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Credit Assessment and Recommendation System (CARS) using Naive Bayesian Algorithm

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Abstract

With the increasing demand for credit services to fuel economic growth, traditional credit assessment methods, relying on outdated regulations and manual evaluations, hinder efficiency. The proposed Credit Assessment and Recommendation System aims to revolutionize this process by using a Naïve Bayes Classifier to swiftly and accurately determine credit eligibility. By analyzing customers' biographic, demographic, and historical data, the system can predict approval outcomes and provide actionable recommendations. This approach promises to streamline the credit application process, reduce risks associated with manual assessments, and achieve a prediction accuracy of 90%.

Keywords: Bayesian Algorithm, Credit Assessment, Recommendation System, Loans, Assessment Efficiency

INTRODUCTION

In the financial landscape of the Philippines, obtaining credit cards and loans is a critical step for many Filipinos, whether for financial recuperation or achieving stability. Loans are often utilized to fund businesses and acquire properties, while credit cards are typically used for purchasing personal items such as gadgets, furniture, and appliances. The increasing reliance on credit services is evident, with the 2022 National Consumer Expectations Survey revealing that approximately one in four households took out loans primarily for essential purchases, with improved access to credit reported by 24.9% of respondents.
Despite the growing demand for credit services, the traditional manual processing of credit card and loan applications remains a significant bottleneck. The lengthy processing time, coupled with risks of human error, biases, and inefficiencies in manual evaluations, hinders the financial system's responsiveness. The Republic Act No. 9510, also known as the Credit Information System Act (CISA) of 2008, was established to streamline credit information systems, yet challenges persist.

To address these issues, the researchers propose the development of a Credit Granting Application System, leveraging the Naive Bayesian Algorithm. This system aims to automate the evaluation process, providing recommendations on credit applications, including loan approvals, credit limit increases, and account upgrades. By utilizing employment details and historical data from banks, the system predicts the likelihood of approval or rejection, significantly reducing processing time and mitigating risks associated with manual evaluations.

The study aims to fill the gap in the current credit evaluation process by introducing a machine learning-based approach that enhances efficiency and accuracy. This research explores how the Philippines Credit Application Recommendation System can revolutionize credit assessments, benefiting both financial institutions and their clients.

LITERATURES

The application of recommendation systems in the financial sector has seen significant progress, with ongoing advancements highlighting substantial potential for further development. Recommendation systems, as noted by Isinkaye, Folajimi, and Ojokoh (2015, 2022), have already been implemented in various banks, demonstrating the sector's readiness to enhance these technologies. By personalizing user experiences, these systems cater to individual customer needs, reflecting a broader trend towards data-driven approaches aimed at improving customer engagement and satisfaction. Notable examples include JPMorgan Chase, Wells Fargo, and Bank of America, which have successfully integrated recommendation engines into their service offerings. This adoption underscores the increasing reliance on personalized, data-driven strategies in banking.

In parallel, Naive Bayes classifiers have emerged as a promising tool for loan risk assessment, addressing critical issues such as credit defaults, which have historically contributed to economic downturns and bank failures (Bangko Sentral ng Pilipinas, 2022). Research indicates that employing Naive Bayes in predicting loan defaults can achieve accuracy rates of up to 78%, particularly when enhanced with techniques like cross-validation and principal component analysis. This approach not only reduces economic losses by minimizing false positives but also streamlines loan administration processes, thereby improving overall operational efficiency.

Comprehensive credit information systems, such as the Negative File Information System (NFIS), are integral to effective credit risk management. These systems maintain detailed records of credit mishandlings, providing banks with crucial data to inform lending decisions. Additionally, regulatory frameworks like the Anti-Money Laundering Council (AMLC), established under Republic Act No. 9160, play a vital role in maintaining the integrity of the banking system by preventing money laundering activities. These measures ensure that the Philippines remains a secure and reliable environment for financial transactions, which is essential for economic stability.

Recent advancements in credit scoring models, particularly those incorporating Naive Bayes classifiers, have shown notable improvements in predictive accuracy. For instance, Krichene (2022) utilized a Naive Bayes classifier to assess loan risk in a Tunisian commercial bank, analyzing a dataset of 924 credit files from 2003 to 2006. The study revealed that including cash flow variables significantly enhanced prediction quality, with further improvements observed when collateral was incorporated. An ROC curve in the study demonstrated a remarkable increase in AUC from 69% to 83% when employing a neural network methodology, underscoring the enhanced predictive power of these advanced models.

