Textile & Leather Review

ISSN 2623-6281 | www.tlr-journal.com | 10.31881/TLR

Construction and Credit Evaluation of Credit Risk Index System of College Student Loan Based on RS

Qing Hao

How to cite: HAO Q. Construction and Credit Evaluation of Credit Risk Index System of College Student Loan Based on RS. Textile & Leather Review. 2026; 9:2743-2758. https://doi.org/10.31881/TLR.2026.2743

How to link: https://doi.org/10.31881/TLR.2026.2743

Published: 25 April 2026

Construction and Credit Evaluation of Credit Risk Index System of College Student Loan Based on RS

Qing Hao
College of Geomatics, Xi'an University of Science and Technology, Xi'an 710054, Shaanxi, China
zxhq2021@163.com

Article
https://doi.org/10.31881/TLR.2026.2743
Published 25 April 2026

ABSTRACT

Traditional credit risk evaluation methods for student loans rely heavily on expert empirical knowledge, leading to limitations in handling uneven sample distribution and indicator redundancy, which makes it difficult to adapt to the increasingly complex credit changes of student loans. To address these problems, this paper proposes a credit risk evaluation and parameter reduction method for college student loans based on Rough Set (RS) theory. First, a preliminary credit risk evaluation index system consisting of 26 indicators was constructed, and each indicator was coded and quantified. On this basis, a five-tuple decision information system for student loan credit risk assessment was established based on classical rough set theory, and the concepts of attribute dependence and attribute importance were defined、 and a dimensionality reduction algorithm is designed. The experimental study was conducted using 6500 groups of student loan data from a university in Shaanxi Province from 2010 to 2025. The KNN algorithm, which exhibited the best classification performance in the comparative test of multiple algorithms, was selected as the classification model to verify the performance of the reduced parameter sets. The experimental results show that the D4 parameter set with 18 reduced indicators achieves the optimal evaluation effect: the classification accuracy reaches 97.14%, the mean square error is only 0.0286, and the symmetric mean absolute percentage error is merely 1.14%, which are significantly better than the original data set and other reduced sets.

KEYWORDS
college student loan, credit risk assessment, rough set, parameter reduction, KNN algorithm

INTRODUCTION

The student loan program is a new attempt to support the development of education through financial means in China, which has played a positive role in alleviating the financial pressure on poor college students, helping some poor students to complete their studies smoothly, and for banks and other lending institutions, it can cultivate potential customers and make banks, schools and students achieve a win-win effect [1-2]. However, due to the lack of China's credit system and the defects in the design of student loan system, various potential contradictions and problems of student loan have been gradually exposed in recent years, and the problem of high default rate has emerged one after another [3-4]. In some stages, the loan default rate is as high as 20%, and some universities even reach 30%~40%, which seriously affects the implementation of this policy and brings great trouble to banks and schools [5-6]. How to solve this problem, build a risk prevention evaluation index system and build a national student loan credit risk evaluation method has become the focus of attention in recent years [7]. Therefore, accurately evaluating the credit risk of national student loans for college students can effectively reduce the credit risk of national student loans and reduce the default rate of loans, which is of great significance to the smooth enrollment of poor students.

In recent years, many scholars have carried out a lot of research around the credit risk prevention of national student loans. For example, Li Pengyan and others [8] applied the analytic hierarchy process to calculate the weight of the risk evaluation index of student loans of commercial banks in China, and summarized the countermeasures to avoid the risk of student loans of commercial banks; Chen Yuan and others [9] analyzed the reasons for the high default rate of national student loans in China at present, and put forward the countermeasures to prevent the high default rate; Zhao Zhenyu and others [10] studied the related issues of credit risk assessment of national student loans, and put forward suggestions on building an evaluation index system; Li Yunmeng and others [11-12] used Delphi method to establish the credit risk early warning index system of national student loans, and made practical application attempts; This kind of method relies too much on empirical knowledge, and it is difficult to cope with the credit risk evaluation of national student loans under the influence of complex factors. It is worth noting that with the development of intelligent technology, banks and schools have accumulated a large number of good and bad monitoring data of college students' national student loan credit, which provides data basis for the data-driven credit evaluation method of college students' national student loan. How to effectively use these data to evaluate the credit risk of college students' national student loans has become a difficult problem to solve this problem. On the basis of analyzing the advantages and disadvantages of the traditional credit evaluation model, Xiao Zhi found that the support vector machine (SVM) method has certain advantages in evaluating the application of personal credit of college students with loans, and tentatively established the personal credit evaluation analysis model of college students' student loans by using the support vector machine method. Although the above research can effectively realize the personal credit evaluation of college students' student loan, it obviously relies on experts' prior knowledge, and there are still limitations in dealing with the uneven distribution of samples and the redundancy of evaluation indicators, which makes it difficult to update the evaluation model and make an accurate evaluation to adapt to the increasingly complex changes in college students' loan credit.

