentic credit information to anticipate the probability of default or wrongdoing for new credit card candidates.(Patel, 2023)

3.1.1 Feature Engineering

Various features such as credit scores, income, employment status, debt-to-income ratio, payment history, and utilization rates are incorporated into predictive models to assess credit risk.

3.1.2 Ensemble Methods

Procedures like random forests, gradient boosting, and ensemble learning are used to combine multiple models including Decision Trees and AdaBoost, to improve prediction accuracy.

3.2 Fraud Detection

Fraud detection is vital before credit card approval, identifying potential risks by analyzing transaction patterns and customer behavior to ensure only qualified applicants receive credit.(Patel, 2023)

3.2.1 Anomaly Detection

Machine learning can distinguish unusual patterns or transactions indicative of fraudulent activity, like unexpected spikes in spending, transactions demonstrative of fraudulent movement, unforeseen spikes in spending, transactions in unfamiliar areas, or purchases outside a cardholder's typical approach to payments.For instance, a transaction that differs from normal spending may be flagged by models like SVM, Random Forest, or other statistical methods.

3.2.2 Behavioral Analytics

Analytical models see cardholder habits for a long time to recognize standard spending plans and perceive any irregularities that could propose likely fraudulent exercises(Mahmoodi et al., 2021).Techniques such as clustering algorithms (e.g., k-means) and neural networks can be used to analyze spending behavior.

3.2.3 Real-time Monitoring

AI frameworks transactions in real-time, flagging possibly fraudulent movements for immediate examination or blocking.Logistic regression and decision trees are often used for real-time scoring of transactions, allowing financial institutions to quickly assess the likelihood of fraud.

3.3 Customer Division and Targeting

Customer division and targeting help financial institutions engage different segments effectively. By using machine learning to analyze spending habits and preferences, they can customize their offerings, which enhances customer satisfaction and increases the chances of credit card approvals.(Zhou et al., 2020)

3.3.1 Clustering Algorithms

Machine learning methods such as k-means and hierarchical clustering order credit card clients into groups in view of their approach to spending ways, inclinations, and segment data.

3.3.2 Personalized Offers

Financial institutions use machine learning to customize credit card offers and rewards for various customer segments, boosting engagement and satisfaction. Models like decision trees and support vector machines analyze customer data to predict the most appealing offers for individuals, enabling targeted marketing strategies.

4 KEY FINDINGS AND SOLUTIONS

Naman Dalsania *et al.,* (Dalsania et al., 2022) proposed a review directed to foresee the endorsement probability of a credit card demand utilizing supervised machine learning models. The review used a dataset from Kaggle and applied pre-processing strategies and exploratory data analysis. Three classification algorithms were carried out: AdaBoost Classifier, Support Vector Classifier, and Gradient Boosting Algorithm. The outcomes show that the Gradient Boosting Algorithm accomplishes the most elevated scores for exactness, accuracy, recall, and F1-Score, while the Support Vector Classifier likewise performed well. The research proposes using deep learning models to expand the framework's accuracy in revealing hidden patterns and correlations inside the information. Besides, it examines different AI approaches zeroed in on gauging credit card approval results.

Yiran Zhao (Zhao, 2022) predicted the precision of numerous regression models and classifiers to find out the ideal model with the highest accuracy. The trial models utilized in the examination incorporate Logistic Regression, Linear SVC, and Naïve Bayes Classifier. The outcomes show that Linear SVC played out the best with the highest Balanced Accuracy (89.09%) and Accuracy Rate (88.48%). In any case, the paper has restrictions as it doesn't think about computational productivity, reject deduction, and exception taking care of variables in surveying prediction performance.a

Harsha Vardhan Peela *et al.,* (Peela et al.,) proposed utilizing data analysis and machine learning to decide the most fundamental boundaries for credit card acceptance. The technique included examining applications, taking care of missing values, and preprocessing the information. A model of logistic regression was fitted to the training set, and devices were utilized to work on the model's performance. The outcomes demonstrated that utilizing both random forest and logistic regression models prompted a pinnacle precision of 86%. In spite of leading a hunt to further develop execution, there could have been no further improvement. Generally, this study offers bits of knowledge into the components affecting credit card approval while additionally revealing insight into the difficulties related to achieving more prominent accuracy.

