Advancement and Approval of Loan Application Using XAI Technique

M. Lokesh^[1], P. Nagendhar^[1], R.Ganga Nandan^[1], P.Mounika^[1] Dr M Ganesh^[2]

^[1]B.Tech IV Year, Department of IT, Malla Reddy Engineering College, Secunderabad, Telangana, India.
^[2]Professor, Department of IT, Malla Reddy Engineering College, Secunderabad, Telangana, India.

Abstract: Significant advancements in technology have led to an expansion of people's needs. In the banking industry, this has led to an increase in loan approval requests. Several factors are taken into account when selecting a candidate for loan approval in order to ascertain the loan's status. When it comes to evaluating loan applications and reducing the risks connected to possible borrower defaults, banks confront significant challenges. This is especially difficult for banks because they have to assess each borrower's eligibility for a loan in great detail. The objective of this paper is to resolve the possibility of approving individual loan requirements by combining ensemble techniques with machine learning models. This strategy can improve the precision with which eligible applicants are chosen from a pool of submissions. Consequently, the issues with loan approval procedures mentioned above can be resolved with this technique. The significant decrease in sanctioning time achieved by the strategy benefits both the bank staff and the loan applicants. The growth of the banking sector resulted in an increase in the number of people applying for bank loans. We employed four distinct algorithms namely Random Forest, Naive Bayes, Decision Tree, and KNN to predict the applicant's loan approval status with accuracy. With the Naïve Baye's algorithm as the best, we were able to achieve a better accuracy of 83.73% by utilizing these.

Keywords: Safe Customers, Bank Loans, Trained Dataset, Random Forests, KNN, Decision Tree, Naive Baye's.

A. INTRODUCTION

The objective of the propelling credit endorsement process project is to foster an expectation model for individuals who are applying for advances and get to know regardless of whether there advance will support. Many banks' essential line of business is credit dispersion. Credits given to shoppers represent most of a bank's income. Premium is charged by these banks on advances given to clients. Banks' dealt with. The only independent and dependent variables are the values x and y. Information essential objective is to put their assets in reliable clients. Many banks have been handling credits up until this point following a regressive course of verifying and confirmation. In any case, as of the present moment, no bank can ensure whether the client who is chosen for a credit application is secure or not. Thus, all together, to keep away from this situation, we executed the Credit Expectation Framework Utilizing Python, a framework for the endorsement of bank credits. The Credit Forecast Framework is a piece of programming that decides whether or not the particular client is able to get an advance. This strategy looks at number of factors, including the client's conjugal status, pay, spending, and different components. For wide quantities of prepared informational collection clients, this strategy/procedure is utilized. These components are, taken to thought while making the important model.

For acquiring the ideal result, this model is applied for the test informational index. The outcome will be introduced as one or the other yes or no. On the off chance that the response is indeed, the client is fit for reimbursing the advance; on the off chance that the response is no, the buyer isn't fit for reimbursing the credit. Clients can receive loans from us based on these criteria. AI is the investigation of how the frameworks of PCs are utilized and created to learn and adjust without express guidelines by examining and deducing designs in information utilizing calculations and measurable models. It is so significant in the twenty-first century that it was utilized basically all over, from Such a capability can't be fitted with a straight line without causing huge mix-ups. Polynomial regression, logistic regression, and even linear regression with

more variables were also developed by scientists using datasets with more than two dimensions to address these issues. A greater number of people became interested in it and began working on it as the accuracy significantly improved. The new period of information science started with the principal utilization of the expression "Huge information" in 2005. Things like a person's credit history, the amount of the loan, their lifestyle, their career, and their assets are some of the factors that influence whether or not a loan will be granted. It is more plausible that your advance will be endorsed if past borrowers with rules like yours have made on-time installments. This dependence on earlier information and correlations with different candidates can be exploited by AI (ML) calculations, which can, then be utilized for make an information science issue to figure the credit status of new candidate utilizing the arrangement of comparable to models. As of late, huge mechanical headways have not just changed the manner in which we live and work however have additionally prompted a development in individuals' necessities and yearnings. This peculiarity has been especially outstanding in the financial area, where the interest for credit endorsements has flooded. With the expansion of advanced stages and the straightforward entry to monetary administrations, more people are looking for credits to satisfy their different necessities, going from individual speculations to undertakings.

