Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Predicting And Classifying User's Behaviour for Improving Student's Information Literacy Using Kernel Techniques

[1]Vaishali Laxmikant Thakare, [2]Smita L. Kasar
[1]Student, Dept. of Computer Science &Technology.
Maharashtra Institute of Technology, Chhatrapati Sambhajinagar India,431010,
vysaraf88@gmail.com
[2]Professor. Dept. of Computer Science &Engineering.
Maharashtra Institute of Technology, Chhatrapati Sambhajinagar, India,431010
smitakasar@gmail.com

ARTICLE INFO

Received: 10 Jul 2025

Revised: 28 Aug 2025

Accepted: 08 Sept 2025

ABSTRACT

The rapid development of information technology has led to widespread use of computers and the Internet in various aspects of society. Key skills in the 21st century include creativity, critical thinking, and information literacy. College students need to develop information literacy to adapt to the information society and meet societal expectations. This research develops a prediction model for learning impact based on literacy in information learning behaviour characteristics, exploring the projected learning effect and examining college students' educational behaviour. The study demonstrates the effectiveness of the direct kernel method in improving college students' information literacy, enhancing prediction and classification models, and making it a promising option for intelligent learning settings.

Keywords: Information literacy, Kernel-based techniques, Direct kernels

Introduction

The rapid growth of information technology has led to the development of three fundamental skills in college students: creativity, critical thinking, and information literacy. Data literacy is a crucial component of a college student's core literacy in the digital age, and developing information literacy is a key concern for modern higher education. Information literacy encompasses social ethics, information awareness, and the fundamental understanding and abilities of information and technology. It is becoming increasingly important in various fields, including learning, collaboration, communication, and problem-solving. Information literacy education has been provided to varying degrees by education departments in the US, UK, Australia, and other nations. The Chinese Ministry of Education and other departments released "key recommendations for improving computer literacy and skills of all people in 2022" in 2022. As a result, students' digital and information literacy will continue to increase. Numerous domestic and international colleges and universities have launched information literacy programs using various approaches, such as mandatory courses for academic research, online courses, and courses on the College of China's MOOC platform.Learning prediction is a crucial aspect of the big data education industry, aiming to forecast learning effects using student data and machine learning techniques. This allows teachers to monitor student progress and make necessary adjustments, such as enhancing study habits or modifying instruction methods. Learning analysis technology has advanced from fundamental investigation to learning behaviour analysis, data visualization, and prediction. Learning achievement, objectives, and capacity are the foundation for learning prediction, which also predicts learning experience and effect based on learning behaviour traits. Techniques like regression analysis, neural networks, and Bayes are used to predict students' learning outcomes. Artificial intelligence technology can enhance equity and quality in education, as highlighted in UNESCO's 2019

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

report. Current research focuses on using educational data mining and machine learning technologies to develop prediction models.

This study builds an integrated data connection based on the information literacy course learning habits of college students by connecting several distinct behavioral data points. College students' learning effects are categorized and predicted through the application of prediction analysis and evaluation of various machine learning classification models. These are the questions that this study aims to answer.
1. Which behavioral traits of college students' information literacy learning have stronger predictive power for learning effects?

2. Given the study sample, which artificial intelligence models perform and are more effective in terms of prediction?

3. From the study results, which diagnostic observations were used to create learning suggestions and instructional interventions?

The research team created an information literacy scale for college students, focusing on information and skills, application and creativity, ethics, and accountability. The scale emphasizes the importance of information technology, knowledge and skills, and creative use of technology. It also examines morality and responsibility, focusing on information laws, regulations, and moral notions. The system's flow and road plan include data gathering, processing, and training using categorization.

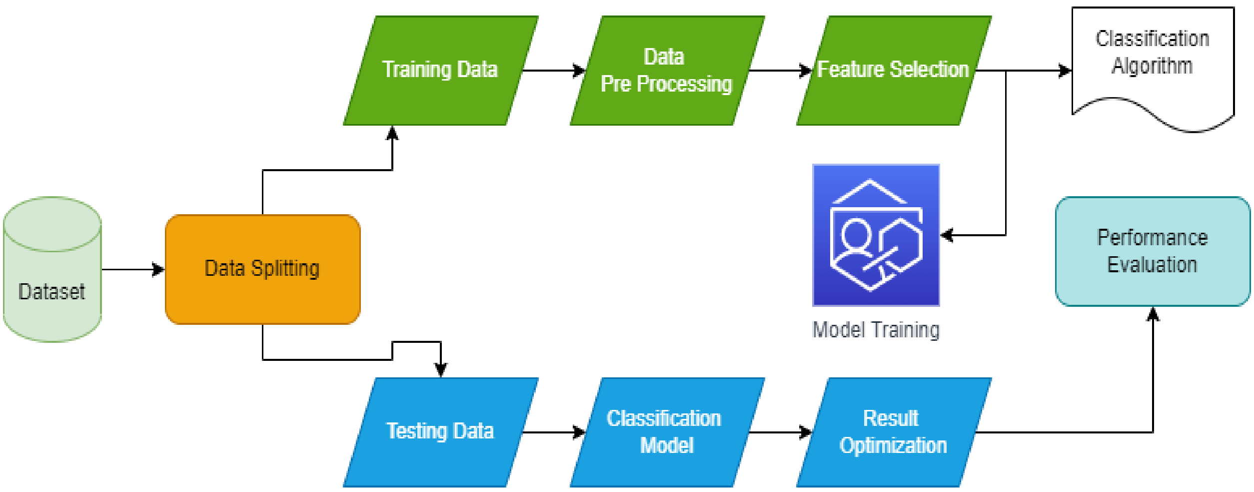


Figure 1 flow diagram of Data Process

Related Work

North Minzu University (NMU) implemented MOOC teaching for computer majors, marking the first time in the Ningxia Hui Autonomous Region. However, the university identified a need for appropriate MOOC teaching theories and techniques. To address this, a new teaching scheme combining MOOC, SPOC, and a flipped classroom was developed, tested with 2018 freshman students [1].The study explores information literacy implications, creates an assessment index framework, and surveys Xiangnan University students' knowledge literacy, presenting strategies for improvement based on current issues [2].The study collected data from 576 students during a five-year software testing course teaching program. Using 39 characteristics, including contest, theoretical, and practical activities, the researchers developed prediction models using convolutional neural networks, random forests, and logical regression [3].This research uses the Support Vector Machine (SVM) optimization method in