Ying Chen *et al.,* (Chen and Zhang,) Proposed a structure for forecasting credit card defaults using a blend of k-means SMOTE and BP neural network methodologies. The creators address the information irregularity issue and propose utilizing the k-means SMOTE algorithm to change the data distribution. They likewise work out the significance of data features utilizing random forest and use it to initialize the weights of the BP neural network. The discoveries exhibit that the upgraded k-means SMOTE algorithm successfully handles data imbalance characteristics and improves forecast precision. Moreover, utilizing the component significance from random forest marginally works on the prediction. The support vector machine accomplished the most noteworthy score among the six models assessed. The paper recognizes the restriction of deficient information for running the BP neural network algorithm and highlights that credit card approval is subjective and uncontrollable.

Md.Golam Kibria *et al.,* (Kibria and Sevkli, 2021) proposed using deep learning to make credit card approval decisions. The researchers developed a profound learning architecture using UCI datasets and then considered its viability in contrast to logistic regression and support vector machine models. The outcomes showed that the deep learning model had the most elevated exactness rate at 87.10%, while the other two models had a precision rate of 86.23%. However, the paper's primary downside is that it just contrasted the deep learning model and two customary machine learning algorithms, and more correlations with different algorithms would be expected to lay out its benefit over other algorithms.

Makumburage Poornima Chathurangi Peiris (Peiris, 2022) recommended the utilization of deep learning for credit card approval decisions, explicitly artificial neural networks and support vector mechanisms, to anticipate client qualification for a credit card and moderate potential credit risk for banks. The review assesses three classifiers and finds that the nonlinear help vector machine (SVM) model outperforms the artificial neural network (ANN) and linear SVM models. The nonlinear SVM model accomplishes an accuracy of 0.88, precision of 0.88, recall of 0.90, and area under the curve (AUC) of 0.89. They feature that the underlying dataset was exceptionally imbalanced, and SMOTE was applied to resolve this issue.

Abhishek Agarwal et al., (Abhishek Agarwal and Verma, 2020) have proposed that PCA can be applied to enhance the credit card dataset classification methods. They evaluated the performance of four algorithms: This includes, Logistic Regression, Decision Tree, K-Nearest Neighbour (K-NN), and Naive Bayes. The results obtained from their study revealed that logistic regression had higher accuracy rates before and after using PCA than other methods. They also established that Naive Bayes had high rates of recall and ROC after using PCA. It can be seen that Logistic Regression is the most accurate model on this dataset, meanwhile PCA does not affect decision tree accuracy at all. Their study can assist banking institutions in their efforts to define probable defaulters by constructing enhanced algorithms with greater accuracy, precision, recall, F1-score, and ROC through PCA.

Rejwan Sulaiman *et al.,* (Sulaiman et al., 2022) proposed the different purposes of machine learning techniques for credit card fraud detection (CCFD) and information classification. Numerous methods were analyzed, such as random forest, artificial neural network, support vector machine, K-Nearest Neighbour, hybrid approach, privacy-preserving techniques, and blockchain technology. The dataset was divided into training, validation, and testing sets. The investigation discovered that a hybrid solution involving neural networks in a federated learning structure accomplished higher precision in CCFD while guaranteeing security. The proposed system may confront restrictions because of severe standards and guidelines from banks and monetary establishments. By and large, the exploration features the capability of machine learning for CCFD; however, it recognizes the need to consider reasonable requirements while executing such frameworks.

Yanbo Shen *et al.,* (Fan et al., 2020) proposed a superior credit evaluation model utilizing the XGBoost machine learning algorithm for Internet financial institutions. The model is contrasted with a customary credit card scoring model utilizing a contextual investigation from a Web loaning organization in China. The trial results show that the Machine Learning model beats the conventional model regarding the KS value, demonstrating specific benefits in Web monetary risk control. Nonetheless, the disadvantages are setting model boundaries in advance and the relatively high error rate in judging bad samples as good samples. In general, the paper features the capability of machine learning-based methods for credit scoring in internet monetary risk control while recognizing areas for development.

Harish Paruchuri (Paruchuri, 2017) proposed the different issues of credit card fraud in online shopping and investigated utilizing different machine learning algorithms to identify fraudulent exchanges. The algorithms referenced in the paper incorporate neural networks, decision trees, SVM, logistic regression, genetic algorithms, and random forests. The paper presents genuine situations where these algorithms were utilized to tackle credit card fraud issues. Nonetheless, it doesn't give a specialized examination or precision evaluation of these algorithms in unambiguous data sets. It sums up how individual calculations have been utilized for credit card fraud prediction.

5 DIFFERENT ALGORITHMS USED IN CREDIT CARD APPROVAL

Machine learning algorithms are employed in credit card approval systems to assess credit risk and make endorsement decisions. The following are some commonly used algorithms: These algorithms primarily operate as classification methods, categorizing applicants into distinct classes such as approved or denied based on a variety of financial and demographic features.