Notwithstanding, this flood in credit demands has represented an extensive test for banks. The process of evaluating loan applications and reducing the dangers posed by potential borrower defaults has become increasingly complicated. Banks are entrusted with fastidiously assessing every borrower's qualification for a credit while guaranteeing that the loaning system stays proficient and productive. This challenge is additionally intensified by the need to adjust to developing administrative systems and market elements. Because of these difficulties, there is a developing interest in utilizing cutting edge innovations, especially AI (ML) models and group learning draws near, to upgrade the exactness and proficiency of the credit endorsement process. By bridling the force of information investigation and prescient demonstrating, banks can all the more successfully recognize qualified competitors from a pool of credit candidates, consequently decreasing the probability of defaults and further developing by and large portfolio execution. The essential target of this exploration is to investigate the capability of consolidating ML models and outfit learning procedures to anticipate the likelihood of tolerating individual credit demands. By utilizing the abundance of information accessible to banks, including segment data, record of loan repayment, and monetary markers, we mean to foster vigorous models that can precisely evaluate the reliability of borrowers. Besides, we try to address the innate constraints of conventional credit scoring strategies by embracing a more comprehensive and information driven way to deal with advance endorsement. By integrating a different arrangement of elements and utilizing modern demonstrating methods, we mean to give banks significant experiences that can illuminate their loaning choices and assist with moderating dangers. To exhibit the viability of our proposed approach, we directed an extensive examination utilizing four distinct ML calculations: Irregular Timberland, Gullible Bayes, Choice Tree, and KNN.

Through thorough trial and error and assessment, we distinguished the Gullible Bayes calculation as the best in foreseeing advance endorsement status, accomplishing a great exactness pace of 83.73%. The financial area assumes a urgent part in working with monetary development by giving monetary assets to people and organizations. Generally, advance endorsements depended intensely on a borrower's record as a consumer and monetary reports. However, significant technological advancements have altered the financial landscape in a number of ways. Our discoveries will be introduced through a complete investigation of the outcomes got from the different ML models utilized. The discussion section will conclude with an analysis of the

implications of the findings for the banking industry and potential research limitations. The report will close by summing up the vital discoveries and recommending future exploration headings.

B. BACKGROUND STUDY

There were a few well known accounts of different bunches for the credit approvals we utilize machine learning calculations. Kumar Arun, Garg Ishan, Kaur Sanmeer[1], dissemination of the advances is the center commerce portion of nearly each bank. The most parcel the bank's resources are straightforwardly came from the benefit earned from the credits disseminated by the banks. The prime objective in managing an account environment is to contribute their resources in secure hands where it is. Nowadays numerous banks/financial companies endorses advance after a relapse prepare of confirmation and validation but still there's no surety whether the chosen candidate is the meriting right candidate out of all candidates. Through this framework we are able foresee whether that specific candidate is secure or not and the complete handle of approval of highlights is robotized by machine learning method. The drawback of this show is that it emphasize different weights to each figure but in genuine life at some point advance can be endorsed on the premise of single solid calculate as it were, which isn't conceivable through this framework. Adyan Nur Alfiyatin, Hilman Taufiq, Ruth Ema Febrita, Wayan Firdaus Mahmudy[2], approaches that can be utilized to decide the cost of the house, one of them is the expectation analysis. The to begin with approach could be a quantitative expectation. A quantitative approach is an approach that utilizes time-series data. The time-series approach is to hunt for the relationship between current costs and winning costs. The moment approach is to utilize straight relapse based on hedonic estimating Past inquire about conducted by Gharehchopogh, et al. utilizing direct relapse approach get 0,929 blunder with the actualprice. In direct relapse, determining coefficients generally using the slightest square method, but it takes a long time to urge the most excellent equation.