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

MATLAB to measure the relationship between information anxiety and data quantity in college students. The study identifies three factors leading to information anxiety, with the degree of anxiety as the dependent variable and the quantity of information received as the independent factors [4].The author presents a model using Logistic Regression and Gradient Boosting Decision Tree to evaluate university students' innovation and entrepreneurship propensity. The model outperforms other credit assessment models, demonstrating better stability and predictive performance, as demonstrated through empirical analysis [5].This study focuses on comparing literature on teaching impact prediction models, learning performance models, teaching model effects, learning quality analysis, and curriculum evaluation [6].Collaborative innovation in higher education is driven by undergraduates' willingness to participate, with research using questionnaire data to study original content, promoting university-industry joint innovation and fostering growth [7].The rapid advancement of internet technology has led to an era of constant information overload, causing information anxiety and negatively impacting academic performance. Support Vector Machine (SVM) is a crucial machine learning technique used in categorization, forecasting, and estimation due to its efficiency and good performance in these applications [8].

Table 1 Summarization of Related Work

Author	Domain	Methodology	Remarks
Sun, Y., Tan, Z., Li, Z., & Long, S [6]	Predicting and Analyzing Performance	LR, RF, CNN	Several prediction models have been created to predict performance.
Guo, J., & Xu, T [7]	Management of Learning Quality of Online Courses	A lightweight CNN model	Corners can be used to detect student attention
Jia, Y., & Wang, E [8]	Information Anxiety	SVM Optimization Alogrithm	The redundant information is filtered through optimization algorithms model
Pei, C et.al [9]	Prediction Model for the Teaching Effect	Apriori algorithm	Predicting the effect of Two courses classroom teaching
Xu, H et. al. [10]	Prediction Model Innovation and Entrepreneurship	GBDT,LR	A model for analyzing students' willingness
Li, T. et. al [11]	Enhanced learning	Several ML algorithms	Numeracy and Literacy Aptitude Analysis and Prediction
Shen, X., & Yuan, C [12]	Behavior Analysis and Management	K-means	Data are selected to describe the student's behavior
Wang, R [13]	Effect of College English Blended Teaching Mode	Comprehensive analysis	Aimed to investigate the students' learning effect.
Purwoko, R.Y.,	Perception of Electronic Learning	Quantitative model	Indicated e-learning perceptions' in knowledge mastery, social

Chamidah et. al [14]			competence, and media literacy abilities.
Liu, X., & Yang, C et. al [15]	Analysis of Practical Teaching Effect	Association analysis algorithm	Assist the training teachers to strengthen management
Akram, H., Abdelrady, A. H. et. al [16]	Technology Integration in Teaching-Learning Practices	Systematic Review	Technology-incorporated teaching effectively enhances teaching practice
Hussain, M., Zhu, W., Zhang [17]	Course Assessment	Several ML algorithms	Assess the effect of engagement on student performance
Karthikeyan, V.G., Thangaraj [18]	Hybrid educational data mining model	Data mining and ML	Proposed model evaluates the student performances based on distinctive factors

Proposed Methodology

The proposed system architecture uses a alogorithm to identify redundant and correlated features in a database. The Augmented Lagrangian Multiplier (ALM) algorithm is used to find similar features, which are then removed using classification algorithms like Biased classifier.

Data Collection

At this step, all four datasets which is named as collected for pre-processing. These datasets are vary in size in the training and testing set. Many quantitative and qualitative aspects may be found in this dataset. The kaggle and uci repositories have collected the dataset.

Data Splitting

The dataset was divided into 80:20 training and testing sections, pre-processed for data separation, and used for machine learning and assessment. This crucial phase aids in data management and provides clear, concise information

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

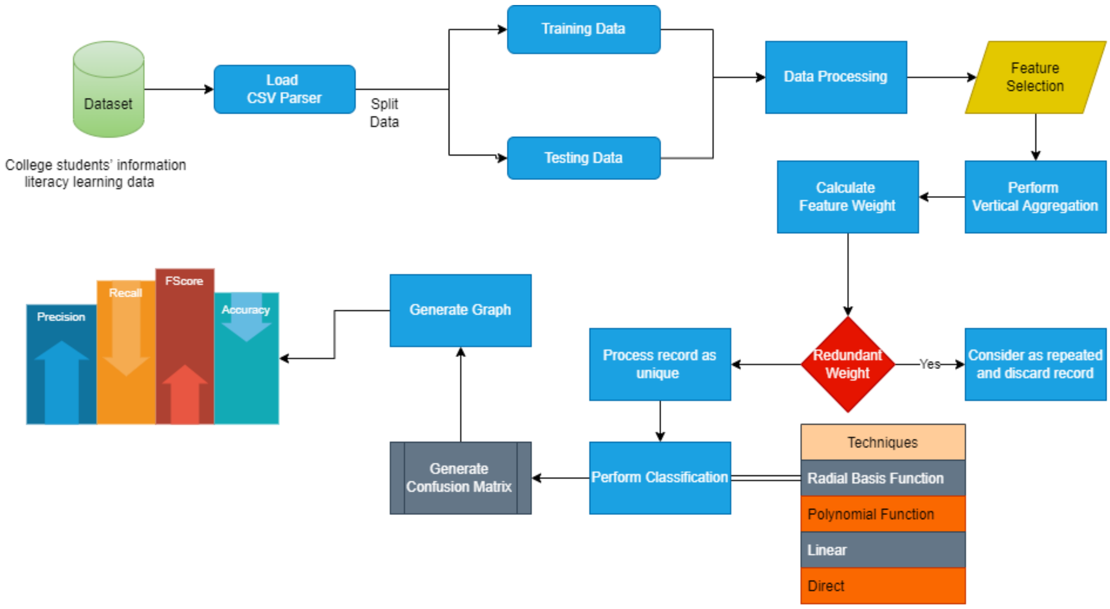


Figure 3 Proposed Methodology

System learning and feature selection metrics

Kernel-based Strategies

Kernel-based techniques or tactics are crucial for system development. In order to calculate the attribute values and update them to the feature selection metrics, we have built direct kernel-based strategies and linear kernel-based strategies.