Rough sets [13] is a data-driven model based on granular computing, which can directly mine the knowledge and laws contained in the data from the credit monitoring data of college students' national student loans without expert knowledge, realize the credit risk assessment of college students' national student loans, and has been widely used in various fields. Gao Fengyang [14] and others use neighborhood rough set to calculate the index weight, and propose a differentiated operation and maintenance strategy for the electrical system of contactless urban rail vehicles, so as to realize accurate state evaluation and fine operation and maintenance of each equipment and subsystem; Yuan Wanling [15] and others combined rough set theory with G1 method to effectively improve the accuracy and reliability of transformer health assessment. The above research fully proves the effectiveness and scalability of rough set theory in state assessment, but there are few reports on the application of credit risk assessment of college students' national student loans.

The monitoring data of national student loan credit risk assessment for college students have the characteristics of many parameters and strong data redundancy. In order to solve the above problems, this paper proposes a parameter reduction method for credit risk assessment of college students' national student loans based on rough sets. The problem of credit risk assessment for national student loans for college students has been solved.

CONSTRUCTION OF CREDIT RISK EVALUATION PARAMETER SET OF NATIONAL STUDENT LOAN FOR COLLEGE STUDENTS

According to a large number of similar research results, the selection of general risk assessment index system adopts the principles of comprehensiveness, dynamics, operability, importance, conciseness and combination of qualitative and quantitative. According to the above principles, this paper initially selects the following indicators. According to the comprehensive and dynamic principles established according to the index system, the pre-enrollment indicators of loan students are set, including: gender, age, education, physical health status, ranking of admission scores, family economic status and health status of family members; During the school period, the indicators mainly include: comprehensive evaluation score ranking, school reward, school punishment, part-time job status, health status, whether there is repayment behavior, the number of professional skills certificates, library default records and other eight indicators; After graduation, the indicators mainly include: employment, monthly income, repayment ratio in one year after graduation, repayment ratio in two years after graduation, repayment ratio in three years after graduation, unit category and credit card consumption record. Environmental indicators include: household registration, average employment rate of major in recent 3 years, professional loan default rate in recent 3 years and school loan default rate in recent three years, totaling 26 indicators. Code the credit risk assessment parameters of national student loan for college students, as shown in Table 1.

Table 1. Credit risk assessment parameters of national student loan for college students

Stage	Parameter	Encode
Before entering school	Gender	c1
	Age	c2
	Academic degree	c3
	My physical health status	c4
	Ranking of entrance scores	c5
	Family economic situation	c6
	Health status of family members	c7
During school days	Comprehensive evaluation score ranking	c8
	School reward	c9
	School punishment	c10
	Part-time status	c11
	Family member health condition	c12
	Is there any repayment behavior?	c13
	Number of professional skill certificates	c14
	Library default record	c15
After graduation	Employment or not	c16
	Monthly income	c17
	Repayment ratio as of 1 year after graduation	c18
	Repayment ratio as of 2 years after graduation	c19
	Repayment ratio for three years after graduation	c20
	Unit category	c21
	Credit card consumption record	c22
Environment	Household registration	c23
	Average employment rate of major in recent 3 years	c24
	Professional loan default rate in recent 3 years	c25
	School loan default rate in recent 3 years	c26

