Predicting and Reducing Peer 2 Peer Late Payments using Large Numerical Models (LNMs)

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Abstract: The inability of borrowers to repay loans poses a significant challenge to the sustainability of the Peer-to-Peer (P2P) lending sector. This study leverages predictive modeling techniques to analyze historical applicant data from Lending Club, focusing on reducing late payments through the proprietary Sriya Expert Index (SXI) Artificial Intelligence-Machine Learning (AI-ML) algorithm. SXI serves as a super feature, synthesizing the outputs of 5–10 machine learning algorithms into a simplified score/index, enabling accurate prediction of late payments. The model dynamically adjusts algorithmic weights to optimize precision, considering critical features such as credit history, income, and repayment behavior. In comparison to traditional machine learning models, the Sriya Expert Index (SXI) algorithm significantly outperforms established approaches in predicting late payments. Models such as Random Forest and XGBoost achieved accuracies of 78.80% and 84.52 %, respectively, while the Mixture of Experts (MOE) neural network reached 92.10%. The Support Vector Machine (SVM) with a linear kernel delivered an AUC of 0.935, slightly higher than the 0.92 AUC of XGBoost. However, SXI surpasses all these models with a near flawless accuracy of 99.80% and an AUC score of 0.998. This demonstrates the model's superiority in identifying late payment risks and its potential to guide effective intervention strategies. One of the standout features of SXI enabled AI-ML is to improve business outcomes with actionable insights. The study outlines a phased methodology for reducing late payments (desired business outcome), achieving an initial 20% reduction and further improvements to 50% and 80% in the mid-term and long-term, respectively. These findings highlight the transformative potential of SXI in enhancing risk management in P2P lending, offering a scalable, data-driven solution to improve the financial health of the sector.

Keywords: Sriya Expert Index (SXI), Peer-to-Peer (P2P) lending platform, lending club, reducing late payments, predictive model

1. Introduction

Traditional financial institutions have high thresholds, low returns, and long investment cycles, driving investors to seek more flexible, higher-yield, and lower-amount investment options. However, limitations in the personal credit information system and slow credit infrastructure development prevent some deserving individuals from accessing funds, leading to the rise of streamlined platforms like Peer-to-Peer (P2P) lending. P2P platforms act as intermediaries, connecting borrowers and lenders online. They offer convenient and accessible lending and money transfer services. Additionally, deep learning techniques provide valuable insights for interpreting various forms of data, potentially enhancing the functionality of P2P platforms. The

demand from both investors and borrowers has fueled the growth of P2P lending platforms significantly, contributing to their rapid expansion. These platforms have become integral to financial markets, fulfilling crucial roles in meeting investment and financing demands while fostering market diversity. However, despite their importance, P2P platforms suffer from deficiencies in financial management and risk control capabilities, leading to a considerable number of defaulted loans [1].

In the context of peer-to-peer lending within the United States, Lending Club stands out as a leading digital platform that facilitates direct interaction between individuals seeking loans and those interested in providing capital. Unlike traditional banks, this platform streamlines the lending process by removing institutional intermediaries. Prospective borrowers are required to submit applications that detail the intended purpose of the loan as well as their financial information. Meanwhile, investors can review available borrower profiles, decide on the amount they wish to invest, and select specific lending opportunities based on their preferences and risk appetite.

In this market, individuals with poor credit history, who might otherwise struggle to obtain credit from traditional financial sources or face high-interest rates, have the chance to access credit at lower rates. Conversely, investors can potentially earn higher returns on their capital compared to traditional bank savings accounts. Nevertheless, there exists a significant risk of borrowers defaulting on their loans, resulting in non-repayment of both the principal amount and interest.

ML principles are applied to assess default risk, or the likelihood of a borrower failing to repay, through techniques like Neural Networks (NN) with backpropagation, as demonstrated by Zang *et al.* [2]. This NN achieved an accuracy rate of 78.6%. In Ref. [3], Freedman and Jin found a positive correlation between borrowers' credit ratings and loan success rates. Fu [4] and Milad [5] conducted experiments merging tree methods like Random Forest (RF) with Neural Networks (NN).

Investigated factors such as loan grade (a Lending Club-assigned score for borrowers) and Fair Isaac Corporation scores (FICO) as predictors of default risk. Milad employed various learning algorithms, including a cost-based RF, which attained the top accuracy score of 78.8%. These studies all approached the task of assessing default risk as a classification problem. Methods such as Back Propagation Neural Network (BPNN) create a loan default prediction model, enabling effective assessment of default risk probability and lowering risk management costs by achieving an AUC Score of 0.79 and a default loan prediction accuracy of 84.05% [6].

However, upon closer examination, it was noted that the classification variable, often labeled as loan_status, exhibited an imbalance in instances. Specifically, instances where borrowers did not default were substantially more prevalent than instances of default. This class imbalance poses challenges for classification models, as they may become biased toward the majority class, potentially leading to overfitting issues, as demonstrated in [7].

Data mining techniques particularly on Support Vector Machine (SVM), are employed to identify distinctive patterns among customers in Indonesia with defaulted and non-defaulted credit. Analyzing 100 borrower records spanning from March 2017 to January 2019, including social media features, revealed SVM Linear as the optimal model, outperforming SVM Radial Basis Function (RBF) and SVM Poly. Specifically, SVM Linear exhibited an AUC of 0.935, while SVM RBF and SVM Poly achieved only 0.755 and 0.42, respectively [8].

Feller *et al.* [9] explored how structured borrower information, often referred to as "hard data," influences financial decision-making within peer-to-peer lending platforms. Utilizing loan records from Lending Club, their analysis applied multiple logistic regression models to assess how borrower characteristics affect both the likelihood of securing funding and the risk of loan default. The findings revealed that certain variables—such as credit grade, FICO score, monthly income, and interest rate—have statistically significant associations with loan outcomes. For instance, borrowers with lower credit grades and FICO scores, despite having higher

monthly incomes, were generally less prone to default, while higher interest rates showed a negative relationship with repayment performance.

Another study on P2P lending platforms aimed to reduce information asymmetry by constructing credit-scoring models using ML and ANN algorithms on Lending Club data. Feature engineering and XGBoost were used to determine the 16 most significant default factors. The dataset was balanced through under sampling, and seven algorithms were optimized using grid search and cross-validation. Gradient Boosting methods, particularly XGBoost and LightGBM, outperformed traditional models like LR and 2-layer neural networks. XGBoost achieved the highest accuracy at around 88%, making it the most suitable model for P2P credit scoring [10].

Another study conducted by Miller Janny integrates profit information into the entire modeling process, including XGBoost learning function, model tuning, and decision-making stages. The results demonstrated that profit-based models could yield higher financial returns while reshaping the role of input variables, favoring factors like low indebtedness and small loan amounts for low-risk, profitable lending. However, the models showed low acceptance rates, reflecting the complexity and risk of the small business segment [11]. In a study exploring credit risk modelling, a Mixture-of-Experts (MOE) neural network framework was utilized to predict default probabilities on peer-to-peer lending platforms, achieving a high accuracy of 92.10% [12]. By combining supervised and unsupervised machine learning techniques, hybrid models demonstrated superior performance in handling complex, nonlinear relationships compared to traditional supervised models.

Previous studies predominantly employed machine learning techniques to address the challenge of predicting late payments in Peer-to-Peer (P2P) lending platforms, focusing primarily on identifying high-risk borrowers. However, these approaches often lacked interpretability regarding the influence of key borrower characteristics and financial behaviors on late payment predictions, failed to propose effective strategies for reducing late payments over short-, mid-, and long-term periods, and relied on models that required extensive prior training. Additionally, there was limited integration of advanced scoring systems, which could leverage diverse borrower data, such as credit history, income stability, and repayment trends, to more accurately assess late payment risks across various lending scenarios. By incorporating a comprehensive scoring system, the potential for more precise and actionable risk analysis is greatly enhanced, offering lenders a holistic understanding of borrower repayment behavior.

To address these gaps, this study focuses on: (i) evaluating the performance of the SXI algorithm as a multivariate scoring system to predict late payment risk as a binary classification problem, (ii) enhancing the SXI scoring methodology using a Proprietary Deep Neural Network algorithm and correlating it with late payment rates over a defined period, and (iii) employing a targeted decision tree framework to interpret the most effective pathways leading to both high- and low-risk borrowers, thereby offering evidence-based recommendations for reducing late payment incidences and improving the financial stability of P2P lending platforms.