Belaid Bouikhalene, Said Safi, Mohamed El Mohadab, The university has firmly decided to facilitate access and treatment for all processes, especially in scientific research, in order to help PhD students, professors, and administrative staff deal with the digital services that they need. This is because of the rapid development of information and communications technologies [3]. The task of evaluating scientific research papers (SRP) from many fields of study has gained significant importance in recent years due to the exponential growth in the number of papers published every day in journals and conferences, which now exceeds 50 million. Another barrier that we may have in general is anticipating the future of any system; nevertheless, we handle both issues in this research by projecting the new level of scientific inquiry. M. Vikas Krishna, A. Damodhar, G. Srinivas, and K. Hanumantha Rao [4] Almost all banks' primary operation is the distribution of loans. The majority of a bank's assets are directly attributable to the profits made on the loans that the banks provide. Investing their assets in safe hands is the main goal in a banking environment. Nowadays, a lot of banks and financial institutions grant loans following a lengthy procedure of verification and validation, but it's still unclear if the selected application is the most worthy candidate out of all of the applicants. This approach allows us to forecast whether a certain application is safe or not, and machine learning techniques automate the entire feature validation procedure. The disadvantage of this model is that it emphasize different weights to each factor but in real life sometime loan can be approved on the basis of single strong factor only, which is not possible through this system.

A machine learning classifier-based analysis approach for credit data is proposed by J. R. Quinlan[5] and G. Arutjothi, C. Senthamarai[6]. It uses a combination of Min-Max

normalization and K-Nearest Neighbor (K-NN) classifier to deliver the most accurate and significant information. Quinlan, J.R. [7] Machine learning has been a major field of study ever since artificial intelligence became recognized as a field in the middle of the 1950s. This prominence can be explained by two factors. Since learning is a defining characteristic of intelligent behavior, understanding learning is essential to any attempt to comprehend intelligence as a phenomenon. In more practical terms, learning offers a possible construction process for high-performing systems. The subfields of learning research are varied. Adaptive systems can be seen at one extreme, where they track their own performance and make internal adjustments to try and enhance it. This method, which was prevalent in most of the early learning research, resulted in self-improving systems for a variety of tasks, including problem-solving (Quinlan, 1969), balancing poles (Michie, 1982), and playing games (Samuel, 1967). Learning.

According to a quite different perspective, is the process of acquiring structured knowledge in the form of concepts (Hunt, 1962; Winston, 1975), discrimination nets (Feigenbaum and Simon, 1963), or production rules (Buchanan, 1978). According to Vishnu Vardhan's[8] case study on bank loan prediction, Dream Housing Finance is a business that handles all house loans. They are present in all areas—rural, semi-urban, and metropolitan. After the company verifies the customer's eligibility for a loan, the consumer applies for a house loan initially. It takes a long time to accomplish this manually, though. As a result, it seeks to automate, using client data, the loan eligibility process in real time. Finding the criteria and client categories that qualify for loans is the last step. The first issue that comes to mind is how giving the customer segments will benefit the organization. The answer lies in banks only lending money to qualified clients, ensuring that they will receive their money back. Thus, the Dream Housing Finance Company would benefit more from our ability to forecast eligible customers with greater accuracy for Proposed Methodology.

C. METHODOLOGY

In this work, we use Kaggle data set which contains, number of loan default prediction data sets. Kaggle is a well-known platform for machine learning (ML) competitions. These datasets (Table-1) frequently comprise a different variety of attributes pertaining to loan applications, borrower profiles, and payment history. We imported Loan Dataset from Kaggle can view in the excel form and the above dataset is used for processing.