Among them, the values of male and female in gender are 1 and 0 respectively; Education includes regular high school students, undergraduate students, graduate students and others, with values of −1, 0, 1and-1 respectively; My physical health status is divided into good, average and poor, with values of 1, 0 and-1 respectively; 20%, 50% and 30% of the entrance scores are 1, 0 and-1 respectively. Family economic status is divided into average and poor, with values of 1 and-1 respectively; The health status of family members is divided into good, average and poor, with values of 1, 0 and-1 respectively; The comprehensive evaluation scores rank 20%, 50% and 30% according to grade, with values of 1, 0 and-1 respectively; The categories of employment units are divided into further education, civil servants and institutions, state-owned enterprises and private enterprises, with values of 1, 2, 3 and 4 respectively; The household registration is divided into six administrative regions, namely, Northeast China, North China, East China, South China, Northwest China and Southwest China, with values of 1, 2, 3, 4, 5 and 6 respectively. The data set of credit risk assessment parameters of national student loan for college students can be characterized as: $c_1 = \{x_{11}, x_{12}, x_{13}, ..., x_{1i}\}$, $c_2 = \{x_{21}, x_{22}, x_{23}, ..., x_{2i}\}, ...$, $c_{26} = \{x_{261}, x_{262}, x_{263}, ..., x_{26i}\}$, where i is the number of samples.

By analyzing the data of credit risk assessment of college students' national student loans, it is found that the monitoring parameters are all discrete data with high dimensionality and strong redundancy. Based on the student loan data from a university in Shaanxi, we have compiled statistics on defaulting students, which effectively reflects the actual loan default situation among college students.

CONSTRUCTION OF PARAMETER REDUCTION MODEL FOR CREDIT RISK ASSESSMENT OF COLLEGE STUDENTS' NATIONAL STUDENT LOAN

High-dimensional and redundant parameters affect the accurate evaluation of the credit risk of college students' national student loans. Therefore, this paper proposes a parameter reduction model for the credit risk evaluation of college students' national student loans based on improved rough sets, as shown in Figure 1, to evaluate the credit risk of college students' national student loans. This model mainly uses the data of national student loan of a university in Shaanxi Province, and filters the key parameters of credit risk assessment of national student loan by improving rough set, so as to provide a basis for credit risk assessment of national student loan.

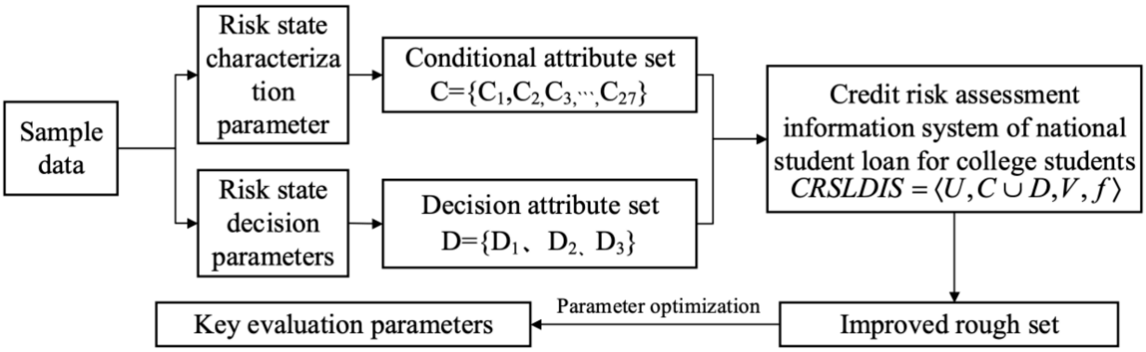


Figure 1. Parameter reduction model for credit risk assessment of national student loan for college students

Construction of Decision-making Information System for Credit Risk Assessment of National Student Loan for College Students

Rough sets theory [16], as a soft computing method of knowledge acquisition, does not need to provide any prior knowledge other than the data set that the problem needs to deal with, and only uses the information provided by the data itself, it can discover the implicit knowledge from it, and divide the data through the indistinguishable relationship to reveal the potential laws. This is the most remarkable difference between rough set theory and many other uncertainty theories, and it is also one of the most important advantages. In addition, because rough set can directly process data, and the dependence of credit risk assessment parameters of national student loans on decision-making parameters can be obtained directly through similarity in high-dimensional and redundant data, the credit risk assessment of national student loans for college students can be realized, so a parameter reduction method of national student loans for college students based on improved rough set is proposed. Based on the classical rough set theory [17], the credit risk assessment decision information system of national student loan for college students is constructed.