2. Materials and Methods

2.1. Data Description

The source of the data for this paper on predicting and reducing the impact of late loan payments using Lending Club's historical loan applicant information likely comes from Lending Club's internal database or archives dated from 2007 to 2020 Q3. Lending Club is a US peer-to-peer lending company, headquartered in San Francisco, California. It was the first peer-to-peer lender to register its offerings as securities with the Securities and Exchange Commission (SEC), and to offer loan trading on a secondary market.

The dataset provides historical insights into borrowers' financial behavior, including whether loan

repayments were made on time or delayed. The core objective of this study is to uncover underlying patterns and risk indicators that signal the likelihood of delayed repayment. Such predictive insights can support more informed lending strategies, such as adjusting the loan amount, applying differentiated interest rates for high-risk individuals, or, in certain cases, declining loan approval altogether.

The initial dataset consists of 2,260,668 rows and 151 features and through further data cleaning 58 features had null values exceeding 35% of the total entries. The features of the dataset are listed in Table 1. Given the significant proportion of missing data in these features was dropped from the dataset which resulted in a reduction in the number of features to 93 which will be used for further data analysis.

Table 1. Dataset Feature Description

Features	Feature Description
id	A unique Lending Club (LC) assigned ID for the loan listing.
acc_now_delinq	The number of accounts on which the borrower is now delinquent.
acc_open_past_24mths	Number of trades opened in past 24 months.
addr_state	The state provided by the borrower in the loan application.
annual_inc	The self-reported annual income provided by the borrower during registration.
application_type	Indicates whether the loan is an individual application or a joint application with two co-borrowers.
avg_cur_bal	Average current balance of all accounts.
bc_open_to_buy	Total open to buy on revolving bankcards.
bc_util	Ratio of total current balance to high credit/credit limit for all bankcard accounts.
chargeoff_within_12_mths	Number of charge-offs within 12 months.
collections_12_mths_ex_med	Number of collections in 12 months excluding medical collections.
delinq_2yrs	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past.
delinq_amnt	The past-due amount owed for the accounts on which the borrower is now delinquent.
dti	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations.
emp_length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year.
emp_title	The job title supplied by the Borrower when applying for the loan.
fico_range_high	The upper boundary ranges the borrower's FICO at loan origination belongs to.
fico_range_low	The lower boundary ranges the borrower's FICO at loan origination belongs to.
funded_amnt	The total amount committed to that loan at that point in time.
funded_amnt_inv	The total amount committed by investors for that loan at that point in time.
grade	LC assigned loan grade
home_ownership	The home ownership status provided by the borrower during registration.
initial_list_status	The initial listing status of the loan. Possible values are – W, F
inq_last_6mths	The number of inquiries in past 6 months (excluding auto and mortgage inquiries)
installment	The monthly payment owed by the borrower if the loan originates.
int_rate	Interest Rate on the loan.
last_fico_range_high	The upper boundary ranges the borrower's last FICO pulled belongs to.
last_fico_range_low	The lower boundary ranges the borrower's last FICO pulled belongs to.
last_pymnt_amnt	Last total payment amount received.
loan_amnt	The listed amount of the loan applied for by the borrower.
mo_sin_old_il_acct	Months since oldest bank installment account opened.
mo_sin_old_rev_tl_op	Months since oldest revolving account opened.
mo_sin_rcnt_rev_tl_op	Months since most recent revolving account opened.
mo_sin_rcnt_tl	Months since most recent account opened.
mort_acc	Number of mortgage accounts.
mths_since_recent_bc	Months since most recent bankcard account opened.
mths_since_recent_inq	Months since most recent inquiry.

num_accts_ever_120_pd	Number of accounts ever 120 or more days past due.
num_actv_bc_tl	Number of currently active bankcard accounts.
num_actv_rev_tl	Number of currently active revolving trades.
num_bc_sats	Number of satisfactory bankcard accounts.
num_bc_tl	Number of bankcard accounts.
num_il_tl	Number of installment accounts.
num_op_rev_tl	Number of open revolving accounts.
num_rev_accts	Number of revolving accounts.
num_rev_tl_bal_gt_0	Number of revolving trades with balance >0.
num_sats	Number of satisfactory accounts.
num_tl_120dpd_2m	Number of accounts currently 120 days past due (updated in past 2 months).
num_tl_30dpd	Number of accounts currently 30 days past due (updated in past 2 months).
num_tl_90g_dpd_24m	Number of accounts 90 or more days past due in last 24 months.
num_tl_op_past_12m	Number of accounts opened in past 12 months.
open_acc	The number of open credit lines in the borrower's credit file.
out_prncp	Remaining outstanding principal for total amount funded
out_prncp_inv	Remaining outstanding principal for portion of total amount funded by investors.
pct_tl_nvr_dlq	Percent of trades never delinquent.
percent_bc_gt_75	Percentage of all bankcard accounts > 75% of limit.
policy_code	publicly available policy_code=1 new products not publicly available policy_code=2.
pub_rec	Number of derogatory public records.
pub_rec_bankruptcies	Number of public record bankruptcies.
purpose	A category provided by the borrower for the loan request.
pymnt_plan	Indicates if a payment plan has been put in place for the loan.
revol_bal	Total credit revolving balance.
revol_util	Revolving line utilization rate.
sub_grade	LC assigned loan subgrade.
tax_liens	Number of tax liens.
term	The number of payments on the loan. Values are in months and can be either 36 or 60.
tot_coll_amt	Total collection amounts ever owed.
tot_cur_bal	Total current balance of all accounts.
tot_hi_cred_lim	Total high credit limit.
total_acc	The total number of credit lines currently in the borrower's credit file.
total_bal_ex_mort	Total credit balance excluding mortgage.
total_bc_limit	Total bankcard high credit/credit limit.
total_il_high_credit_limit	Total installment high credit/credit limit.
total_pymnt	Payments received to date for total amount funded.
total_pymnt_inv	Payments received to date for portion of total amount funded by investors.
total_rec_int	Interest received to date.
total_rec_late_fee	Late fees received to date.
total_rec_prncp	Principal received to date.
total_rev_hi_lim	Total revolving high credit/credit limit.
verification_status	Indicates if income was verified by LC, not verified, or if the income source was verified.
hardship_flag	Flags whether or not the borrower is on a hardship plan
disbursement_method	The method by which the borrower receives their loan. Possible values are: CASH, DIRECT_PAY.
debt_settlement_flag	Flags whether or not the borrower, who has charged-off, is working with a debt-settlement company.
loan_status	Status of the loan (Current/Ongoing or Late Payments).

The target variable for this analysis is the Loan Status (Fig. 1), which has two categories: "Current" and "Late Payments" from the reformatted data. The "Current" category represents applicants who are in the process of paying their loan installments, meaning the loan tenure has not yet been completed. The "Late-Payments" category represents applicants who have paid their installments after the due date. To ensure a

balanced dataset for model building, a random sample of 26,000 records was taken from the "Current" category and combined with the 25,816 records from the "Late Payments" category (Late (31–120 days) and Late (16–30 days)), resulting in a final dataset of 51,816 rows.

```
Out[104]: loan_status
          Fully Paid                                                 1076751
          Current                                                     878317
          Charged Off                                                 268559
          Late (31-120 days)                                           21467
          In Grace Period                                              8436
          Late (16-30 days)                                            4349
          Does not meet the credit policy. Status:Fully Paid           1988
          Does not meet the credit policy. Status:Charged Off           761
          Default                                                        40
          Name: count, dtype: int64
```

Fig. 1. Loan status.

We consider three categories, Current, Late (31–120 days), and Late (16–30 days)) to represent the loan status.

The dataset contains a mix of categorical and numerical features. There are 16 categorical features, and 69 numerical features. It's worth noting that 2 features, both categorical and numerical, had only 1 unique value across the entire dataset, which may indicate limited variability in those features. In addition to the categorical and numerical features, the dataset also includes 8 features that are related to dates, IDs, zip codes, and other non-predictive information. The categorical features are one hot encoded thus increasing the number of features from 82 to 171 features. The final dataset used for model building will consist of 51,816 rows and 171 features, after excluding 35% of missing values and the non-predictive features.