Obtaining threshold values

The training approach uses kernel-based algorithms to derive weight or score values from each attribute, increasing the threshold value incrementally until the best threshold is found.

Classification using biased classifier

The categorization process involves dividing recordings into regular and problematic values, using scores and threshold values. A sample of normal data is taken, compared to a cutoff value, and the system is trained using this value to determine the record's label as positive or negative.

The parameters which are used to machine learning task are explained below.

- **Task Selection**

Learn & Evaluate Classifier: Train a classifier using examples with labels in a training data file, and then verify the classifier's accuracy using examples with labels in a test data file or using some other method of cross-validation.
Learn & Use Classifier: Use a classifier that has been learned based on labelled samples in a training data file to categories a batch of unlabeled data.
Training Data: The training data file, which contains the labelled examples used to train a classifier, is necessary. Each named example should have its own row in the file, with items separated by spaces. The last column chosen to represent the class labels of that record of datasets is the class label for the training and testing dataset. There is also the choice to choose a column as the dataset's class label.

Evaluation Options

Use Test Data: The test data file, which should have one row for each labelled example with entries separated by spaces or commas, must be specified in the record.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

K-Fold Cross Validation: is a test evaluating a classifier's generalization by dividing training data into K equal-sized subsets, one kept out, and using the classifier to classify the held-out subset.

Randomization

Within Classes:
Make sure that each class is represented in each subset or subgroup in the same proportion as in the entire training set when choosing the K subsets for K-fold cross-validation.

Cross Validation: Randomly choose the K subsets for K-fold cross validation, but partition without taking into account class membership. The order of the instances in the training data file should always be taken into consideration when choosing the K subsets for K-fold cross-validation.

Parameter Selection

- **Bias:** The dataset features should be biased, with a constant bias term set to 1.0. This allows the classifier to detect decision boundaries without passing through the origin. Multiple bias values can be entered, or a zero bias value is acceptable.
- **Priors Laplacian:** The MAP estimate of weights under a l-1 penalty prior promotes sparsity, with Laplacian as the default option due to its emphasis on sparsity.
- **Gaussian:** As a result, the weights are estimated using MAP under a l-2 penalty prior, which favors shrinkage but not sparsity. In essence, gaussian is similar to ridge regression.
- **No Prior:** With no shrinkage or sparsity, this yields a straightforward maximum likelihood (ML) estimate of the weights.
- **Sparsity:** Lambda scales the log prior, regulating weight regularisation, with Gaussian and Laplacian priors monitoring shrinkage and sparsity. Positive values indicate more regularisation, with multiple options specified.
- **Update Rule**
- **Component-Wise:** An algorithm updates weight vector elements one-at-a-time using a round-robin strategy, converges to the same final weight vector as non-component-wise, offering significant computational savings when the product of classes and features is large.
- **Non-Component-Wise:** The algorithm updates weight vector elements simultaneously per iteration, converges to the same final weight vector as component-wise, and may save computationally when large examples are present.

Convergence Settings

Kill Threshold: Weights are zero if absolute value is smaller than kill threshold, accelerating convergence but not altering final solution. This applies to non-component-wise update procedure and component-wise update procedure.

Convergence Tolerance: The weight vector of a classifier converges to a final solution if the Euclidean difference between weight vectors is smaller than the convergence tolerance, and the learning process stops if it exceeds this.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Cache Kernel Functions: This option creates a cache of results from applying the kernel to all points in cross-validation, excluding data from each fold and requiring pre-normalization on the full data set.

Using Linear Kernel Technique

Linear Kernel Function:

$$K(x, y) = x^T y + b \text{(Equation 1)}$$

where:

- K(x, y) is the linear kernel function
- x and y are input vectors
- x^T is the transpose of x
- b is the bias term (optional)

Linear Kernel-based Classification:
Given a training dataset {(x1, y1), (x2, y2), ..., (xn, yn)}, where xi is the input vector and yi is the corresponding class label, the linear kernel-based classification algorithm can be formulated as:

Minimize:

$$L(w) = (1/2)||w||^2 + C * \sum[i = 1ton]\xi i \text{(Equation 2)}$$

Subject to:

$$y_i(w^T x_i + b) \geq 1 - \xi i, \forall i \text{(Equation 3)}$$

$$\xi i \geq 0, \forall i \text{(Equation 4)}$$

where:

- L(w) is the loss function
- w is the weight vector
- C is the regularization parameter
- ξi is the slack variable

- b is the bias term (optional)

The optimal weight vector w can be obtained by solving the above optimization problem. Once w is obtained, the classification decision function can be formulated as:

$$f(x) = sign(w^T x + b) \text{(Equation 5)}$$ where sign(·) is the sign function.

Feature Filters

Feature selection in machine learning uses filter methods for high-dimensional data, ensuring accurate predictive models with minimal data. These methods remove irrelevant attributes, preventing biased results and are crucial for internet-based opinion analysis.

Feature Weighting Algorithms

Feature weighting assigns a continuous valued weight to each feature, enhancing differentiation and similarity calculations, but increases overfitting risk and data dimensionality.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Efficient Algorithm

The user provides a pre-processed and discretized data matrix with n output features, with the first objective being to calculate the relevance of each gene, and the highest scorer gene is extracted and added.