Definition 1: Decision information system for credit risk assessment of national student loan for college students, CRSLDIS is formulated as a five-tuple, $CRSLDIS = \langle U, A, V, f \rangle$, where $U = \{x_1, x_2, \cdots, x_n\}$ is a nonempty set including finite objects x_i , i =1,2,..., n . $A = C \cup \{d\} \neq \varnothing$ and $C \cap \{d\} = \varnothing$ are the set of attributes of the objects, $C = \{c_1, c_2, \cdots, c_{27}\}$ is the set of condition attributes, and d is the decision attribute. The value of d is 1 when there is credit risk, and 0 when there is no risk. Where $V = \{v_1, v_2, \cdots, v_{27}, v_d\}$ is the value range of the attributes, f is the information function, and $f : U \times A \to V$ is used to define the attribute values of the sample.

Definition 2: $CRSLDIS = \langle U, C \cup d, V, f \rangle$, $\forall B \subseteq C$, attribute set B can generate relationships between objects:

$$R_B = \{ x \mid (x, y) \in U \times U : f(x, a) = f(y, a), \forall a \in B\} \tag{1}$$

Where R_B is the attribute set B , the relationship between objects can be generated.

Definition 3: $CRSLDIS = \langle U, C \cup d, V, f \rangle$, $B \subseteq C$, generating equivalence relation B on universe R_B , then (U , R_B) is called approximate space. For $\forall X \subseteq U$

$$\overline{R_B}(X) = \{x \in U : [x]_B \cap X \neq \phi\} \tag{2}$$

$$\underline{R_B}(X) = \{x \in U : [x]_B \subseteq X\} \tag{3}$$

Where $\underline{R_B}(X)$ is the lower approximation of X and $\overline{R_B}(X)$ is the upper approximation of X .

$\forall X \in U$, define the positive domain, negative domain and boundary domain of X in this approximate space as follows:

$$POS(X) = \underline{N}X \tag{4}$$

$$NEG(X) = U - \overline{N}X \tag{5}$$

$$BN(X) = \overline{N}X - \underline{N}X \tag{6}$$

Definition 4: $CRSLDIS = \langle U, C \cup d, V, f \rangle$, $B \subseteq C$, the dependence $\gamma_B(D)$ of decision attribute D on conditional attribute B is defined as:

$$\gamma_B(D) = \frac{\parallel POS_B(D) \parallel}{\parallel U \parallel} \tag{7}$$

Definition 5: Attribute importance is defined as the degree of influence of conditional attributes on decision attributes. $CRSLDIS = \langle U, C \cup d, V, f \rangle, B \subseteq C, \quad a \in C - B$, then the importance of conditional attribute A to decision attribute D is:

$$SIG(a, B, D) = \gamma_{B \cup \{a\}}(D) - \gamma_B(D) \tag{8}$$

Aiming at the problem of uneven sample distribution and noise interference in the data set of national student loan for college students. Classical rough set can't fully consider the statistical information of sample distribution in data set, and it is highly sensitive to noise samples. A single noise sample may lead to multiple adjacent samples being wrongly classified into the boundary domain, which will lead to inaccurate parameter dependence in the risk assessment of college students' national student loan, and the result of parameter reduction is unreliable, eventually missing key evaluation parameters or retaining redundant evaluation parameters.

Parameter Reduction Algorithm for Credit Risk Assessment of National Student Loan for College Students

Based on rough set theory, a parameter reduction algorithm for credit risk assessment of college students' national student loans is proposed. The whole algorithm takes the national student loan risk assessment data set of a university as the input and the key assessment parameters of risk assessment as the output, aiming at obtaining the important parameters that affect the credit risk assessment of college students' national student loans and supporting the accurate assessment of the credit risk of college students' national student loans. The whole algorithm flow is shown in Figure 2.