2.2. Descriptive Statistics

2.2.1. Missing values

The dataset reveals significant missing values in the top 10 features (Fig. 2), with open_acc_6m having the highest at 85.36%, followed by open_il_12m (84.11%). Key secondary applicant features like FICO range (high) (79%) and FICO range (low) (78.01%) also exhibit substantial missingness. Other notable features, including open_il_24m (78.12%), open_act_il (73.97%), andsec_app_inq_last_6mths (70.25%), show similar trends.Features such as sec_app_open_acc and sec_app_revol_util (both 68.04%) and sec_app_open_act_il (66.66%) indicate critical gaps in credit-related attributes. Overall, 58 features with missing values exceeding 35% of total entries were dropped from the dataset. This reduction resulted in 93 features being retained for further data analysis, ensuring better data quality and improved modeling potential.
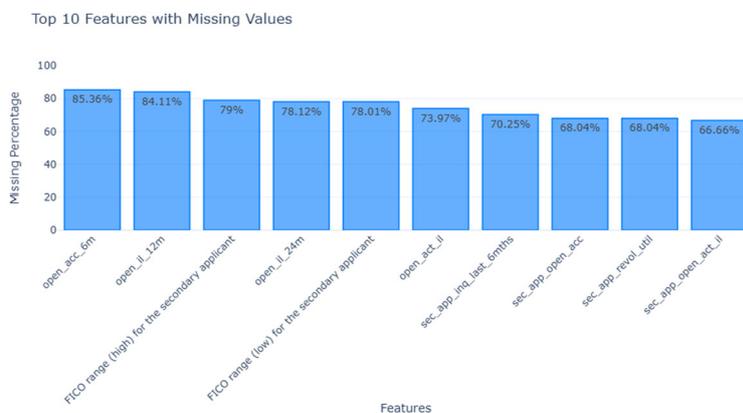
Fig. 2. Top 10 Features with Missing Values. Overall, 58 features with missing values exceeding 35% of total entries were dropped from the dataset.

2.2.2. Descriptive analysis of numerical features (see Table 2)

Table 2. Descriptive Analysis of Numerical Features

Features	Mean	Std. Dev	Min Value	25 %ile	50 %ile	75 %ile	Max Value
loan_amnt	16472	9776	1000	9600	15000	23450	40000
funde d_amnt	16472	9776	1000	9600	15000	23450	40000
funded_amnt_inv	16468	9774	750	9600	15000	23431	40000
int_rate	14	5	5	10	14	17	31
installment	479	283	8	271	405	640	1715
annual_inc	78547	81756	0	46000	65000	94000	9573072
dti	20	18	0	12	19	26	999
delinq_2yrs	0	1	0	0	0	0	36
fico_range_low	698	32	660	670	690	715	845
fico_range_high	702	32	664	674	694	719	850
inq_last_6mths	1	1	0	0	0	1	6
open_acc	12	6	0	8	11	15	62
pub_rec	0	1	0	0	0	0	45
revol_bal	16182	22897	0	5595	11061	19773	1392002
revol_util	49	25	0	30	48	68	143
total_acc	23	12	2	14	21	29	148
out_prncp	10837	8385	0	4276	8749	15418	40000
out_prncp_inv	10835	8384	0	4275	8747	15412	40000
total_pymnt	8533	7694	0	2971	6102	11682	60511
total_pymnt_inv	8530	7691	0	2971	6101	11679	60424
total_rec_prncp	5635	5344	0	1867	3906	7609	40000
total_rec_int	2891	3089	0	822	1788	3882	27394
total_rec_late_fee	8	34	0	0	0	0	1484
last_pymnt_amnt	512	739	0	264	402	646	38341
last_fico_range_high	659	75	0	599	669	714	850
last_fico_range_low	647	109	0	595	665	710	845
collections_12_mths_ex_med	0	0	0	0	0	0	6
policy_code	1	0	1	1	1	1	1
acc_now_delinq	0	0	0	0	0	0	2
tot_coll_amt	220	1712	0	0	0	0	197765
tot_cur_bal	137087	160456	0	27349	68989	204094	4170862
total_rev_hi_lim	34290	34783	0	14500	25600	43100	1656900
acc_open_past_24mths	5	3	0	2	4	6	43
avg_cur_bal	12847	15910	0	2940	6581	17599	370743
bc_open_to_buy	11577	16591	0	2021	5798	14476	284588
bc_util	56	29	0	33	57	81	216
chargeoff_within_00312_mths	0	0	0	0	0	0	3
delinq_amnt	12	689	0	0	0	0	112524
mo_sin_old_il_acct	124	55	1	91	129	153	686
mo_sin_old_rev_tl_op	176	101	2	109	157	227	800
mo_sin_rcnt_rev_tl_op	14	18	0	4	8	17	368
mo_sin_rcnt_tl	8	9	0	3	6	11	368
mort_acc	1	2	0	0	1	2	23
mths_since_recent_bc	24	32	0	6	14	28	487
mths_since_recent_inq	7	6	0	2	5	10	24
num_accts_ever_120_pd	1	1	0	0	0	0	34
num_actv_bc_tl	4	2	0	2	3	5	25
num_actv_rev_tl	6	4	0	3	5	7	44
num_bc_sats	5	3	0	3	4	6	37
num_bc_tl	7	5	0	4	6	9	49
num_il_tl	8	7	0	3	6	11	99
num_op_rev_tl	8	5	0	5	7	11	60
num_rev_accts	13	8	2	8	12	17	116
num_rev_tl_bal_gt_0	6	3	0	3	5	7	41
num_sats	12	6	0	7	11	15	62
num_tl_120dpd_2m	0	0	0	0	0	0	1

num_tl_30dpd	0	0	0	0	0	0	2
num_tl_90g_dpd_24m	0	0	0	0	0	0	36
num_tl_op_past_12m	2	2	0	1	2	3	18
pct_tl_nvr_dlq	94	10	0	91	98	100	100
percent_bc_gt_75	40	36	0	0	33	67	100
pub_rec_bankruptcies	0	0	0	0	0	0	7
tax_liens	0	0	0	0	0	0	45
tot_hi_cred_lim	172769	179167	0	49018	104864	249270	4562297
total_bal_ex_mort	52443	52269	0	20842	38610	66228	1392002
total_bc_limit	23092	23117	0	8300	16400	30000	711400
total_il_high_credit_limit	45790	46841	0	15443	34084	61867	976075

2.2.3. Loan amount Vs interest rate vs loan status

The descriptive statistics for loan amounts indicate a noticeable difference in the distribution between Current and Late payments. On average, borrowers with late payments tend to take slightly higher loan amounts ($17,021.50) compared to those who are current ($15,926.56). Additionally, (Fig. 3) the interquartile range (IQR) is broader for late payments ($14,000: from $10,000 to $24,000) than for current payments ($13,125: from $8,400 to $21,525), suggesting that late payments are associated with more variability in loan sizes. This difference may point to a pattern where larger loans (Fig. 4) or a certain borrower profile could be contributing to increased likelihood of delinquency.
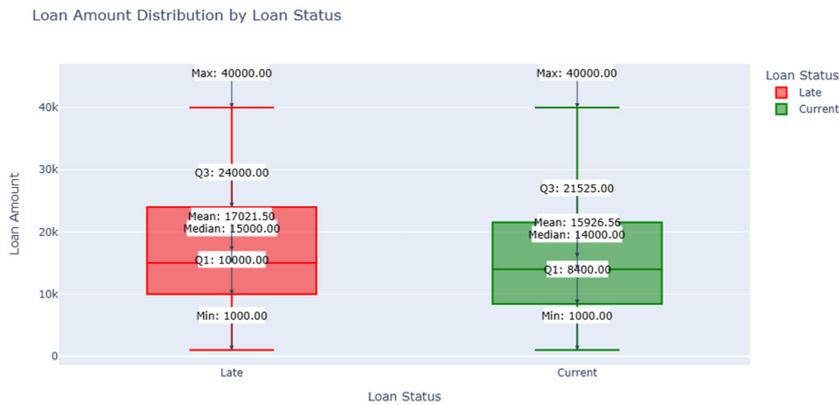
Fig. 3. Loan amount distribution w.r.t loan status.