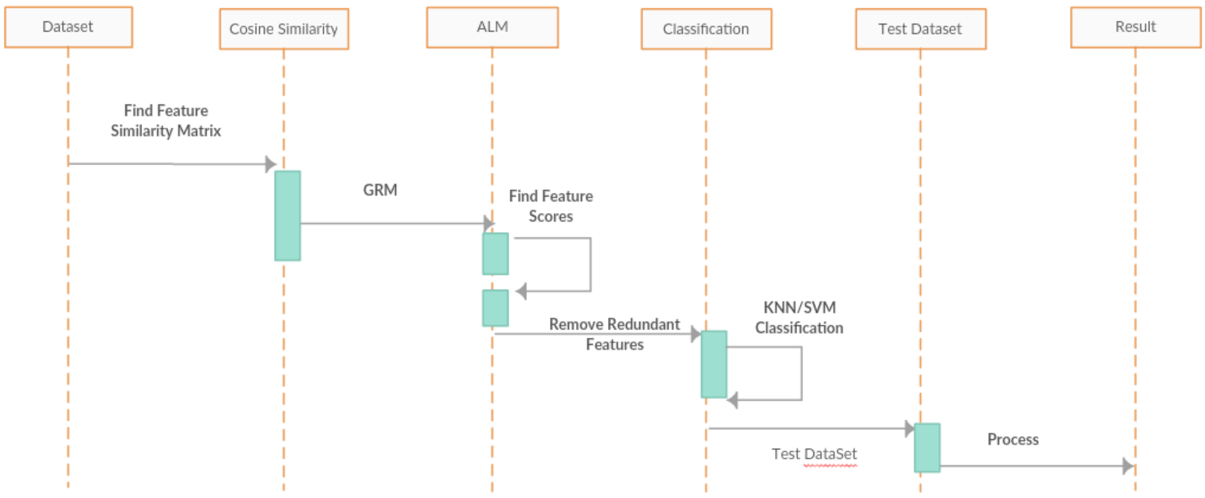


Figure 1.0 Sequence for proposed architecture

Algorithm 1 Proposed Feature Selection

Input: The feature id $idleft$, first objective $obj1$, second objective $obj2$, $|obj1| = |obj2| = |idleft|$.

Output: Non-dominated feature id $idns$, the second objective $obj2ns$ of non-dominated features.

$k = 1$;
for $i = 1 : |idleft|$ do
$t = 0$;
for $j = 1 : |idleft|$ do
if then$(i! = j)$
if then$(obj1(i) \leq obj1(j)\&obj2(i) \leq obj2(j))$;
else if then$(obj1(i) < obj1(j)\&obj2(i) > obj2(j)||obj1(i) > obj1(j)\&obj2(i) < obj2(j))$;
else
$t = 1$;
break;
end if
end if
end for
if then$(t == 0\&j == |idleft|)$
$idns(k) = i$;
$obj2ns(k) = obj2(i)$;
$k = k + 1$;
end if
end for

Next a looping is performed for the remaining output features. Now the redundancy between the output feature and the remaining features ($idleft$) is calculated as per Equation 5. If the output feature set contains more than one feature then the mean is considered as the redundancy score as in Equation 9.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

$$\text{mean-redundancy}(i) = \sum_{k=1}^{F}(\text{mutual-info}[x_k, x_i]))/|F|),$$

where F is output feature set, Xk is output feature vector and xi is the ith feature vector. Then the second objective (obj2) is modeled as the ratio of relevance to the redundancy and it is to be maximized. After calculating the two objectives for each feature the non-dominated features are identified. A reference feature is called the non-dominated feature if it satisfies the following conditions: 1) if the obj1 of the reference feature is greater than or equal to all the other futures' obj1 and the obj2 of the reference feature is greater than or equal to all the other features' obj2 2) if the obj1 of the reference feature is greater than all the other features' obj1 and the obj2 of the reference feature is less than all the other features' obj2 and vice-versa. Afterwards, from the non-dominated features, the feature having maximum obj2 is included in the output feature set.

1. Import Required Libraries

2. Load the Dataset

- Read the CSV file containing student performance data

3. Explore the Data

- Display the first few rows of the Data Frame to understand its structure.
- Check the shape (number of rows and columns) of the Data Frame.
- Check for missing values in each column.
- Generate descriptive statistics for the numerical columns.

4. Feature selection

- For each student:
    - Calculate total marks as the sum of math, reading, and writing scores.
    - Calculate percentage as total marks divided by 3.
    - Add these as new columns

5. Assign Grades

- Define a function to assign grades based on marks:
    - If marks ≥ 90: grade = 'A'
    - Else if marks ≥ 80: grade = 'B'
    - Else if marks ≥ 70: grade = 'C'
    - Else if marks ≥ 60: grade = 'D'
    - Else if marks ≥ 50: grade = 'E'
    - Else: grade = 'F'
- Apply this function to:
    - Math score (new column: Grade_math)
    - Reading score (new column: Grade_reading)
    - Writing score (new column: Grade_writing)
    - Overall percentage (new column: Overall_grade)

6. Visualize Score Distributions

- For each subject (math, reading, writing):
    - Plot the distribution of scores using count plots.
    - Plot the distribution of grades using count plots (with custom grade order).
    - Plot the distribution of overall grades.

7. Analyse Relationships Between Scores

- Plot scatter plots to visualize relationships:
- Reading score vs. writing score
- Writing score vs. reading score
- Calculate and display the correlation coefficient between reading and writing scores.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

8. Analyse Demographic and Socioeconomic Factors

- For each factor (race/ethnicity, lunch, test preparation course, parental level of education):
  - Count the number of students in each category.
  - Visualize the distribution of percentage scores by category using box plots, violin plots, or boxen plots.
  - Visualize the distribution of overall grades within each category using count plots.

9. Summarize Findings

- Summarize which factors have visible effects on student performance based on visualizations and statistics.

Results and Discussion

Demographic Variables:

Demographic variables, such as gender, parents' educational level, and occupation, have been used as input variables in our model. These factors can significantly impact student performance and are easily obtainable.