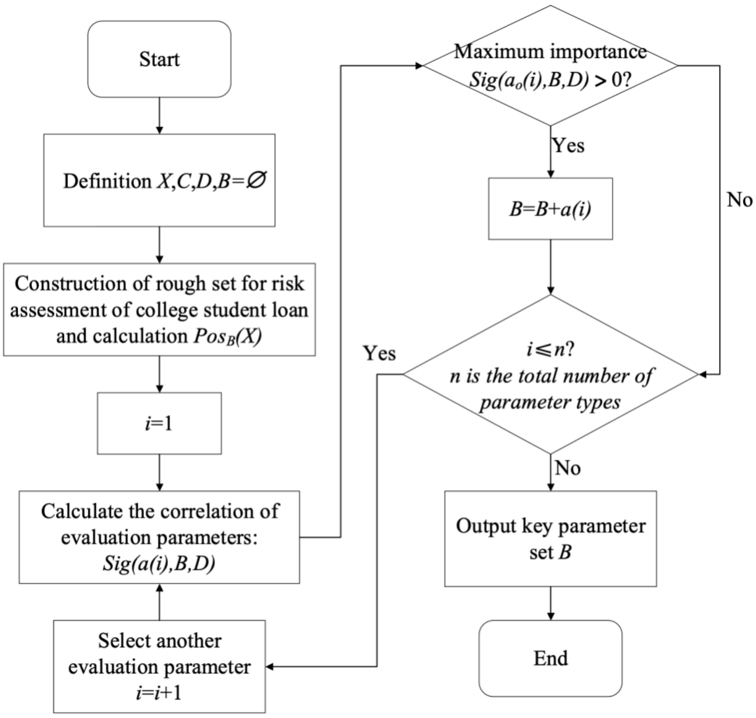


Figure 2. Flow chart of parameter reduction algorithm for credit risk assessment of national student loan for college students

The specific implementation steps are as follows:

Step1: Define the data set X of risk assessment parameters of national student loan for college students, in which the risk assessment condition parameter set is C , the decision-making parameter set is D , and the key assessment parameter set B is initially ϕ ;

Step2: According to the actual risk assessment sample, the positive domain $Pos_B(X)$ of the sample is calculated for any parameter A in the risk assessment condition parameter set C through the decision information system for credit risk assessment of national student loans;

Step3: Calculate the dependence degree $\gamma_{B\cup\{a\}}(D)$ of risk assessment parameter a and the dependence degree $\gamma_B(D)$ when removing risk assessment parameter a , and then obtain the importance degree $\gamma_{B\cup\{a\}}(D)$ of risk assessment parameter a to decision parameter d ;

Step4: Find out the risk assessment parameter a_0 with the greatest importance, and judge the positive and negative of its maximum importance $Sig(a_0, B, D)$ to determine whether the assessment parameter is redundant;

Step5: If the maximum importance of the evaluation parameter is not greater than 0, return to Step2 and select another risk evaluation parameter a for analysis;

Step6: If the maximum importance of the evaluation parameter is greater than 0, add parameter a_0 to key evaluation parameter B and return to Step2;

Step7: After the redundancy judgment of all evaluation parameters is completed, the key parameter set B of risk evaluation of national student loan for college students is output.

EXPERIMENTAL DESIGN AND RESULT ANALYSIS

Original Data Set Construction

The data used in this study is derived from the student loan data of a university in Shaanxi Province from 2010 to 2025. Specifically, the data for 2010 pertains to the graduates of the 2007 class, while the data for 2025 pertains to the graduates of the 2022 class. According to the established initial evaluation indicators, Table 2 lists some data.

Table 2. Partial sample data

Sample number	1	2	3	…	2050	…	6499	6500
c1	1	1	0	…	1	…	1	0
c2	18	19	19	…	18	…	20	18
c3	1	1	1	…	1	…	1	1
c4	1	1	0	…	1	…	1	0
c5	0	0	1	…	1	…	1	−1
c6	1	1	1	…	0	…	1	1
c7	1	1	0	…	−1	…	0	1
…	…	…	…	…	…	…	…	…
c24/%	85	82	86	…	81	…	88	83
c25/%	3.0	1.0	5.0	…	5.0	…	1.0	0
c26/%	8.2	10.8	6.9	…	11.8	…	8.4	6.9
d	0	1	1	…	0	…	0	1

Determination of Evaluation Indicators

In this paper, there are 6500 groups of sample data for the risk assessment of college students' national student loans. The data set is divided into training set and test set with a ratio of 4:1, which are used for training model and testing training results respectively. In order to better select the risk assessment parameters of college students' national student loan, a binary confusion matrix is constructed, as shown in Table 3.

Table 3. Two-Class Confusion Matrix

Actual / Predicted	T	F
T	TT	TF
F	FT	FF

Table 3 is the confusion matrix for classifications of the credit risk assessment of national student loan for college students regulating mode, where T and F represent increasing prediction correctly and prediction wrongly. TT and FF represent the number of samples with correct predictions, and other combinations represent the number of samples with incorrect predictions. In this paper, Classification Accuracy (CA), Precision (P), Recall (R), F1 score, mean square error, symmetrical average absolute percentage error and parameter reduction rate are selected as the performance indexes of the model [18].