This boxplot displays the distribution of loan amounts by loan status, highlighting key statistics such as the median, Q1, Q3, and extremes to compare current and late payments.
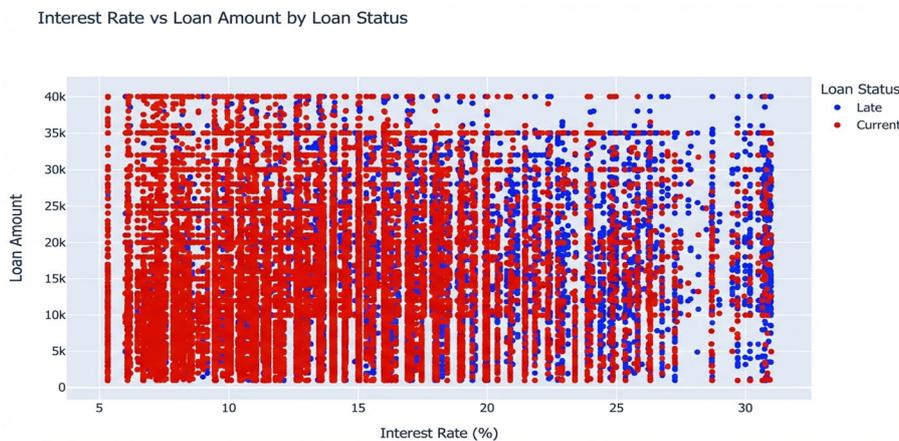
Fig. 4. Interest rate Vs loan amount w.r.t loan status.

This figure visualizes the relationship between interest rates and loan amounts, highlighting differences in trends for borrowers classified as current versus late payments.

Fig. 5. Correlation of loan amount & interest rate wr.t loan status.

This figure examines the correlation between loan amounts and interest rates, providing insights into how these variables interact for current and late payment borrowers.

2.2.4. Loan status distribution

Table 3. Loan Status Distribution

Loan Status	Training	Testing	Validation	Total
Late Payments	18146 (50.03%)	5088 (49.10%)	2582 (49.83%)	25816 (49.82%)
Current Payments	18125 (49.97%)	5275 (50.90%)	2600 (50.17%)	26000 (50.18%)
Total	36271	10363	5182	51816

The dataset used for the analysis is well-balanced across the different splits, ensuring reliable and unbiased model training, testing, and validation (Table 3). The training set comprises 36,271 records, nearly evenly divided between Late Payments (18,146 or 50.03%) and Current Payments (18,125 or 49.97%). This balance is critical for developing a model that does not favor one class over the other, particularly for binary classification problems like loan payment prediction.

Similarly, the testing set of 10,363 records maintains a near-even distribution, with 49.10% (5,088 records) classified as Late Payments and 50.90% (5,275 records) as Current Payments. The validation set also follows this trend, with 49.83% (2,582 records) representing Late Payments and 50.17% (2,600 records) as Current Payments. This consistent class distribution across all subsets (training, testing, and validation) ensures that the model's performance metrics, such as accuracy and precision, are not influenced by an imbalanced dataset, thereby enhancing the credibility of the results. Overall, the dataset's balance supports robust statistical analysis and reliable model evaluation.

2.3. Method

2.3.1. SXI score calculation

SXI is a dynamic score/index obtained from a proprietary formula consisting of weights from 5-10 ML algorithms [13]. SXI is a super feature and is a true weighted representative of all important features which

converts a multi-dimensional hard-to-solve problem into a simpler 2-dimensional solution. SXI with Proprietary Deep Neural Network algorithm involves an iterative approach where it dynamically adjusts algorithm weights based on the most significant weights provided by the 5 to 10 ML algorithms. This process aims to enhance the correlation between SXI scores and business outcomes, thereby improving accuracy and delineation.
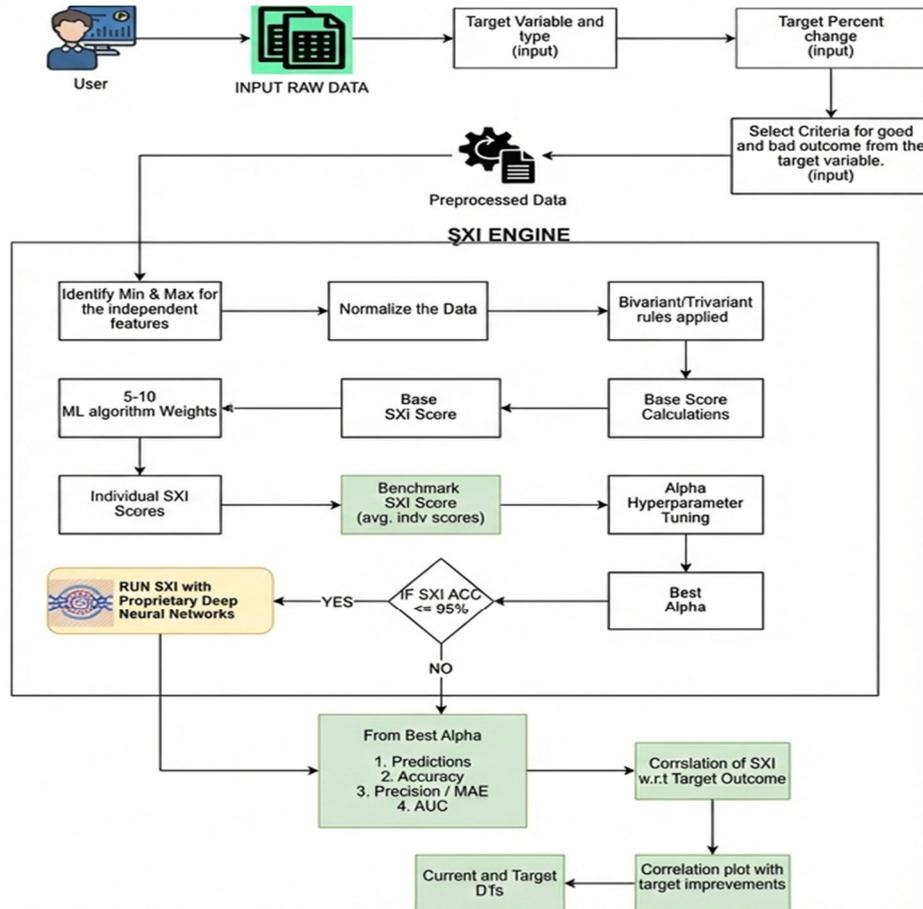

Fig. 6. SXI framework.

The SXI Framework (Fig. 6) employs a variety of mathematical techniques ranging from arithmetic to statistical analyses and non-machine learning algorithms to process cleaned data effectively. By leveraging this diverse framework, the SXI utilizes multiple functions, including statistical measures like Standard Deviation and various types of correlations, alongside algebraic operations such as proportionality constants. Through these operations, the SXI Engine calculates a Base SXI score by bringing together various statistical analysis and algebraic computations.

The SXI Engine utilizes algebraic and statistical methods to derive weights for individual user input parameters within a user vector. These weights act as multipliers, enabling adjustments to the significance of each parameter. For example, bi-variate and multi-variate analyses may yield correlation coefficients, which are then employed as multipliers for the user vector components. This process contributes to the generation of a robust Base SXI score, serving as the foundation for subsequent steps in the SXI algorithm.

Once the Base SXI score is established, the system incorporates weights obtained from 5 to 10 machine learning algorithms. These weights collectively contribute to form the Final SXI scores, which serve as the Initial SXI or the Benchmark SXI score in the SXI algorithm. This integration of diverse mathematical functions, statistical analyses, and machine learning algorithms highlights the versatility of the SXI, providing a comprehensive approach to scoring and delineating business outcomes based on user input parameters.