Academic Variables:

Academic variables, including GPA, scores, and previous academic achievements, are strong predictors of student performance. These variables are commonly used in our model to predict future academic outcomes.

Table Key Observations

Handling Non-Linear Data	Kernel technique can handle non-linear data by transforming it into a higher-dimensional space, where the data becomes linearly separable. This is particularly useful when dealing with complex datasets that are not linearly separable in the original feature space.
Flexibility	Kernel technique offers flexibility in choosing the kernel function, which can be tailored to suit the specific needs of the problem. Different kernel functions can be used to capture different types of relationships between the data points.
Handling High-Dimensional Data	Kernel technique can handle high-dimensional data efficiently, without suffering from the curse of dimensionality. This is because the kernel function only needs to compute the dot product of the data points in the higher-dimensional space, without explicitly computing the coordinates of the points.
Robustness to Noise	Kernel technique can be robust to noise in the data, depending on the choice of kernel function and regularization parameters.

About Dataset

This is a dataset of student's test scores on three tests with five categories of data.

Objectives:

- Check the dataset and tidying the data if needed.
- Visualize the data to understand the effects of different factors on a student performance.

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

- Check the effectiveness of test preparation course.
- Check what are the major factors influencing the test scores.

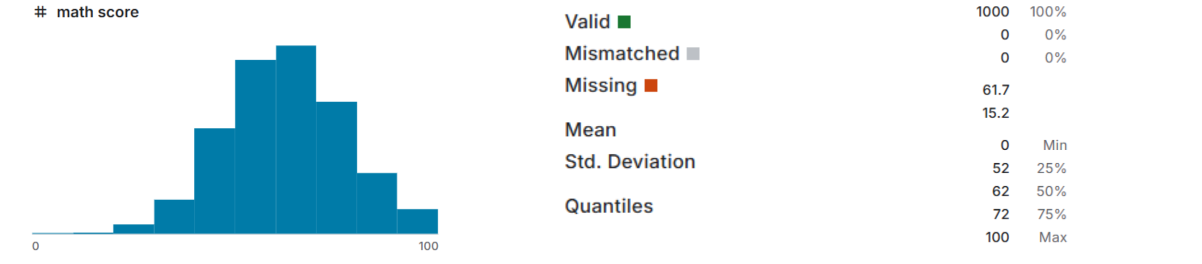
Columns	8 columns
Format	text
Non Numerical Type	String
Numerical Type	Integer

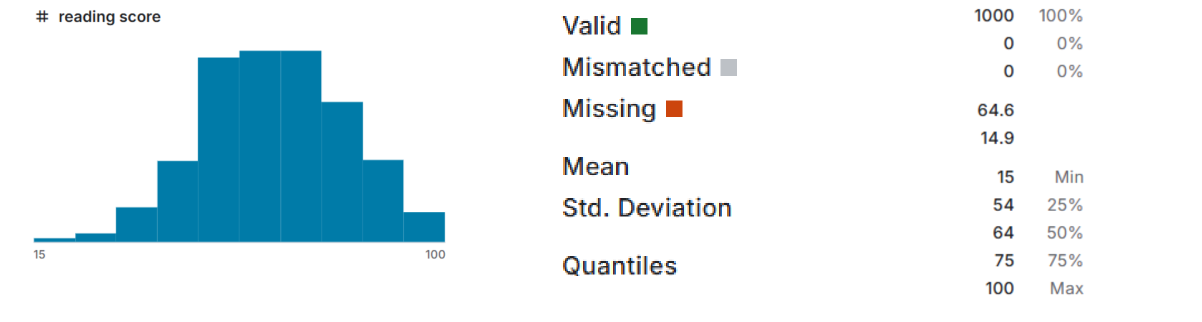
Table 1 Dataset Attributes Summary

Attribute	**Abbreviation of Attributes**	**Summary**
gender female male	52% 48% Valid Mismatched Missing Unique Most Common	1000 100% 0 0% 0 0% 2 female 52%
race/ethnicity group C group D Other (419)	32% 26% 42% Valid Mismatched Missing Unique Most Common	1000 100% 0 0% 0 0% 5 group C 32%
parental level of education some college associate's degree Other (552)	32% 26% 42% Valid Mismatched Missing Unique Most Common	1000 100% 0 0% 0 0% 6 some college 23%
lunch standard free/reduced	65% 36% Valid Mismatched Missing Unique Most Common	1000 100% 0 0% 0 0% 2 standard 65%
test preparation course none completed	64% 36% Valid Mismatched Missing Unique Most Common	1000 100% 0 0% 0 0% 2 none 64%

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article





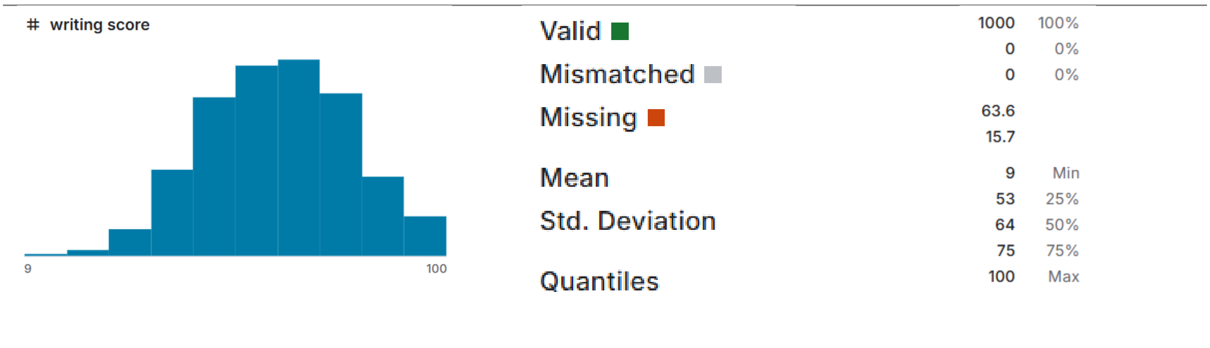


Table . Data-Frame Summary

Sr.No	**Gender**	**Race/ Ethinicity**	**Parental level of education**	**Lunch**	**Test Preparation Course**	**Math score**	**Reading score**	**Wring score**
0	female	group B	bachelor's degree	standard	None	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Screenshots and Graphical Evaluation