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1	A	В	С	D	E	F	G	Н	I	J	K
1	SK_ID_PR	SK_ID_CU	NAME_CC	AMT_ANN	AMT_APP	AMT_CRE	AMT_DOV	AMT_GOO	WEEKDAY	HOUR_AP	FLAG_LA
2	2030495	271877	Consumer	1730.43	17145	17145	0	17145	SATURDA	15	Y
3	2802425	108129	Cash loan:	25188.6	607500	679671		607500	THURSDA	11	Y
4	2523466	122040	Cash loan:	15060.7	112500	136445		112500	TUESDAY	11	Y
5	2819243	176158	Cash loan:	47041.3	450000	470790		450000	MONDAY	7	Y
6	1784265	202054	Cash loan:	31924.4	337500	404055		337500	THURSDA	9	Y
7	1383531	199383	Cash loan:	23703.9	315000	340574		315000	SATURDA	8	Y
8	2315218	175704	Cash loans	6	0	0			TUESDAY	11	Y
9	1656711	296299	Cash loans	5	0	0			MONDAY	7	Y
10	2367563	342292	Cash loans	6	0	0			MONDAY	15	Υ
11	2579447	334349	Cash loans	6	0	0			SATURDA	15	Y
12	1715995	447712	Cash loan:	11368.6	270000	335754		270000	FRIDAY	7	Y
13	2257824	161140	Cash loan:	13832.8	211500	246398		211500	FRIDAY	10	Y
14	2330894	258628	Cash loan:	12165.2	148500	174362		148500	TUESDAY	15	Y
15	1397919	321676	Consumer	7654.86	53779.5	57564	0	53779.5	SUNDAY	15	Y
16	2273188	270658	Consumer	9644.22	26550	27252	0	26550	SATURDA	10	Y
17	1232483	151612	Consumer	21307.5	126491	119853	12649.5	126491	TUESDAY	7	Y
18	2163253	154602	Consumer	4187.34	26955	27297	1350	26955	SATURDA	12	Y
19	1285768	142748	Revolving	9000	180000	180000		180000	FRIDAY	13	Y
20	2393109	396305	Cash loan:	10181.7	180000	180000		180000	THURSDA	14	Y

Table-1: Sample Dataset



Fig 1. Proposed method Model

Initially clean and pre-process the data then Handle missing values, remove outliers, and normalize or standardize features as necessary. Explore the data to identify any initial patterns or trends; though do not expect and if there is any undistributed data we can remove or fix it accordingly. In Feature Engineering select potential features for your predictive model. These might include previous data, for preprocess and to train the model by giving previous approval or rejection data which used for future predictions.

Choosing machine learning algorithms suitable for loan approvals. Given that loan approval is essentially a approval or rejection task (predicting the loan will approve or not consider algorithms that excel at predicting, such as Decision Trees, Random Forests, Navie Bayes. To evaluate your model's performance, partition the dataset into training and testing sets. We partitioned the data total of 100 outcomes into 80 of training and 20 of test data. Train your chosen machine learning model on the training data. Access your model's performance using appropriate evaluation metrics for classification, such as accuracy, precision Implement cross-validation to ensure the model's performance is consistent across different data subsets.

D. RESULT ANALYSIS

The implementation of the loan approval system using Machine Learning has yielded promising results in enhancing Prediction of loan approvals outcomes.

	Future of Loan Approvals with Explainable AI					
Upload Loan Application Dataset	Preprocess Dataset	Split Dataset Train &	Test			
Train AI on Loan Approval	Train AI on Loan Rejections	Explainable AI	Predict Loan Status using Test Data			

Fig 2. Interface of the application

As we are using command prompt to host the application we need to open command prompt and type command python LoanStatus.py to run the application as the app name is saved with that name. After that we can see a pop up window of our application interface as shown in figure 2.

load Loan Applicati	on Dataset	Preprocess Data	et	Split Da	taset Train & T	fest
in AI on Loan Appr	oval	Train AI on Loan	Reiections	Explaina	ble AI ×	Predict Loan Status using Test Dat
$\leftrightarrow \rightarrow \sim \uparrow$	🚞 « Desktop > Loan	> Dataset	~ 0	Search Dataset	P	
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> Pictures	testData		0	15-12-2023 11:18	Microsoft Excel C	
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Pictures 📌						

Fig 3. Loading the training dataset

After the running of the application we need to upload the dataset for the training of the application the data set consists of 37 columns and 5 rows which consists of the previous loan approval and rejection data the loading of the dataset was shown in below figure 3.

				Futur	e of Loan Approv	als with Explainable AI
Upload Loan Appli	cation Dataset	Preproc	ess Dataset		Split Dataset Train	& Test
Train AI on Loan A	pproval	Train AI	on Loan Rejecti	ons	Explainable AI	Predict Loan Status using Test Data
SK_ID_PREV SK 1 2030495 27181 2 2502425 10811 2 2523466 1220- 3 2810243 1761- 1 1784265 2020- [5 rows x 37 columns]	ID_CURR NAME_CC 7 Consumer loans 9 Cash loans 0 Cash loans 8 Cash loans 4 Cash loans	DNTRACT_T 42.0 365243.0 365243.0 -182.0 NaN	VPE DAYS_L/ 37.0 365243.0 365243.0 -177.0 NaN	AST_DUE D/ 0.0 1.0 1.0 1.0 NaN	AVS_TERMINATION	NFLAG_INSURED_ON_APPROVAL

Fig 4. Testing Results

After the training dataset is loaded we can see the data which is taken for the training of the application and it gives the description of the columns which we are taken shown in the figure 4.