Experimental Results and Analysis

The experiment mainly reduces the parameters of the original data set, and compares the classification effects of each reduced data set. Experimental environment: eight-core sixteen-thread CPU CPU Intel(R) Core

(TM) i7-10870H with a main frequency of 2.20 GHz, with 16G memory, operating system Windows11 and programming environment of MATLAB R2023b.

Selection of classification model

According to the reduction algorithm proposed in this paper, the data in Table 2 are used for parameter reduction, and the results are shown in Table 4.

Table 4. Comparison of simplified datasets

Data set	Number of selected parameters	Reduced parameters
D0	26	C1~C26
D1	21	C1, C4, C6~C14, C16~C19, C21~C26
D2	20	C1, C3~C7, C9, C10, C12~C13, C16~C19, C22~C26
D3	20	C4, C6~C14, C16~C19, C22~C26
D4	18	C1, C3~C7, C9, C10, C12~C13, C16~C19, C22~C24, C26

In order to further obtain the best parameter set in the above parameter set, this paper selects Decision Trees (DT), Random Forests (RF) and Support Vector Machine (SVM) [19] as reference for comparative analysis. Input the original data set into each classification algorithm for comparison. KNN is an example-based learning algorithm, which calculates the distance between the item to be classified and each item in the data set according to the distance metric. Then select the nearest k items, vote according to the categories of these k items, and take the category with the most votes as the prediction category of the items to be classified. DT is a nonparametric supervised learning method, which learns a set of rules from known data and can predict unknown data through simple rule judgment. Based on the decision tree algorithm, RF generates multiple decision trees by randomly selecting samples and features, and then takes the most results as the final classification results by voting. SVM is a supervised learning algorithm, which is widely used in statistical classification and regression analysis. Its goal is to find a hyperplane that can correctly classify the points in the data set while maximizing the interval. Among them, the number of nearest neighbor samples of KNN is 5; The penalty parameter in SVM is 0.5, and the kernel function adopts Radial Basis Function Kernel. The results on the test set are shown in Table 5, and the comparison of the results is shown in Figure 3.

Table 5. Results of different classification algorithms

Classification model	DT	RF	SVM	KNN
Classification accuracy (CA)	88.71%	89.41%	89.33%	92.88%
Accuracy (A)	89.63%	91.12%	92.52%	95.31%
Recall (R)	90.88%	90.74%	93.01%	96.19%
F1	90.25%	90.93%	92.76%	95.75%

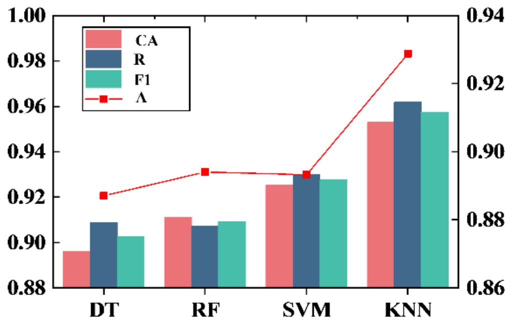


Figure 3. Comparison of results of different classification algorithms for original data inputs

Obviously, KNN classification algorithm has significant advantages in the classification of the stent data in terms of accuracy, recall, F1 score and classification accuracy.