Benchmark analysis of the baseline score involves extracting key metrics such as the Average SXI Score (Benchmark Score), percentage of good and bad outcomes, and the distribution of outcomes above and below the average SXI. This analysis offers insights into the performance of the SXI algorithm in distinguishing between positive and negative outcomes.
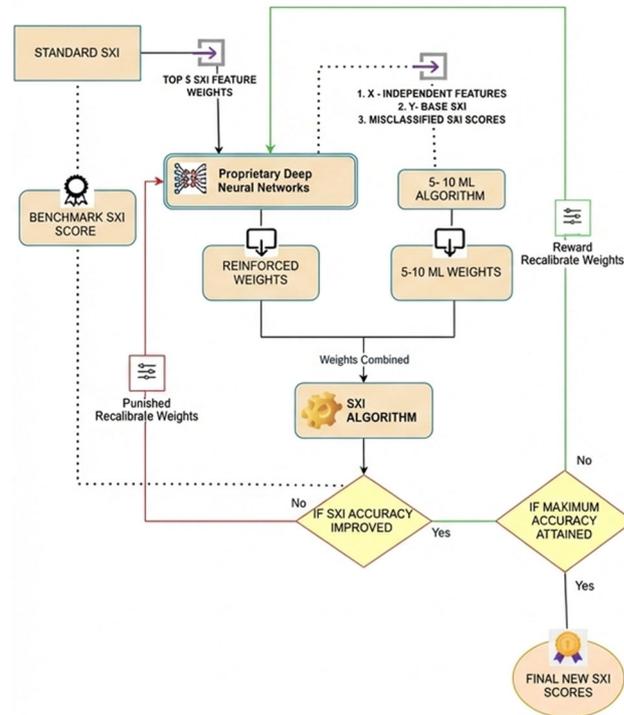

Fig. 7. Proprietary Deep Neural Network (DNN) architecture.

The Proprietary Deep Neural Network algorithm (Fig. 7) plays a crucial role in optimizing the SXI algorithm. It adjusts weights dynamically based on the performance of the system, aiming to enhance the correlation between SXI scores and business outcomes. The Proprietary Deep Neural Network algorithm agent identifies the top features from machine learning weights and adjusts the weights accordingly. Additionally, it introduces a custom weight initialization strategy based on feature importance, aligning the weight initialization process with the significance of individual features [13].

The Deep Learning Architecture consists of automated hyperparameter tuning, flexibility in activation functions and optimizers, dynamic architecture based on dataset size, and structured evaluation metrics. These characteristics ensure adaptability, efficiency, and thorough evaluation of the deep neural network model.

In this study, we structured our data processing and model evaluation workflow using a systematic data partitioning strategy. The dataset was divided into three distinct subsets: 70% for model training, 10% for validation during development, and the remaining 20% for final testing. The validation set was crucial in adjusting model parameters, identifying signs of overfitting, and supporting robust model selection within the SXI algorithm framework. This helped ensure the network's ability to generalize beyond the training data. By assessing performance on this separate validation set, we avoided the risk of tailoring the model too closely to the training samples. Once the architecture was finalized, the test set was used to provide an unbiased evaluation of model performance on previously unseen data. This comprehensive strategy enabled a more reliable assessment of accuracy and stability across the entire dataset.

Bayesian optimization for hyperparameter tuning, model configuration, and model training and evaluation

with the best hyperparameters. Iterative weight calibration is performed to refine the SXI algorithm, where it adjusts weights, applies rewards and punishments based on performance improvements, until an optimal delineator is achieved.

In the reward and punishment mechanism, improvements in both SXI score and class delineation accuracy lead to a reward. This involves integrating the newly adjusted weights into the existing ones and recalculating SXI scores to evaluate the enhancements in delineation and accuracy. If these improvements occur without any weight adjustment, there is a positive weight adjustment, initially ranging from 0 to 100% percentage increase weights. Further iterations iteratively adjust weights until maximum accuracy is achieved. If positive adjustments fail to surpass the initial class delineation, negative weight adjustments from 0 to -100% percentage increase weights are implemented. If these adjustments yield improved delineation and accuracy, subsequent iterations continue adjusting feature weights negatively until no further improvement is possible. In cases where no improvement is observed for both positive and negative adjustments, the reinforced function penalizes by providing the next set of weights, along with additional weightage for the top 5 most important features in the hidden layers of the deep neural network.

The iterative process continues until the SXI scores cannot be further improved. The final new SXI scores are then updated to the system for further analysis and decision-making regarding business outcomes.

2.3.2. Correlation of SXI w.r.t late payments

In the context of business outcomes, this score can be correlated with specific classes such as "good" and "bad" within the data set. One common metric for evaluating the strength of this correlation is the coefficient of determination, often denoted as R-squared (R^2).

If the SXI scores (x) are the independent variable and the target outcome (y) is the dependent variable, a polynomial regression equation can be expressed as:

$$y = b_0 + b_1 x + b_2 x^2 + \cdots + b_n x^n + \in$$

where:

y is the target outcome.

x is the SXI scores.

$b_0, b_1, b_2, \ldots, b_n$ are the coefficients representing the weights of the polynomial terms.

n is the degree of the polynomial.

$\in$ is the error term.

The coefficient of determination, denoted as R^2, quantifies how well the SXI scores explain the variance in the business outcomes. By analyzing polynomial regression plots, distinct improvement phases can be identified: initial, mid-term, and long-term improvements. These phases delineate where changes in SXI scores most significantly impact business outcomes, aiding in the strategic interpretation of data trends and patterns.

2.3.3. Model training and evaluation

The model training process starts with hyper parameter tuning, specifically focusing on the alpha parameter. This involves adjusting the SXI score by varying the alpha value between 0.5 and 1.5 in increments of 0.1. During each iteration, the SXI score is recalculated by multiplying the current SXI score with the alpha value, enabling fine-tuning to optimize the model's performance.

$$SXI_{new} = \propto * SXI_{Current},$$

where:

- $\propto$ is the tuning parameter, ranging from 0.5 to 1.5 in increments of 0.1,
- $SXI_{Current}$ is the Benchmark SXI score, and
- SXI_{new} is the new SXI score after applying the alpha adjustment.

To ensure a balanced and effective learning process, the dataset is systematically divided into three subsets:

70% allocated for training, 20% reserved for model testing, and the remaining 10% set aside for validation. This partitioning strategy is designed to provide the model with sufficient data for learning while preserving separate sets for evaluating both its generalization capability and robustness against overfitting.

During the training phase, the adjusted SXI scores—refined through alpha-based tuning—are introduced as a high-impact feature, often referred to as a "Super Feature". This enriched feature representation contributes significantly to the model's predictive performance by embedding domain-specific insights directly into the learning process.

To comprehensively assess how well the model performs, several evaluation indicators are applied. The metric known as accuracy reflects the proportion of correct predictions across all test samples, whereas precision highlights the share of correctly identified positive cases out of all instances predicted as positive. To gain a deeper understanding of classification effectiveness, a confusion matrix is utilized—offering a structured view of true positives, true negatives, false positives, and false negatives. Furthermore, the Area Under the Curve (AUC) serves as a quantitative measure of the model's capability to differentiate between distinct categories. These metrics provide a holistic view of prediction quality. The formal descriptions for both accuracy and precision are presented as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision/PPV = \frac{TP}{TP + FP}$$

where:

TP is the number of true positives,

TN is the number of true negatives,

FP is the number of false positives, and

FN is the number of false negatives.

The AUC for the Receiver Operating Characteristic (ROC) curve measures the classifier's ability to distinguish between positive and negative classes. It is calculated based on the True Positive Rate (TPR) and False Positive Rate (FPR), with the ROC curve plotting TPR against FPR at different threshold settings. TPR, FPR and AUC are defined as follows:

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$AUC \approx \sum_{i=1}^{n-1} \left(\frac{TPR_{i+1} + TPR_i}{2}\right)(FPR_{i+1} - FPR_i)$$

where:

TPR_i and TPR_{i+1} denote true positive rates corresponding to adjacent threshold points.

FPR_i and FPR_{i+1} denote false positive rates corresponding to adjacent threshold points.

2.3.4. Actionable insights for reducing late payments

In the decision tree model, borrower and financial behavior features contributing to late payments are assigned positive weights, while those mitigating late payments are assigned negative weights. To implement strategies for reducing late payments, users specify a percentage increase for positive weighted features and a percentage decrease for negative weighted features. During the data transformation process, these adjustments are applied to each observation: positive weighted features are increased by the specified percentage, and negative weighted features are decreased, simulating an initial enhancement in the dataset to reduce late payment risks [14].