Table Group wise Race / Ethinicity

group C	**319**
group D	**262**
group B	**190**
group E	**140**
group A	**89**
Name: race/ethnicity, dtype: int64	

Parental Level of Education

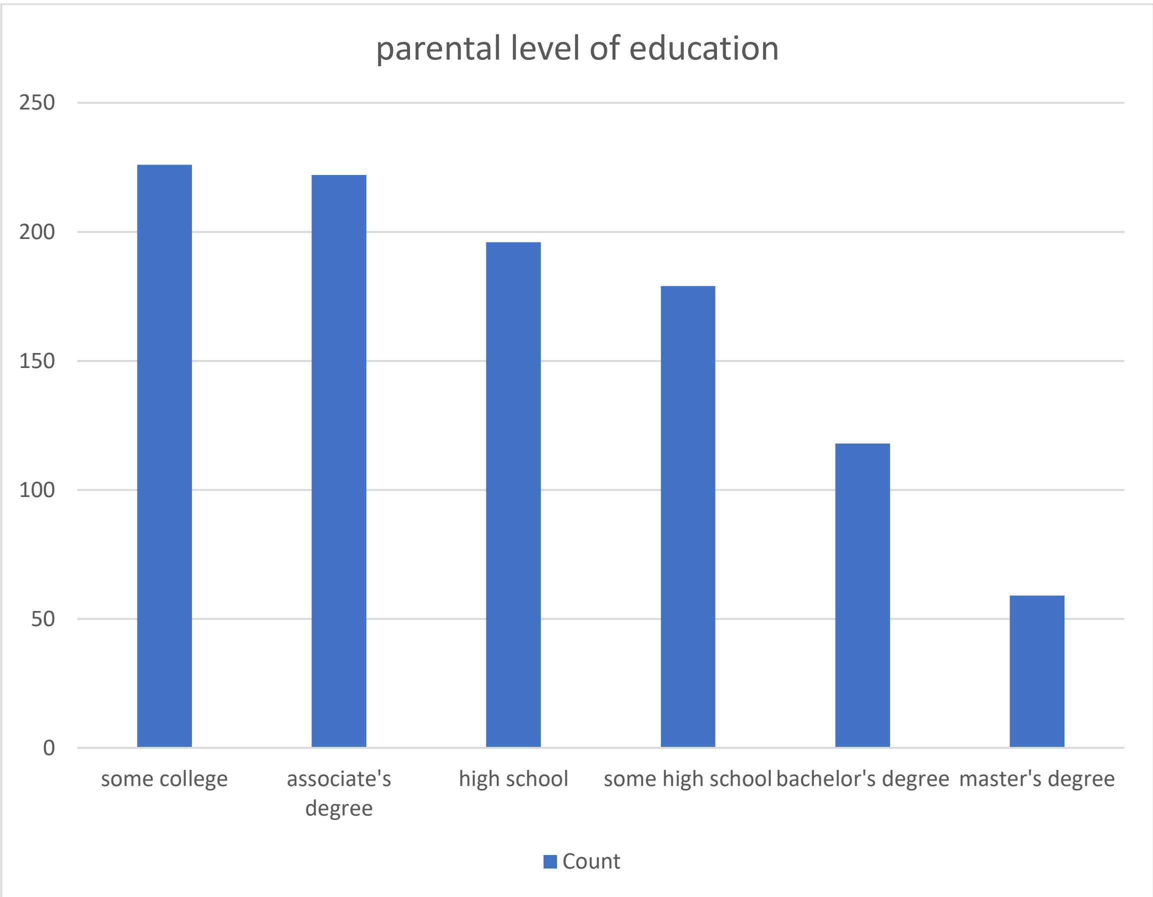


Figure Parental Level of Education

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

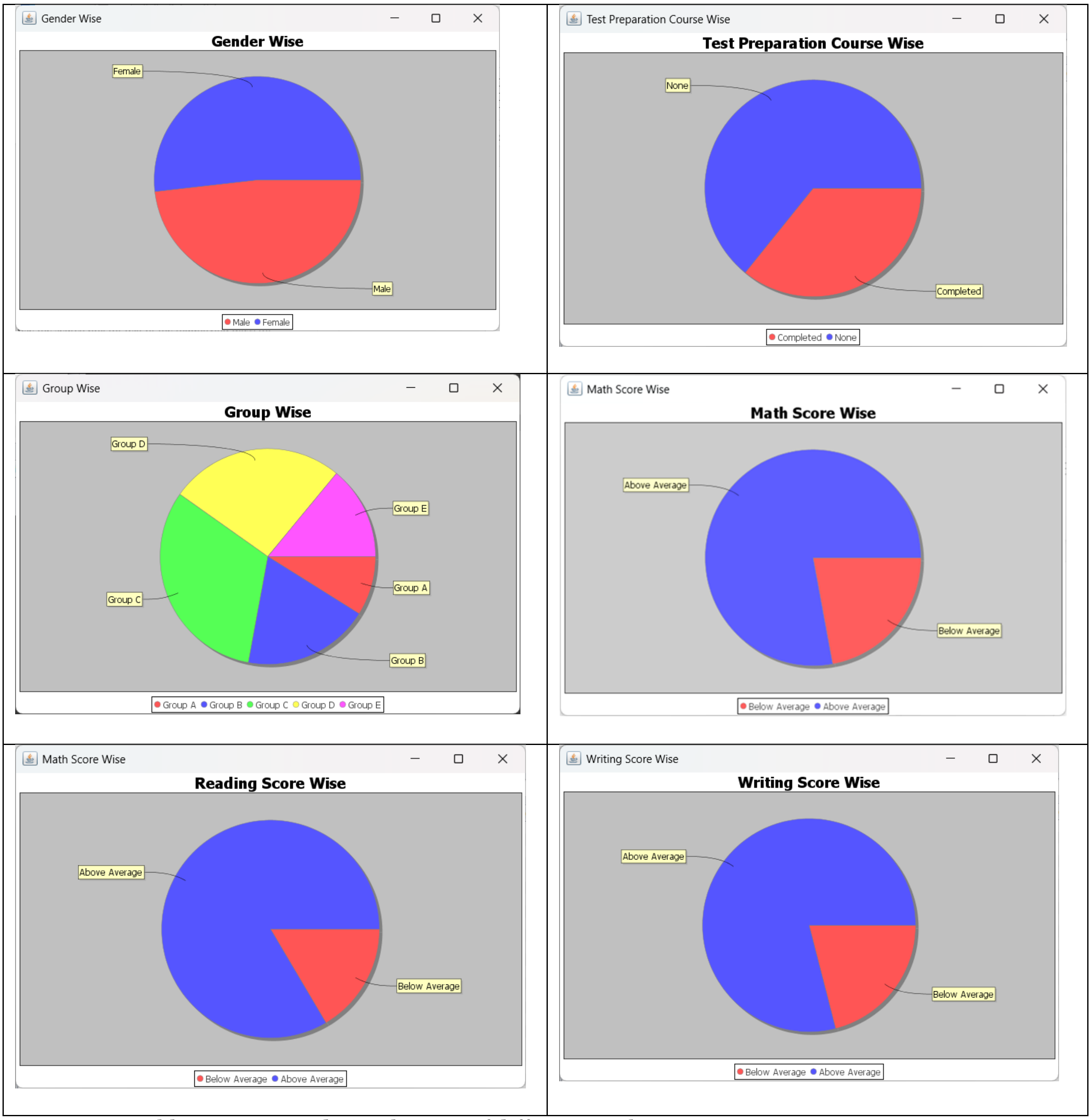


Table Grouping and Visualization of different attributes