Fig 5. Graph showing loan application status and rejection status

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After the data is loaded we can see two bar graphs which consists one with loan application status graph and other consists data of the rejection reason graph. The loan application status consists of count and loan status and the rejection reason consist of count and rejection reason that was shown in the figure 5.

	Future of Loan Approvals with Explainable AI							
Upload Loan Application Dataset	Preprocess Dataset	Split Dataset Train &	t Test					
Train AI on Loan Approval	Train AI on Loan Rejections	Explainable AI	Predict Loan Status using Test Data					
	178964 2.53016275 178964 2.53016275 7673097 -0.39076936 7673097 -0.39076936 7673097 -0.39076936							

Fig 6. Preprocess of a dataset

After that we need to preprocess the data and the data after preprocessing will be shown in figure 6.

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Future of Loan Approvals with Explainable Al			
	1	Future of Loan Approvals with Explainable AI	
Upload Loan Application Dataset	Preprocess Dataset	Split Dataset Train & Test	
Train AI on Loan Approval	Train AI on Loan Rejections	Explainable AI Predict Loan Status using Test Data	
Total records found in dataset = 20000			
Total features found in dataset= 35			
80% dataset for training : 16000			
20% dataset for testing : 4000			

Fig 7. Splitting of the training and testing data.

After the preprocess of the dataset the data will be split into training and testing the data in that some of the records will be taken for training and remaining records will be taken for testing the information was shown in the figure 7.

Future of Loan Approvals with Explainable Al			
		Future of Loan Approvals w	ith Explainable AI
Upload Loan Application Dataset	Preprocess Dataset	Split Dataset Train & Tes	t
Train AI on Loan Approval	Train AI on Loan Rejections	Explainable AI	Predict Loan Status using Test Data
Random Forest Loan Status Accuracy : 95.25	,		
Random Forest Loan Status Precision : 87.0880	9167044171		
Random Forest Loan Status Recall : 92.2446: Random Forest Loan Status FScore : 89.4123	5089442889 5347146265		

Fig 8. The values of accuracy, precision, recall, Fscore.

And completing of the training and testing the data we need to train AI on loan approval it gives the random forest accuracy, precision, recall and F score values as shown in the figure 8.



Fig 9. Confusion matrix of XAI Loan Approvals

The Dataset after training on AI loan approval it also generates the confusion matrix with specified details the confusion matrix gives detailed information on the loan status of the given data and matrix was shown in figure 9.



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Future of Loan Approvals with Explainable Al			
		Future of Loan Approvals v	with Explainable AI
Upload Loan Application Dataset	Preprocess Dataset	Split Dataset Train & Te	est
Train AI on Loan Approval	Train AI on Loan Rejections	Explainable AI	Predict Loan Status using Test Data
Random Forest Loan Status Accuracy : 95.42 Random Forest Loan Status Precision : 86.431 Random Forest Loan Status Recail : 92.5559 Random Forest Loan Status FScore : 89.1294 Random Forest Loan Rejection Accuracy : 90 Random Forest Loan Rejection Precision : 440 Random Forest Loan Rejection Recail : 41.35 Random Forest Loan Rejection FScore : 41.1	50000000001 23557912905 1504224376 5590278456 5525 575702477293405 5100079385085 4472035910171		

Fig 10. confusion matrix of XAI on loan rejections.

Fig 11. accuracy values of the approval and rejection.

After training model on loan approval we need to train it for finding the loan rejection for that we need to press the train AI on loan rejection button so that we can get to know how many loans are rejected in the give data and detailed information about the data as in figure 10.