If the late payment risk model shows a positive correlation between SXI scores and late payment risk, the strategy for positive weighted features is:

Adjusted Feature Value = Original Feature Values × (1 + Percentage Increase)

For features that reduce late payment risk, the strategy is:

Adjusted Feature Value = Original Feature Values × (1 – Percentage Decrease)

In cases where a negative correlation exists between SXI scores and late payment risk (where higher SXI scores indicate lower late payment risks), the weights are reversed. Features negatively impacting late payment risks (increasing them) are given positive weights, while features reducing late payment risks receive negative weights. Under this scenario, positive weighted features (which increase late payment risk) require a strategy involving a percentage decrease, and negative weighted features (which reduce late payment risk) call for a percentage increase.

For positive weighted features, the strategy is:

Adjusted Feature Value = Original Feature Values × (1 – Percentage Decrease)

For negative weighted features the strategy is:

Adjusted Feature Value = Original Feature Values × (1 + Percentage Increase)

Once the dataset has been adjusted using these transformations, it is used to train a Random Forest model. The model learns the relationships between borrower attributes, financial behaviors, and late payment risks by analyzing data through multiple decision trees. Each decision tree captures distinct aspects of the feature-risk relationship, and among these, a target decision tree path is identified. This path represents the sequence of feature splits that most accurately predicts late payment risks based on the adjusted dataset, offering a detailed understanding of the factors contributing to late payments and actionable insights into effective mitigation strategies.

3. Results and Discussions

The SXI stands at 0.97, serving as the benchmark score. In terms of overall payments, 49.82% are categorized as good outcomes (current payments), while 50.18% are identified as bad outcomes (late payments). According to the initial delineation based on the benchmark, there is a slight inclination towards categorizing late payments as above SXI and current payments as below SXI.
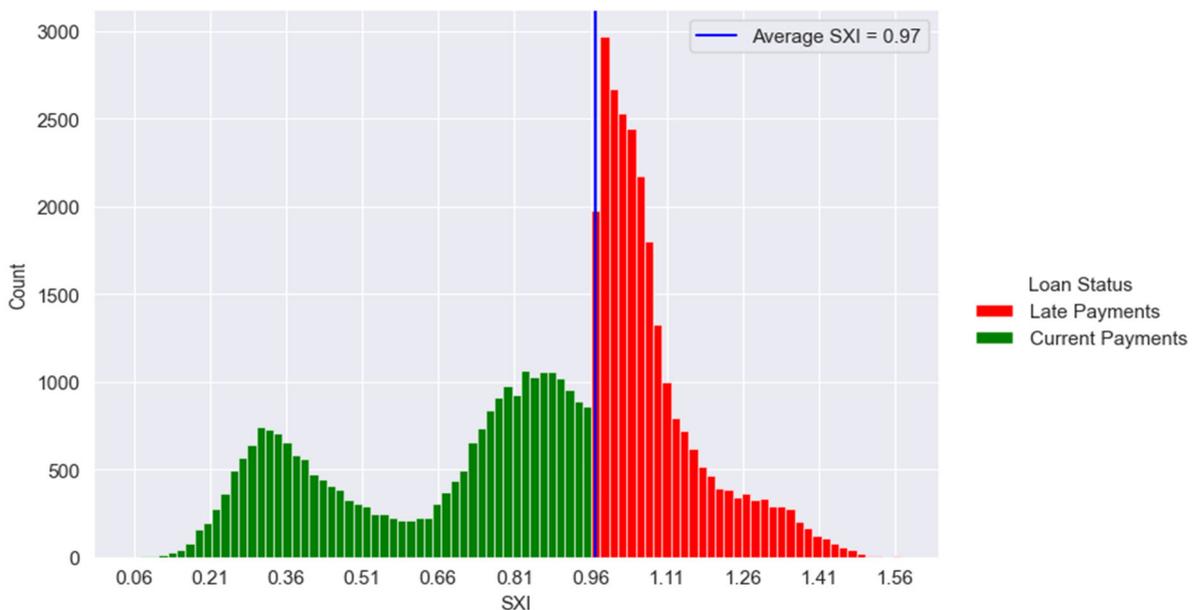

Fig. 8. SXI Distribution. This figure shows the distribution of SXI scores, illustrating how scores differ between borrowers likely to make timely repayments and those at risk of late payments.
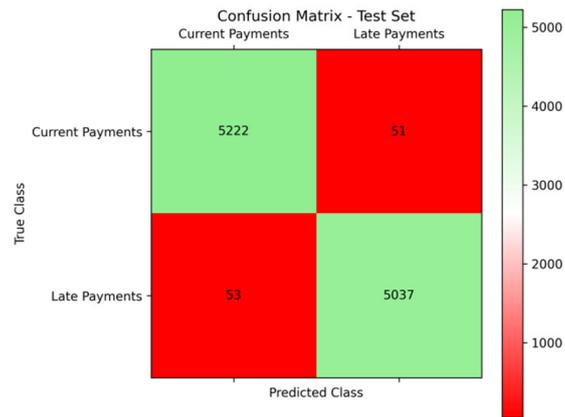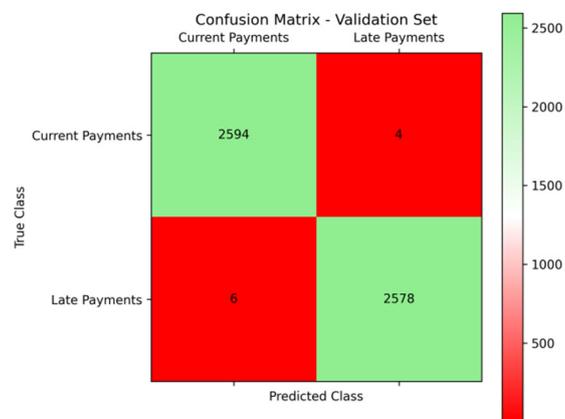
Fig. 9. Confusion matrix—Test set.

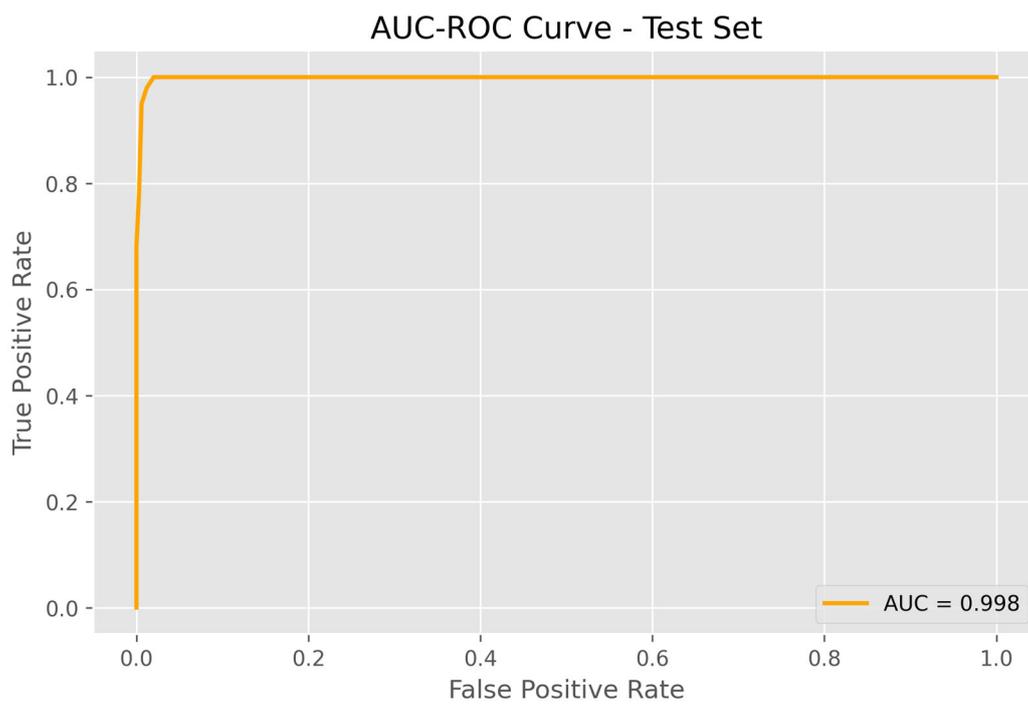Fig. 10. Confusion matrix—Validation set.