Comparative analyses further highlight the effectiveness of Naive Bayes classifiers in credit scoring. Vedala and Kumar (2012) compared various classification techniques and found that Naive Bayes achieved an 83.3% prediction accuracy on an e-lending platform, outperforming other methods such as classification trees (82%) and K-nearest neighbor (82.8%). The Naive Bayes classifier's ability to efficiently handle categorical predictors, along with its speed and low memory usage, positions it as a highly effective tool for building credit scoring models in banking. These attributes contribute to its suitability for practical applications within financial institutions, offering both high accuracy and operational efficiency.

In conclusion, the integration of recommendation systems and advanced classification techniques like Naive Bayes classifiers marks a significant advancement in the financial sector. These technologies enhance personalization, improve risk management, and increase operational efficiency. Their adoption by leading financial institutions underscores their transformative potential in financial decision-making processes, particularly in mitigating risks associated with credit and loan defaults. As the financial sector continues to evolve, further development and refinement of these technologies will be critical in addressing emerging challenges and capitalizing on new opportunities for growth and innovation.

METHODS

This study utilized an experimental-developmental research method to predict loan and credit card approvals using the Naive Bayesian Algorithm. The research design was chosen due to its suitability for building and testing predictive models, which is essential for developing a reliable credit assessment system. By using this method, the researchers aimed to develop a model that could be replicated and applied in real-world banking environments.

Posterior Classifier Rule. The core of the predictive model is based on the Naive Bayesian classifier, which operates on Bayes' theorem with the assumption of predictor independence. The simplicity and efficiency of the Naive Bayesian classifier make it ideal for handling large datasets, as it allows for quick construction without the need for iterative parameter estimation. Despite its simplicity, the Naive Bayesian classifier has proven to outperform more complex algorithms in various classification tasks, making it a popular choice in the financial sector.

The Bayes theorem provides a framework for calculating the posterior probability, $P(c|x)P(c|x)P(c|x)$, given the prior probabilities $P(c)P(c)P(c)$, $P(x)P(x)P(x)$, and $P(x|c)P(x|c)P(x|c)$. The Naive Bayesian classifier assumes that the effect of a particular predictor (x) on a given class (c) is independent of other predictors—a concept known as class conditional independence. This assumption simplifies the computation and is critical for the model's application in this study.

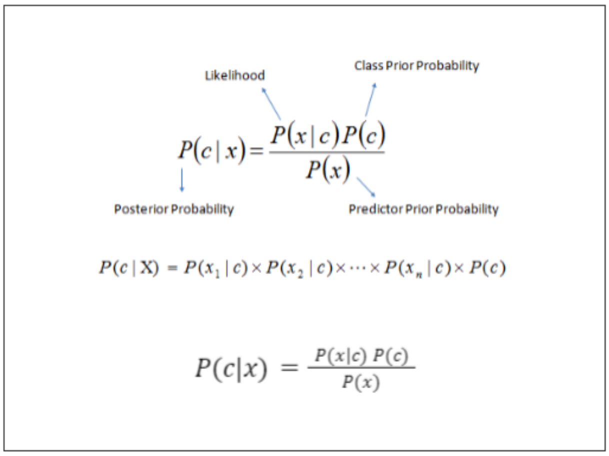

Figure 1
Naive Bayesian - Posterior Probability

- $P(c|x)$ is the posterior probability of class (target) given predictor (attribute).
- $P(c)$ is the prior probability of class.
- $P(x|c)$ is the likelihood which is the probability of the predictor given the class.
- $P(x)$ is the prior probability of the predictor.

A naïve Bayes classifier is a probabilistic classifier based on applying Bayes' theorem with strong independence assumptions. The naïve Bayesian classifier was first described in [6] in 1973 and then in [6] in 1992. When represented as a Bayesian network, a naïve Bayes classifier has the structure depicted in Figure 2. It shows the independence assumption among all features in a data instance.

While the Naive Bayesian classifier offers several advantages, including simplicity and speed, its assumption of predictor independence may not always hold true in real-world scenarios. This could potentially limit the model's accuracy in cases where predictors are interdependent. To address this, the researchers carefully selected attributes that are likely to be independent and used cross-validation to enhance the model's robustness.

Additionally, the model's performance is contingent on the quality of the data used. Any inaccuracies or inconsistencies in the dataset could lead to biased predictions. The researchers mitigated this risk by employing rigorous data cleaning and validation procedures to ensure the dataset's integrity.