Open				×	
→ ~ ↑	🚞 « Desktop > Loan > Dataset	×2	🔿 Search Dataset	¢ n &	Test
ganize 🔹 New fo	lder		1		Predict Loan Status using 1
Desktop	Name	Status	Date modified	Туре	
Documents	loan_application	Ø	11-12-2019 02:58	Microsoft Excel C	
Pictures	testData	0	15-12-2023 11:18	Microsoft Excel C	
Desktop Downloads Documents Pictures Music					
File	name: testData				

Fig 12. Uploading of the test data.

And after completion of both approval and rejection the dataset gives the random forest accuracy of both the fields which is given in figure 12.

	Fu	ture of Loan Approvals w	ith Explainable AI
Upload Loan Application Dataset	Preprocess Dataset	Split Dataset Train & Tes	t
Train AI on Loan Approval	Train AI on Loan Rejections	Explainable AI	Predict Loan Status using Test Data
Test Data = [2.352627e+06 2.665600e+05 2. 0.000000e+00 0.000000e+00 0.000000e+00 1.000000e+01 0.00000e+00 0.000000e+00 2.100000e+01 0.000000e+00 0.000000e+00 1.000000e+01 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00 Loaa Approval Status = Canceled Loan Approval Status = Canceled Loan Approval Rejection Reason = XAP Test Data = [1.343316e+06 1.048260e+05 2. 4.500000e+50 0.000000e+00 0.500000e+50 1.000000e+10 1.330000e+00 0.200000e+00 2.500000e+10 1.330000e+10 0.200000e+00 2.500000e+10 0.000000e+00 0.000000e+00	000000e+00 0.00000e+00 0.00000e+0 6.000000e+00 7.000000e+00 0.000000e+00 0.000000e+00 1.000000e+00 1.000000e+00 1.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00 1.400000e+01 1.000000e+00 1.400000e+01 0.000000e+00 1.400000e+01 0.000000e+00 0.000000e+00 5.000000e+00 0.000000e+00	90 95	



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After the completion of the preprocess and training of the data under AI we need to test the model with our test data by uploading the test data we can find the loan approval the uploading of test data is shown in figure 13. The system's performance was evaluated through various metrics, including Accuracy Table-2 shows the various algorithms and theirs evaluation metrics. **Table-2:** Accuracy of various algorithms

Sl.No	Algorithms	Accuracy
1	Random Forest	77.23%
2	Naive Bayes	83.73%
3	Decision Tree	63.41%
4	k-Nearest Neighbors	77.23%



Fig 14. Accuracy Comparison of various algorithms

The overall result will be given by clicking on the predict loan data by using XAI we can get the final result as shown in Fig.14 and it shows the detailed information about the data and also shows the reason for approval or rejection the final result.

E. CONCLUSION

In this research, we created and assessed machine learning (ML) models for chances of loan acceptance. In order to comprehend the dataset and gain understanding of the loan approval procedure, we started by undertaking exploratory data analysis. In order for address missing values, we imputed them with suitable values depending on the distribution of the data. In order to get the data ready for modeling, we additionally did log transformation and scaling. Then, we trained and assessed several classification models, including the K- Nearest Neighbors Classifier, the Decision Tree Classifier, the Random Forest Classifier, and the Gaussian Naïve Bayes Classifier. We used accuracy as the evaluation criteria to assess these models' performance. Based on our findings, we discovered that the Random Forest Classifier outperformed the other models and had the greatest accuracy of X% on the test set. As a result, it can be concluded that the Random Forest model is effective in forecasting loan approvals based on the provided features. Our models have produced encouraging results, but there is still potential for development and additional research. Here are some potential paths this project could go in the future. To create more informative features from the ones that already exist, we can investigate further feature engineering strategies. To increase the models' capacity for prediction, this may entail developing interaction terms, polynomial features, or incorporating domain-specific information. In an order to recognise best possible combination of hyper parameters, we can adjust the models' hyper parameters using methods such as grid search otherwise randomized

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search. This might enhance the models' functionality and result in more accurate forecasts. We can use techniques like oversampling, under sampling, or using various evaluation metrics such as precision, recall, or F1 score to address the class imbalance issue if the loan approval dataset exhibits class imbalance, where the number of approved loans significantly differs from the number of rejected loans.

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