5.1 Logistic Regression

- Logistic regression is a well-known algorithm for binary classification undertakings like credit card approval. In light of info highlights, it estimates the likelihood that an occurrence has a place with a specific class (e.g., approved or denied). It's straightforward, interpretable, and efficient, making it reasonable for credit risk evaluation undertakings where transperancy and explainability are significant(Peela et al., ; Karthiban et al., 2019; Fan et al., 2020; Zhao, 2022; Kibria and Sevkli, 2021; Paruchuri, 2017).

5.2 Decision Trees

- Decision trees recursively split the dataset into subsets according to the worth of input features, making a tree-like design where each interior node addresses a decision in light of a feature, and the leaf node shows the last grouping or result. Decision trees are justifiable and can perceive non-linear connections between features. They might be inclined to overfitting, particularly with complex datasets(Marqués et al., 2012; Arora et al., 2022; Bansal and Punjabi, 2021; Sutedja et al., 2024).

Table 1: Algorithm Comparison Table

Algorithm	Papers	Acc.	Prec.	Rec.	F1
Gradient Boosting	(Dalsania et al., 2022)	0.90	0.90	0.90	0.90
SVM	(Dalsania et al., 2022)	0.85	0.83	0.88	0.86
	(Chen and Zhang,)	0.88	0.88	0.88	0.88
	(Kibria and Sevkli, 2021)	0.86	0.868	0.862	0.863
	(Sulaiman et al., 2022)	0.91	-	-	-
	(Peiris, 2022)	0.71	0.83	0.55	0.71
	(Fan et al., 2020)	0.77	-	-	-
Random Forest	(Peela et al.,)	0.86	-	-	-
	(Chen and Zhang,)	0.81	0.87	0.87	0.87
Logistic Reg.	(Abhishek Agarwal and Verma, 2020)	0.806	0.699	0.225	0.341
	(Peela et al.,)	0.86	-	-	-
	(Chen and Zhang,)	0.87	0.87	0.88	0.87
	(Kibria and Sevkli, 2021)	0.86	0.864	0.862	0.861
	(Sulaiman et al., 2022)	0.95	-	-	-
	(Fan et al., 2020)	0.70	-	-	-
KNN	(Abhishek Agarwal and Verma, 2020)	0.801	0.592	0.339	0.431
	(Chen and Zhang,)	0.86	0.87	0.87	0.87
	(Sulaiman et al., 2022)	0.72	-	-	-
Decision Tree	(Abhishek Agarwal and Verma, 2020)	0.729	0.392	0.396	0.394
	(Chen and Zhang,)	0.87	0.82	0.815	0.817
Deep Learning	(Kibria and Sevkli, 2021)	0.87	0.879	0.892	0.886
	(Sulaiman et al., 2022)	0.95	-	-	-
ANN	-	0.87	-	-	-
	(Sulaiman et al., 2022)	0.92	-	-	-
	(Peiris, 2022)	0.78	0.81	0.73	0.76

5.3 Random Forests

- Random Forests resemble a group of leaders. They assemble many rather than depending on only one individual (or decision tree). Every choice tree checks out various pieces of an individual's monetary circumstance, similar to pay and record. Then, at that point, they all decide whether to support the individual with a credit card. This cooperation approach assists banks with settling on additional exact decisions about who to approve for a credit card, lessening the risk of giving cards to individuals who can't repay them(Peela et al., ; Chen and Zhang, ; Kibria and Sevkli, 2021; Arora et al., 2022; Sutedja et al., 2024; Alarfaj et al., 2022).

5.4 Support Vector Machines (SVM)

- Support Vector Machines (SVMs) resemble walls that differentiate various gatherings by defining boundaries between them to maximize the distance between the groups. In credit card approval systems, SVMs utilize monetary data like pay and credit records as consumers to conclude who ought to get a card and who shouldn't. By tracking down the best line to isolate great candidates from risky ones, SVMs assist banks with settling on more smart decisions about who to approve for a credit card, limiting the possibility of giving cards to individuals who could battle to repay them(Bhatore et al., 2020; Fan et al., 2020; Zhao, 2022; Arora et al., 2022; Kibria and Sevkli, 2021; Sutedja et al., 2024).