This methodology outlines the detailed steps taken to develop a predictive model for credit application approvals using the Naive Bayesian Algorithm. By thoroughly preparing the data, partitioning it effectively, and carefully selecting the attributes, the researchers created a model that is both accurate and reliable, providing a valuable tool for the financial sector.

Sources Of Data. The researchers used a historical dataset generated from live data entered by users in the Detail Generator Application. This semi-supervised dataset is composed of thirteen attributes that are instrumental in determining whether a client's credit application will be approved or declined. The primary goal of data preparation was to ensure accuracy and consistency in processing, thereby validating the results. The attributes and/or columns are as follows:

Table 1
Data Definition

Attribute	Classification	Descriptions
Job Rank	Employment Information	is a job rating system that classifies positions inside an organization according to their significance or value.
Previous Job Rank	Employment Information	
Salary Range	Employment Information	is the difference between the lowest and highest base wage that a company will pay for a certain job or set of occupations.
Top 5000 Employer	Employment Information	
Employer Type	Employment Information	
On Us Bank Account	Financial Information	Refers to whether the applicant has an account with the bank where he or she is applying for a Credit Card or Loan.
Off Us Bank Account	Financial Information	Refers to whether the applicant has an account at a bank other than the issuing bank from which she asks for credit cards and loans.
Active On Us Loan	Financial Information	Refers to whether the applicant has an active loan account with the bank where he or she is applying for a Credit Card or Loan.
Active Off Us Loan	Financial Information	Refers to whether the applicant has an active account at a bank other than the issuing bank from which she asks for credit cards and loans.
NFIS	Credit Record	Negative File Information System Flag
CMAP	Credit Record	Credit Management Association of the Philippines Flag
AMLA	Credit Record	Anti-Money Laundering Act of 2001 Flag
Credit Score	Credit Record	a score between 300 and 850 that represents a consumer's creditworthiness. Depends on credit history, including the number of active accounts, total debt, and repayment history, among other things. Credit scores are used by lenders to determine the likelihood that borrowers will repay loans on time.

The researchers intend to adapt the posterior probabilities for all conditions of the aforementioned attributes and produce a systematic output that will be useful for the banks in developing a strategy to achieve end-goals. Furthermore, once the researchers have successfully developed a system that utilizes the Credit Assessment dataset, it will provide a reference and guidance to those in the Finance Industry in developing a software/application that is demand as well as reflected based on the customer's biographic, demographic, and historical records.

Table 2
Data Partition

Data set Partition		Percentage %
Testing	20	20%
Validation	10	10%
Training Set	70	70%

This partitioning approach ensured that the model was trained on a sufficient amount of data while allowing for effective validation and testing to evaluate its performance.

Name	JobRank	PreviousJobRank	SalaryRange	Top5000Employer	EmployerType	OnUsBankAccounts	OffUsBankAccount	ActiveOnUsLoan	ActiveOffUsLoan	NFIS	CMAP	AMLA	CreditScore
[redacted]	0	7	3	1	1	0	1	0	0	1	1	1	10
[redacted]	4	3	2	0	0	1	1	0	1	0	1	1	0
[redacted]	6	5	1	1	0	1	1	1	0	0	0	0	3
[redacted]	0	3	5	0	1	1	0	1	0	1	1	0	6
[redacted]	4	4	6	0	0	0	1	1	0	1	1	0	2
[redacted]	0	6	4	0	0	0	1	1	1	1	1	0	0
[redacted]	4	7	6	0	0	0	0	1	1	0	0	0	10
[redacted]	5	3	6	1	0	0	1	1	0	1	0	0	5
[redacted]	0	6	3	0	0	0	1	0	0	0	0	0	3
[redacted]	2	0	0	1	1	1	1	1	1	1	1	0	3
[redacted]	5	0	1	0	0	1	0	1	0	0	0	0	6
[redacted]	3	7	6	1	1	1	0	0	0	1	0	0	9
[redacted]	0	2	6	0	0	1	0	1	0	1	0	0	7
[redacted]	7	3	3	1	1	0	1	0	1	0	1	0	10
[redacted]	2	6	3	0	1	1	1	1	1	1	0	0	2
[redacted]	5	2	0	0	0	1	1	1	1	0	0	0	0
[redacted]	3	4	4	1	1	0	0	1	1	1	1	0	0
[redacted]	7	3	5	1	1	0	1	1	1	1	0	0	5
[redacted]	6	5	6	0	0	1	1	1	1	1	0	0	4
[redacted]	1	7	3	0	1	0	1	0	0	1	1	1	1
[redacted]	0	3	0	1	1	0	1	0	0	1	1	1	2
[redacted]	4	0	2	0	1	0	0	1	1	1	1	0	7
[redacted]	2	7	5	0	0	1	0	0	1	0	1	0	4
[redacted]	2	6	5	1	0	1	0	0	1	1	1	0	0
[redacted]	1	1	5	1	0	0	1	0	1	0	0	0	9