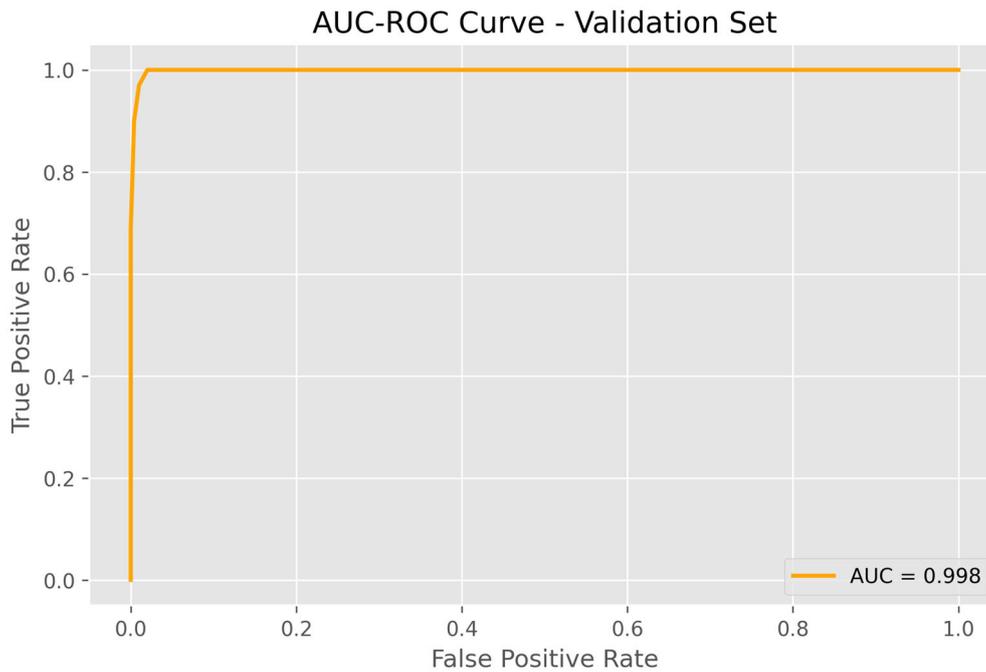

Fig. 11. AUC-ROC graph—Test set.

Fig. 12. AUC-ROC graph—Validation set.

The SXI algorithm demonstrated outstanding performance in classifying loan payment statuses, achieving excellent metrics across both the test and validation sets. In the test set (Fig. 9), with 10,363 records, the model correctly classified 5,222 current payments and 5,037 late payments. Only 53 current payments were misclassified as late payments, and 51 late payments were misclassified as current payments. This resulted in an impressive accuracy of 99.80% and an AUC of 0.998 (Fig. 11), reflecting the model's accuracy and precision in predicting loan payment outcomes.

Similarly, in the validation set of 5,182 records, the SXI algorithm maintained its exceptional performance. It correctly classified 2,594 current payments and 2,578 late payments, with only 6 current payments misclassified as late payments and 4 late payments misclassified as current payments (Fig. 10). This also resulted in an accuracy of 99.80% and an AUC of 0.998 (Fig. 12), demonstrating the robustness of the SXI algorithm. These results underscore its effectiveness in accurately predicting loan payment statuses, establishing the SXI algorithm as a reliable tool for applications where precise classification is crucial.

The delineation of SXI reveals that all late payments are above the SXI threshold (Fig. 8), constituting 100%, while all current payments fall below SXI, also at 100% (Table 4). In terms of the overall class, late payments above SXI represent 49.82% of the total, while current payments below SXI make up 50.18%. The model evaluation indicates a training size of 36,271 and a test size of 10,363, totaling 14,470 instances. Among the test cases, the SXI algorithm correctly predicted 5,222 current payments and 5,037 late payments, with a very small number of misclassifications (53 current payments predicted as late and 51 late payments predicted as current). This resulted in an accuracy of 99.80%, highlighting the model's precision in correctly classifying payment statuses.

The correlation coefficient of 0.99 (positively) between SXI and Late Payments (Fig. 13) indicates an exceptionally strong and positive correlation between these two variables. In practical terms, this implies that as the SXI score increases, there is a proportional and highly positive impact on Late Payments. So based on the correlation, higher SXI scores are strongly resulted to an increased likelihood of late payments. Consequently, lowering the SXI score should result in a reduction in late payments.
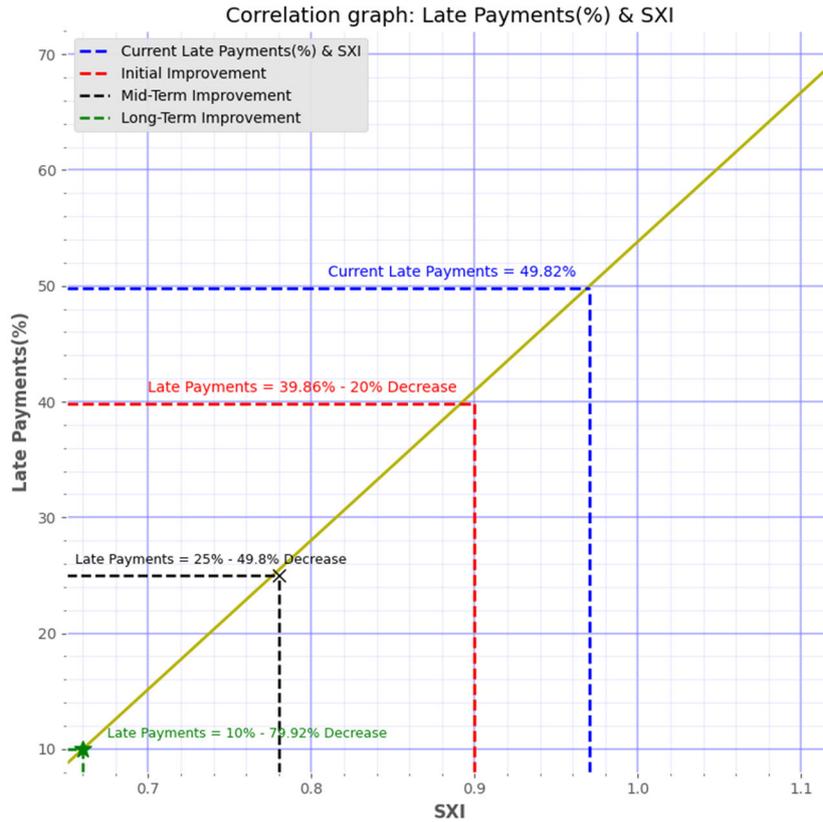
Fig. 13. Correlation: Late payments vs SXI.