5.5 Neural Networks

- Neural Networks like multi-layer perceptrons (MLPs) or convolutional neural networks (CNNs) go about as cutting-edge analysts in credit card endorsement frameworks, dissecting different monetary variables to foresee an individual's probability of capably dealing with credit cards. They require loads of information and processing power but battle with interpretation. Despite this, they further improve decision-making accuracy, helping banks approve credit cards wisely and reduce default risks(Bhatore et al., 2020; Sulaiman et al., 2022; Peiris, 2022).

5.6 K-Nearest Neighbors (KNN)

- KNN, or K-Nearest Neighbors, resembles requesting neighbors for advice to make decisions. It notices the way of behaving of comparative people in a neighborhood of data of interest and uses their majority behavior part to foresee results. In credit card approval systems, KNN assists banks with surveying a candidate's reliability by contrasting their monetary profile with those of comparable people who have recently been supported or turned down regarding credit cards. Despite its simplicity and usability, KNN might be slow and computationally costly with enormous datasets or various monetary factors. Yet, it helps banks arrive at additional educated conclusions about broadening credit while overseeing chances(Arora et al., 2022; Awoyemi et al., 2017; Sulaiman et al., 2022).

6 CHALLENGES AND OPPORTUNITIES

6.1 Challenges

6.1.1 Data Imbalance

Fraud detection in credit card approval systems is a problem because the number of positive and negative instances is highly uneven(Ahmed and Shamsuddin, 2021). This can make the machine learning models predict that there was no fraud, this leads to failure to detect fraud incidences.

6.1.2 Fairness and Bias

Machine learning models may unintentionally reflect biases found in historical data, influencing decisions based on gender, race, or income level. Ensuring fairness in credit decisions is an important concern(Wu, 2024).

6.1.3 Regulatory Compliance

Regulatory compliance focuses on organizations following legislation laws and guidelines to achieve organizational objectives and increase stakeholder value.(Hassan et al., 2023) Policies regarding the credit approval models should be adhered to strictly because they provide guidelines on how a customer's creditworthiness is determined. These regulations and model compliance make the deployment of these machine-learning systems challenging.

6.1.4 Evolving Fraud Patterns

The nature of fraud strategies is not static, so the models will always find it hard to cope.(Faraji, 2022) To counter such trends, machine learning models have to be trained constantly – a process that requires a lot of time and money.

6.2 Opportunities

6.2.1 Improved Predictive Accuracy

Machine learning techniques, such as Logistic Regression and RF models, lead to improved prediction of credit card approvals, which can help detect fraud more effectively than traditional methods (Mahbobi et al., 2023).

6.2.2 Advanced Fraud Detection

Techniques such as the anomaly detection technique and the real-time monitoring technique will detect fraudulence more efficiently.(Faraji, 2022) Examining the spending pattern makes it possible for banks to identify potentially fraudulent transactions before they happen.

6.2.3 Enhanced Personalization

Deep learning can be adopted to process customer spending behavior to ensure that financial institutions develop and provide credit card products and services that suit market needs and increase customer satisfaction(Gigante and Zago, 2023).

6.2.4 Quantum Computing Potential

Quantum computing has the potential to revolutionize the use of predictive analytics in credit card fraud solutions(Egger et al., 2020). Future work could investigate how such quantum algorithms may enhance real-time fraud detection given even massive data sets.

Therefore, credit card approval systems offer many chances for improvement even if they also confront many obstacles, including data imbalance, interpretability issues, regulatory compliance, and changing fraud trends. By utilizing machine learning techniques, financial organizations can increase fraud detection skills and forecast accuracy. Furthermore, there are encouraging opportunities to provide more individualized and efficient credit services because of developments like quantum computing and behavioral economics.

7 CONCLUSION

In conclusion, the approval of credit cards will be effective for financial institutions that apply standard analytical tools combined with modern artificial intelligence approaches. This assessment should be used to study a person's financial stability, primarily based on his credit payment history, credit benefits, and working conditions. Credit risk appraisal and detection of fraud, client segmentation, speeding up approvals, and reducing the probable risks are made possible with the help of Machine Learning.

However, there are clear assessment opportunities and prospects here. Many concepts are valuable in this process, mainly settling sensibility, control, interpretability, and dynamic risk appraisal, as they help guarantee impartial treatment and trust from the people being governed. Future assessments can target using valid artificial intelligence approaches and moral standards and changing the organization to maintain customer satisfaction and financial health. Similarly, the mixture of adopting advances such as blockchain and decentralized finance offers security for reformed credit frameworks and economic considerations.

By overcoming these challenges and paying attention to the new strategies for potential customers, applying Machine Learning to credit card approval can introduce transparent, effective, and profitable financial systems for both organizations and customers.

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