Figure 3
Extracted Data from Applicant Table

Figure 3 shows the screenshot of the Extracted Data from Applicants Table, this will be used as FeedFile to Phyton and will be the basis of generation of the report file where the results/recommendation is provided.

Legend:

Job Rank / Previous Job Rank	Salary Range	Top 5000 Employer / On Us and Off Us Bank Accounts / On Us and Off Us Active Loans / NFIS / CMAP / AMLA	Credit Score	Employer Type
0- Business Owner	0 - G 0-10000	0 - False	1	0 - Government
1- Director	1 - F 10001 - 49999	1 - True	2	1 - Private
2- Executive	2 - E 50000 - 99999		3	
3- Manager	3 - D 100000 - 199999		4	
4- Mayor	4 - C 200000 - 299999		5	
5- None	5 - B 300000 - 499999		6	
6- Staff	6 - A 500000 and above		7	
7- Supervisor			8	
			9	
			10	

Figure 4
Data Mapping

Data Case Analysis. The Naive Bayesian Algorithm was employed to compute the posterior probabilities of each feature, determining the likelihood of approval or rejection of a credit application.

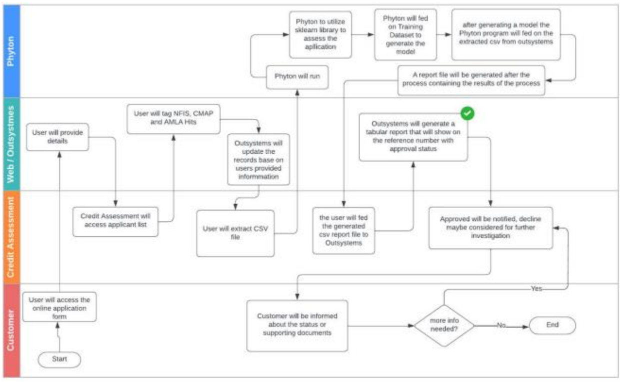

Diagram 1
Process flow

The model used is Gaussian Naive Bayes (GaussianNB), chosen for its effectiveness in predictive modeling under supervised learning conditions. The accuracy of the model was determined to be 90%, indicating a high level of reliability in predicting the outcomes based on the selected attributes.

```
ft_train, ft_test, tg_train, tg_test = train_test_split
    (get_training[ft],get_training[tg], test_size = 0.30
    ,random_state = 10)
model = GaussianNB()
model.fit(ft_train, tg_train)
pred = model.predict(ft_test)
print("Accuracy of Suggestion is at",(accuracy_score(tg_test,
    pred))*100,"%")
#with open(r'.\FeedFile.csv') as file:
with open(genFeedFile) as file:
    next(file,None)
    while (line := file.readline().rstrip()):
        arr_in = line.split(",")
        # print(arr_in)
        answer = model.predict([arr_in])
        if answer == 1:
            result[index] = "Approve"
            index = index + 1
            # print("Approve\n")
        elif answer == 0:
            result[index] = "Decline"
            index = index + 1
            # print("Decline\n")
```

Figure 5
Program snippet that will tag if Approve or Decline MODULE OF THE SYSTEM

The researchers developed a user interface, the Loan Application Form, to gather live data, which was subsequently processed and used to train the model. This interface was designed to be user-friendly, allowing applicants to input their information, which was then transformed into CSV files for analysis. The output interface displayed the results and recommendations generated by the model, providing valuable insights for both the bank and the applicant.

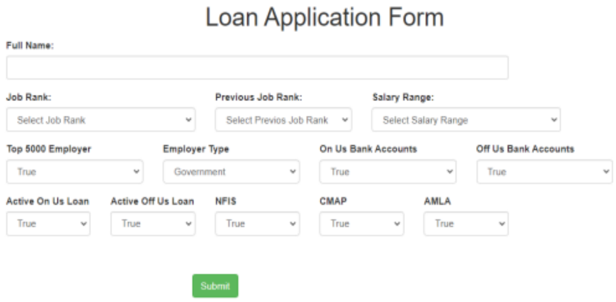

Figure 6
Loan Application Form

The user interface we designed is shown in Figure 6; the user inputs their information, which is subsequently delivered to the database. The data will then be transformed into csv files, as seen in Figure 7.