In more specific terms, with an initial 7.22% decrease in SXI scores, there is a corresponding and proportional 20% decrease in Late Payments. Moving into the mid-term, a 19.59% decrease in SXI scores corresponds to a similar 49.80% decrease in Late Payments. Looking towards the long-term, a 30.93% decrease in SXI scores is associated with a substantial 79.92% decrease in the likelihood of Late Payments. This demonstrates the compounding effect of long-term improvements in business outcomes, reinforcing the notion that a sustained focus on reducing the SXI can lead to significant and reducing the impact of Late Payments.
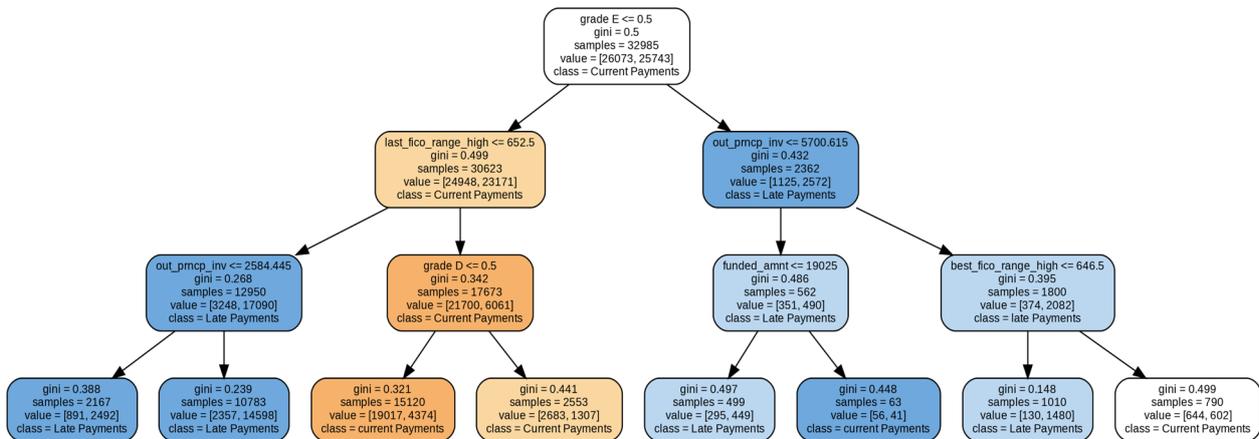
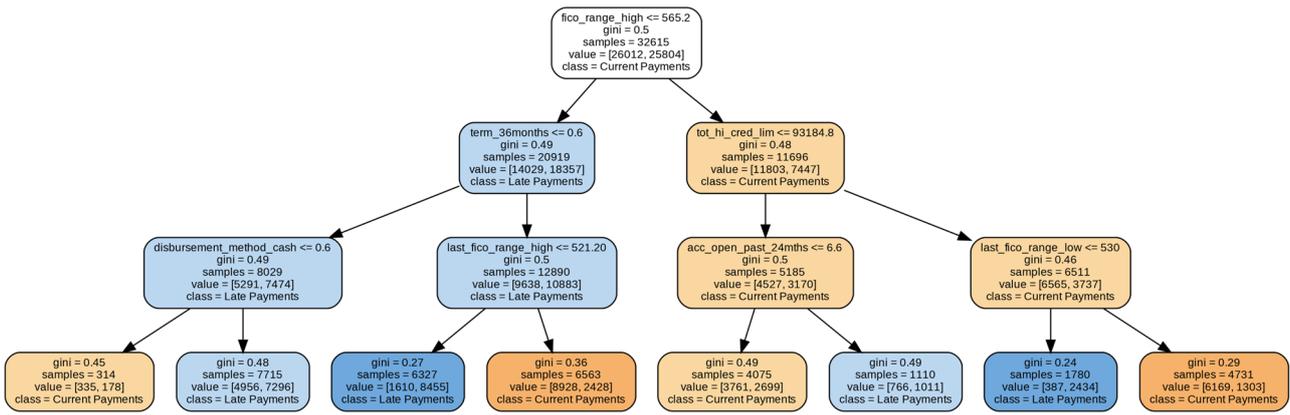Fig. 14. Current decision tree.

Fig. 15. Target decision tree.

The current decision tree (Fig. 14) reflects the existing state of loan payments. Customers are more likely to make current payments if their loan grade is less likely to be classified as "E" and their lower FICO score (last_fico_range_low) is at least $652.5. On the other hand, late payments are more common for customers with a loan grade likely classified as "E", outstanding loan balances (out_prncp_inv) above $5700.615, and upper FICO scores (last_fico_range_high) below $646.5. This analysis helps explain why late payments are currently at 49.82%.

The target decision tree (Fig.15) outlines recommended changes to reduce late payments to 39.86%. It suggests that current payments are more likely when borrowers have higher FICO scores at loan origination (fico_range_high) above $562.2, total credit limits (tot_hi_cred_lim) over $93,184.8, and lower FICO scores (last_fico_range_low) above $530. Late payments, however, are linked to shorter loan terms (36 months) and lower upper FICO scores (last_fico_range_high) under $521.2, even if the fico_range_high is above $562.2. These recommendations use key financial indicators to guide strategies for reducing late payments effectively.

Table 4. Performance Metrics Table

Performance Metrics	Other Studies					This Study	
	NN	Randomforest	BPNN	MOE	SVM Linear	XGBoost	SXI
Accuracy	78.60%	78.80%	84.05%	92.10%	NA	84.52%	99.80%
Precision	NA	NA	NA	NA	NA	86.29%	98.95%
AUC	NA	NA	0.79	NA	0.935	0.92	0.998

The results of the study and accuracy are shown in Table 4. The study's results clearly indicate that the SXI algorithm outperforms Traditional ML in terms of accuracy, precision, and AUC. Notably, the SXI algorithm shows a substantial improvement over XGBoost and Traditional ML from different studies, achieving a perfect accuracy rate of 99.80% representing an 8%–27% increase in improvements. Additionally, the SXI algorithm demonstrates significantly higher precision, reaching 99.80% compared to XGBoost and other Traditional ML algorithms used in different studies. Moreover, with an AUC score of 1, the SXI algorithm significantly outshines XGBoost AUC of 0.92 and 0.935 of SVM Linear further highlighting the superiority of the SXI algorithm.

4. Conclusions

Traditional machine learning models are trained once for prediction, while SXI scoring is utilized for individual data points to determine their likelihood of late payment. The scoring system correlates with late payments by identifying the strong relationship with r-squared value, informing decision trees for achieving target reductions in late payments. These experimental suggestions inform necessary business decisions,

including initial, mid-term, and long-term strategies. Future data points will receive scores based on which we'll determine whether they are likely to result in late payments or not.

This study emphasizes the remarkable predictive capabilities of the Sriya Expert Index (SXI) algorithm in addressing late loan payments within the peer-to-peer lending sector. Utilizing historical applicant data from Lending Club, the SXI algorithm dynamically generates a score that captures the likelihood of late payments, leveraging a Proprietary Deep Neural Network to optimize predictive accuracy. The model achieves exceptional results, with an accuracy rate of 99.80% and an AUC score of 0.998, the model significantly outperforms traditional approaches such as XGBoost, Random Forest, and Hybrid models such as Mixture of Experts Neural Networks. These findings underscore the SXI algorithm's robustness and its potential as a transformative tool for mitigating late payment risks and enhancing financial decision-making in lending practices.

Furthermore, the study introduces a comprehensive methodology for predicting and reducing the impact of late loan payments, offering insights into both short-term and long-term strategies for mitigating late payments. Through targeted reductions in late payments, initially from 49.82% to 39.86%, and further reductions to 25% and 10% in the mid-term and long-term, significant improvements in business outcomes can be achieved. The compounding effect of reducing the SXI score demonstrates the potential for sustained focus on improving business performance and minimizing the impact of late payments over time.

Overall, the findings of this research underly the importance of advanced predictive modeling techniques and improvements of business outcomes over time by using the SXI algorithm, in enhancing decision-making processes within the peer-to-peer lending sector. By accurately assessing the risk of late payments and providing actionable insights for risk management, this model offers valuable tools for lenders to optimize lending practices, improve loan repayment rates, and ultimately foster the long-term sustainability of the P2P lending industry.

Despite these achievements, the study has several limitations that must be acknowledged. First, the dataset is limited to Lending Club's approved borrowers, which may introduce bias and restrict the model's ability to generalize to broader or more diverse lending contexts. Second, the analysis does not account for the impact of external factors such as economic shifts, borrower behavior changes, or alternative data sources like social media or transaction history. These factors could play a significant role in refining the model's predictive capabilities and enhancing its applicability across different markets.

Future research should focus on addressing these limitations to extend the scope and utility of the SXI framework. Incorporating reject inference techniques to analyze unapproved borrowers could provide a more comprehensive understanding of credit risk. Testing the model on datasets from other P2P platforms or traditional financial institutions would also help validate its robustness and generalizability. Furthermore, integrating real-time data streams or alternative indicators, such as behavioral analytics or macroeconomic variables, could offer a more nuanced perspective on borrower risk profiles.

The results obtained in this study contribute to the development of more refined risk assessment approaches within peer-to-peer lending systems. The SXI model demonstrates a practical balance between interpretability and predictive strength, offering a strategic advantage for platforms aiming to reduce loan defaults and improve portfolio performance. As digital finance continues to progress, adapting this framework for multi-label classification tasks or dynamic credit evaluation processes will be essential. These future enhancements can broaden the algorithm's relevance, supporting greater financial accessibility and contributing to a more equitable and sustainable credit environment that addresses existing gaps in lending services.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

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