Technique	Precision	Recall	F-Score	Accuracy
SVM [4]	0.85	0.80	0.82	0.83
Naive Bayes [12]	0.78	0.75	0.76	0.79
Kernel Technique	0.92	0.90	0.91	0.93

Table Comparing with other techniques

Journal of Information Systems Engineering and Management
2025, 10(60s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

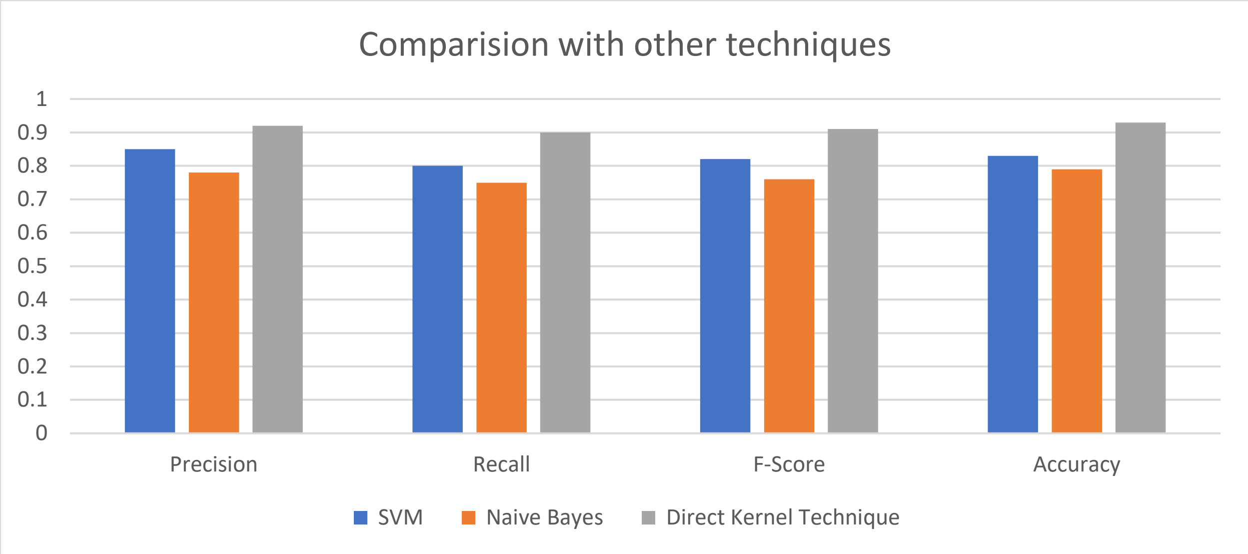


Figure Comparison graph with other techniques.