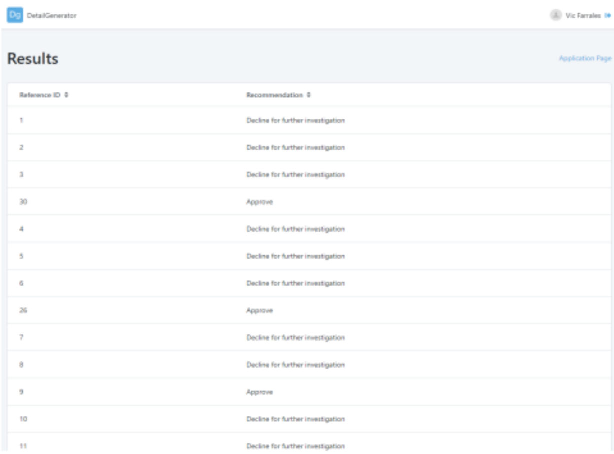

Figure 7
Web Output User Interface

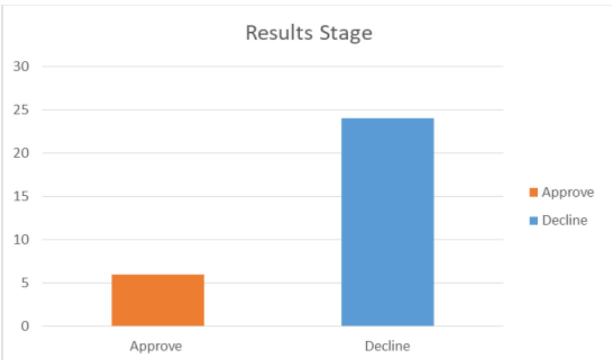

Figure 8
Application Results Statistics

Figure 8 depicts the applicants' evaluation report. Figure 9 shows that of the 30 outcomes, 20% are approved and 80% are declined.

RESULTS AND DISCUSSION

The prototype developed for this study was designed to provide recommendations to credit assessors on whether an applicant should be approved or declined, based on their employment records, bank records, credit history, and background checks. The program achieved an accuracy rate of 90% when tested with a dataset of 100 records. The dataset was divided with 30% allocated to the testing set, and the configuration included a randomization frequency of 10. To validate the program's performance, the team conducted a test where 10 records were randomly selected from the dataset and used as a feed file. The results showed a 100% match between the program's recommendations and the dataset records, confirming the reliability of the prototype in real-world scenarios.

The researcher created mock data for various groups of applicants to evaluate the prototype’s performance across different scenarios. The groups were as follows:

Table 3
Mocked Data

Group 1	Employees with low salary, clean bank accounts, no derogatory records
Group 2	Employees with low salary, clean bank accounts, with derogatory records
Group 3	Employees with high salary, clean bank accounts, no derogatory records
Group 4	Employees with high salary, clean bank accounts, with derogatory records
Group 5	Business Personnel not AMLA exposed, clean bank accounts, no derogatory records
Group 6	Business Personnel not AMLA exposed, clean bank accounts, with derogatory records
Group 7	Business Personnel AMLA exposed, clean bank accounts, no derogatory records
Group 8	Business Personnel AMLA exposed, clean bank accounts, with derogatory records
Group 9	AMLA exposed personnel, clean bank accounts, no derogatory records
Group 10	AMLA exposed personnel, clean bank accounts, with derogatory records

Impact of Credit Records. The presence of negative credit records, such as hits on the Negative File Information System (NFIS), Credit Management Association of the Philippines (CMAP), and Anti-Money Laundering Act (AMLA) checks, significantly influenced the approval decision. Only 10% of applicants with derogatory records were recommended for approval, indicating the critical weight of these factors in the credit assessment process.

Relationship Between Credit Records and Employment. Employment information played a balancing role in the credit assessment. Applicants with strong employment records (e.g., high salary grades) were sometimes approved despite having negative credit records, especially if they had managed to recover their credit score. This suggests that while credit history is vital, strong employment credentials can mitigate some of the risks associated with poor credit records.