Performance verification of parameter reduction set

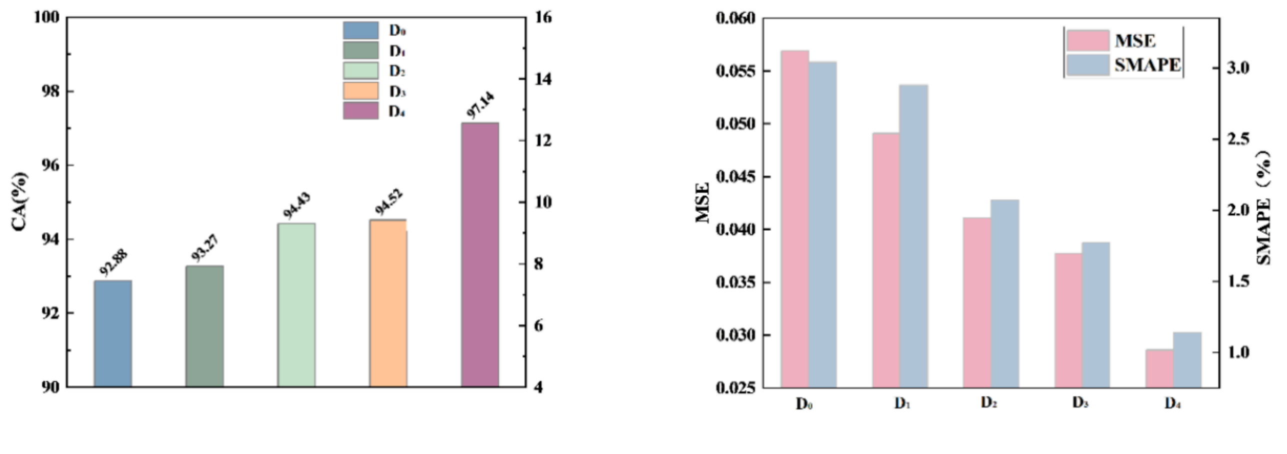
In order to verify the performance of parameter reduction set, this paper uses KNN classification algorithm, taking data sets D_0 , D_1 , D_2 , D_3 and D_4 as inputs respectively, and compares the corresponding unreduced data set with the data reduced by RS model according to the accuracy CA, mean square error MSE and symmetrical average absolute percentage error SMAPE. The test results of each model are shown in Table 6, and the comparison results are shown in Figure 4.

Table 6. Test results of KNN algorithm with different data inputs

Reduction model			RS		
Data set	D0	D1	D2	D3	D4
Number of parameters	26	21	20	20	18
CA	92.88%	93.27%	94.43%	94.52%	97.14%
MSE	0.0569	0.0491	0.0411	0.0377	0.0286
SMAPE	3.04%	2.88%	2.07%	1.77%	1.14%

As can be seen from the data in Table 6, the classification accuracy of the RS model reduction data set D_4 proposed in this study is 97.14% after being input into KNN algorithm, which is obviously higher than other reduction data sets.

As shown in Figure 4, D_4 data set shows a better effect on the whole. As can be seen from Figure 4(a), compared with other parameter reduction data sets, D_4 can use fewer parameters to realize the classification task of credit risk of college student loan, reaching 97.14% classification accuracy, which is 4.26% higher than that when using original data sets, and 3.87%, 2.71% and 2.62% higher than that when using D_1 , D_2 and D_3 data sets, which shows that D_4 can deal with college student loan. Fig. 4(b) compares the corresponding mean square error and symmetrical average absolute percentage error when using data reduced by different models, in which MSE corresponding to D_3 data set reaches the lowest value of each model of 0.0286, which is 49.74% lower than that when using original data for direct classification, 0.0283 lower than that when using original data for classification, and 0.0205, 0.0125 and 0.03 lower than that when using D_1 , D_2 and D_3 data sets. At the same time, SMAPE reaches 1.14%, which is 1.90% lower than the original data classification, and 1.74%, 0.93% and 0.63% lower than the D_1 , D_2 and D_3 data sets. It shows that the difference between the predicted value and the actual value is smaller when the D_4 data set is used for data classification, and the prediction accuracy of the feature reduction set is higher.



(a) (b)

Figure 4. Comparison of test results: (a) Classification accuracy; (b) Mean Square Error and Symmetric Average Absolute Percentage Error

CONCLUSION

In order to solve the problem that the uneven distribution of credit risk assessment data sets of college students' national student loans affects their risk assessment, this study proposes a decision-making method for credit risk assessment of college students' national student loans based on rough sets. A parameter reduction information system for credit risk assessment of national student loan for college students based on rough set is constructed, and a parameter reduction algorithm is given. Taking the data of a university in Shaanxi Province as a sample, the performance of this method in the credit risk assessment of college students' national student loan is verified. The results show that the accuracy of risk assessment is as high as 97.14%, the mean square error is only 0.0286, and the symmetrical average absolute percentage error is only 1.14%.

Author Contributions

Methodology and writing are all done by Qing Hao. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The author declares no conflict of interest.

Funding

This research received no external funding.

Acknowledgements

Not applicable.