The results highlight the significant role that credit history plays in the approval process, with derogatory records being a major factor leading to declines. However, the prototype's ability to consider employment details alongside credit records adds a layer of nuance to the decision-making process, allowing for a more balanced assessment of applicants. This approach aligns with the study's objectives of improving credit assessment accuracy and fairness.

The findings suggest that the prototype effectively balances multiple factors in credit assessment, providing accurate and reliable recommendations for credit assessors. The emphasis on both credit records and employment details ensures that the system not only identifies high-risk applicants but also recognizes those who have the potential for approval despite past financial challenges.

Conclusions and Recommendations. The prototype is somehow reliable but still needs human intervention on further investigating the applicant's background. The weakness of the system is (1) Victims of Identity Theft, applicants name may be included on the Negative File Information System without their knowledge and will result in a rejection upon credit application. (2) Manual Checking on Credit Records, the users of the system need to check each system (NFIS, CMAP, AMLA) to see the credit record.

The findings from this study are significant in several ways. The prototype developed demonstrates a high level of accuracy (90%) in predicting credit application approvals, which is a crucial advancement in automating and improving credit assessment processes in the financial sector. This system not only validates the effectiveness of using Naive Bayesian algorithms in financial decision-making but also provides practical insights into how employment records, bank records, credit history, and background checks interact to influence credit decisions.

The successful implementation of the prototype highlights the potential for data-driven models to significantly reduce the biases and inefficiencies associated with traditional manual credit assessment processes. By providing a balanced consideration of both credit history and employment details, the system ensures a more comprehensive evaluation of applicants, which could lead to more fair and accurate credit decisions.

This study adds to the growing body of literature on the application of machine learning techniques in the financial sector. Previous studies, as noted in the literature review, have emphasized the importance of credit records in determining loan and credit approvals. However, this study goes further by demonstrating how employment information can mitigate the impact of negative credit records. This finding aligns with and extends the work of Krichene (2022) and Vedala and Kumar (2012), who explored the predictive power of Naive Bayesian classifiers in financial contexts.

Moreover, the study provides empirical evidence supporting the use of Naive Bayes classifiers in contexts where quick and accurate decision-making is required, such as in credit assessments. The prototype's ability to correctly assess 10 out of 10 records in a validation test underscores the robustness and reliability of this approach, confirming its practical applicability in real-world banking scenarios.

The findings of this study are consistent with existing literature in several respects. Like Krichene (2022), who demonstrated the effectiveness of Naive Bayes classifiers in improving predictive accuracy by incorporating various financial ratios, this study confirms the model's strength in handling complex, multi-attribute data sets. However, the study also introduces a new perspective by highlighting the balancing role of employment information, which was not as prominently featured in previous research.

One notable difference is the finding that applicants with strong employment records could overcome negative credit records to some extent. This outcome suggests a more dynamic interplay between credit history and employment status than previously understood, indicating that financial institutions might benefit from incorporating more diverse data points in their decision-making processes.

Unexpectedly, the study found that even in cases of significant negative credit records, a small percentage (10%) of applicants were still recommended for approval. This suggests that the model may be identifying nuanced patterns in the data that could signal recovery or potential in applicants who might otherwise be dismissed by traditional assessment methods.

Practical Implications. The findings have immediate practical implications for the financial sector. By integrating this prototype into existing credit assessment workflows, banks can significantly reduce the time and human error associated with manual processing. Additionally, the ability to factor in employment details alongside credit records offers a more rounded view of an applicant's financial situation, potentially leading to more inclusive and fair lending practices.

The model's 90% accuracy also implies a high level of trustworthiness in its recommendations, which could enhance the efficiency and consistency of credit approvals. This would not only improve customer satisfaction but also optimize resource allocation within financial institutions, reducing the cost associated with bad debts.

Theoretical Implications. Theoretically, this study contributes to the understanding of how different attributes interact in credit decision-making. It challenges the traditional over-reliance on credit scores by demonstrating the importance of considering employment information as a significant factor. This could inspire further research into other non-traditional data points that might be relevant in financial assessments.

Future Directions. The study opens several avenues for future research. One potential direction is to explore the integration of additional data points, such as social media behavior or alternative financial histories, to further enhance the model's predictive power. Additionally, longitudinal studies could investigate how the model's recommendations play out over time, providing insights into the long-term effectiveness of machine learning-based credit assessments.

Further research could also compare the performance of Naive Bayes classifiers with other machine learning models, such as neural networks or support vector machines, in the context of credit assessment. This would help determine the most effective approaches for different types of financial decision-making processes.

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