REFERENCES

[1] Agbonlahor O. The Impact of Student Loan Debt on Civic Engagement: Evidence from the College and Beyond II Dataset. Education Sciences. 2025;15(6):764-764. doi: 10.3390/educsci15060764

[2] Julie M, Alexa B, Samantha B, Joseph C. Help When You Need It: Sources of Advice for Student Loan Borrowers Across the Life Course. Families in Society: The Journal of Contemporary Social Services. 2022;103(1):49-64. doi: 10.1177/10443894211059137

[3] Manuel V S. Debiasing the availability heuristic in student loan decision-making. Empirica. 2024;51(2):501-528. doi: 10.1007/s10663-024-09609-z

[4] Lam W H., Lange A C. The Debt Trap: How Student Loans Became a National Catastrophe. Journal of Student Affairs Research and Practice. 2024;61(1):130-132. doi: 10.1080/19496591.2023.2186243

[5] Hu X D, Ortagus J C. National Evidence of the Relationship Between Dual Enrollment and Student Loan Debt. Educational Polcy. 2023;37(5):1241-1276. doi: 10.1177/08959048221087204

[6] Paulsen R J. Student loan debt and the career choices of college graduates with majors in the arts. Journal of Cultural Economics. 2023;48(1):95-115. doi: 10.1007/s10824-023-09474-x

[7] David C, Alex S. Measuring the Effect of Student Loans on College Persistence. Education Finance and Policy. 2022;17(2):335-366. doi: 10.1162/edfp_a_00342

[8] Song P, Li L, Huang D, Wei Q J, Xue C. Loan risk assessment based on Pythagorean fuzzy analytic hierarchy process. Journal of Physics: Conference Series. 2020;1437:012101. doi: 10.1088/1742-6596/1437/1/012101

[9] Gao T P, Green R L, Hamilton A, Kopelson E S, Kuo L E. From Debt to Dollars: Assessing a General Surgeon's Career Value. The Journal of surgical research. 2023;291:527-535. doi: 10.1016/j.jss.2023.07.007

[10] Ferreira F A F, Santos SP. Comparing trade-off adjustments in credit risk analysis of mortgage loans using AHP, Delphi and MACBETH. International Journal of Strategic Property Management. 2016;20(1):44-63. doi: 10.3846/1648715X.2015.1105321

[11] Li Y M, Gui R G, Tu Y. Construction and application of credit risk early warning index system of national student loan. Journal of Inner Mongolia University (Natural Science Edition). 2012;43(6):579-585. doi: 10.54097/rhkc6j37

[12] Xiao Z, Wang M K, Xie L L. Personal credit evaluation of college student loans with support vector machines. Journal of Tsinghua University (Natural Science Edition). 2006;46(S1):1120-1124. doi: 10.1016/j.eswa.2006.07.046

[13] Ju H R, Shan T T, Liu K Y, Khan M J, Huang J, Yang X. Bi-directional fuzzy granular cabin parallel attribute reduction acceleration method with granular-group collaboration. Systems Engineering Theory & Practice. 2025;45(3):1029-1046. doi: 10.1109/tfuzz.2024.3392328

[14] Olesen F J, Shaker H R. Predictive Maintenance for Pump Systems and Thermal Power Plants: State-of-the-Art Review, Trends and Challenges. Sensors. 2020;20(8):2425. doi: 10.3390/s20082425

[15] Yuan W L, Cui Z X, Yu H B, Zhao Z. Transformer Health Status Evaluation Based on Rough Set G1 Combined Weighting. Electric Power Construction. 2022;43(03):50-57. doi: 10.1007/978-981-16-8430-2_31

[16] Hu S D, Miao D Q, Yao Y Y. Three-Way Label Propagation Based Semi-Supervised Attribute Reduction. Chinese Journal of Computers. 2021;44(11):2332-2343. doi: 10.11897/sp.j.1016.2021.02332

[17] Hu Q H, Yu D R, Xie Z X. Numerical attribute approximation based on neighborhood granularity and rough approximation. Journal of Software. 2008;19(3):640-649. doi: 10.3724/sp.j.1001.2008.00640

[18] Yan Z Y, Zhu J B, Liu H Y, Song J D, Li Y S. CEEMDAN-LSTM framework for distinguishing natural and mining-induced seismicity. Journal of China Coal Society. 2024;49(S2):731-745. doi: 10.13225/j.cnki.jccs.2024.0539

[19] Liu Y X, Zhang J C, Wang X P. Blast furnace fault diagnosis method based on trace distance partitioning decision tree. Control and Decision. 2025;40(05):1533-1540. doi: 10.13195/j.kzyjc.2024.0843