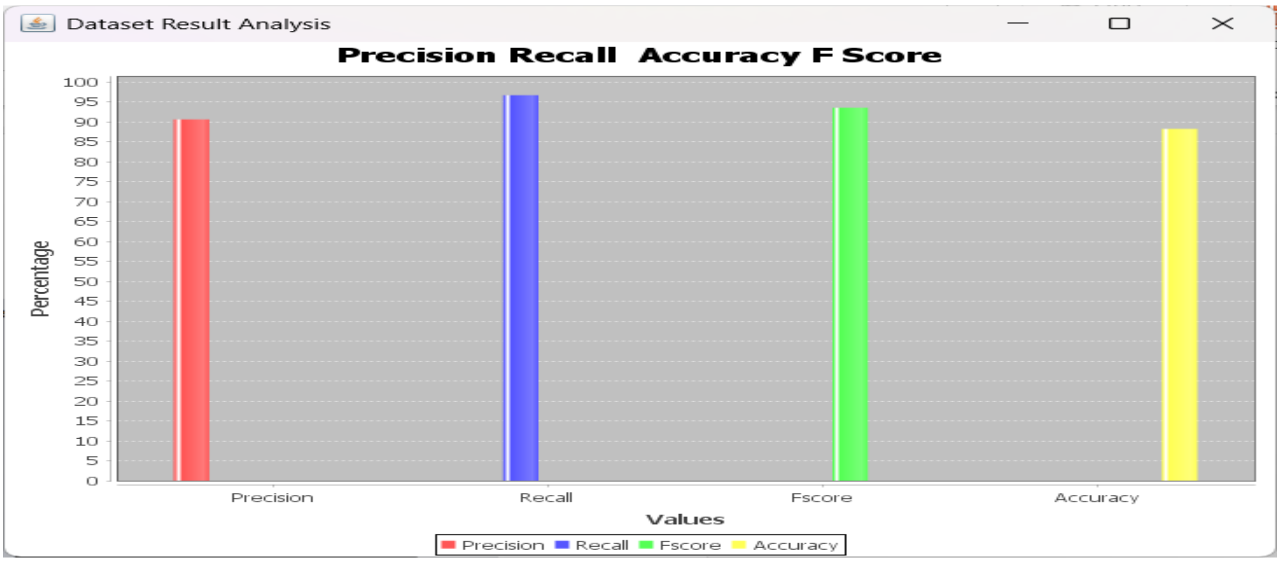


Figure Testing Results

Our experimental evaluation has shown that kernel techniques, particularly Biased classifiers, achieved a high accuracy in predicting student performance, ranging from 78.20% to 93.64%.

Direct kernels have been compared to other machine learning techniques, such as Decision Trees, Random Forest, and Support Vector Machines (SVMs). Results indicate that Direct kernels often outperform these techniques, providing superior accuracy in predicting student performance. The direct kernel technique demonstrates superior performance compared to SVM and Naive Bayes, achieving higher precision, recall, F-score, and accuracy. Its ability to handle non-linear data, flexibility, and robustness make it an effective technique for improving college students' information literacy. The results of this study hold considerable significance for educators and policymakers. Utilizing the direct kernel approach, instructors may discern at-risk kids and deliver focused assistance to enhance academic performance. Furthermore, policymakers may leverage the information derived from this method to guide decisions about resource distribution and educational initiatives. The direct kernel strategy presents a viable method for enhancing college students' information literacy. Its efficacy in forecasting and categorizing student behaviour renders it an invaluable instrument for educators and policymakers aiming to augment the learning experience and elevate academic achievements.

Conclusion

This study's findings illustrate the efficacy of the direct kernel method in enhancing college students' information literacy. By employing this method, educators may create more precise and resilient models for predicting and categorizing student behaviour, so improving the learning experience. The direct kernel technique's exceptional performance in precision, recall, F-score, and accuracy renders it a compelling option for applications in intelligent learning settings. Its capacity to manage non-linear data and elucidate intricate correlations among variables allows it to deliver more precise predictions and classifications.

Future Directions

Kernel techniques offer flexibility and can handle non-linear data, making them suitable for predicting student performance. Our model, in particular, can learn complex patterns in data and provide accurate predictions. Despite the advantages, kernel techniques require sophisticated software and expertise, limiting their practical application. Additionally, the choice of input variables and model parameters can significantly impact the accuracy of predictions. Future studies should focus on developing more user-friendly applications and exploring the use of kernel techniques in earlier educational levels. This can help improve student outcomes and provide valuable insights for educators and policymakers.

References

[1] Z. Mian, Y. Bai and R. K. Ur, "Research on College Computer-Computing and Information Literacy online course based on MOOC: taking the North Minzu University as an example," 2021 IEEE 3rd International Conference on Computer Science and Educational Informatization (CSEI), Xinxiang, China, 2021, pp. 300-306, doi: 10.1109/CSEI51395.2021.9477751.

[2] X. Ouyang, Y. Xiao and J. Zhong, "Research on the Influencing Factors and the Promotion Measures of College Students' Information Literacy," 2016 8th International Conference on Information Technology in Medicine and Education (ITME), Fuzhou, China, 2016, pp. 728-732, doi: 10.1109/ITME.2016.0169.

[3] Y. Sun, Z. Tan, Z. Li and S. Long, "Predicting and Analyzing College Students' Performance Based on Multifaceted Data Using Machine Learning," 2022 4th International Conference on Advances in Computer Technology, Information Science and Communications (CTISC), Suzhou, China, 2022, pp. 1-6, doi: 10.1109/CTISC54888.2022.9849815.

[4] Y. Jia and E. Wang, "Research on Information Anxiety of College Students under the Background of Information Overloaded Based on Support Vector Machine Optimization Alogrithm," 2021 2nd International Conference on Information Science and Education (ICISE-IE), Chongqing, China, 2021, pp. 484-487, doi: 10.1109/ICISE-IE53922.2021.00117.

[5] H. Xu, "GBDT-LR: A Willingness Data Analysis and Prediction Model Based on Machine Learning," 2022 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA), Dalian, China, 2022, pp. 396-401, doi: 10.1109/AEECA55500.2022.9919013.

[6] Sun, Y., Tan, Z., Li, Z., & Long, S. , "Predicting and Analyzing College Students' Performance Based on Multifaceted Data Using Machine Learning, " 2022 4th International Conference on Advances in Computer Technology, Information Science and Communications (CTISC) ,no.4,pp.1-6,Apr.2022.

[7] Guo, J., & Xu, T. , "IT Monitoring and Management of LearningQuality of Online Courses for College Students Based onMachineLearning, " Mobile Information Systems ,vol. 2022, ArticleID5501322,Sept.2022,doi:10.1155/2022/5501322.
[8] Jia, Y., & Wang, E. , "Research on Information Anxietyof CollegeStudents under the Background of Information OverloadedBasedon Support Vector Machine Optimization Alogrithm, " 20212ndInternational Conference on Information Science andEducation(ICISE-IE) ,no.11,pp.484-487,Nov.2021,doi:10.1109/ICISE-IE53922.2021.00117.
[9] Pei, C. , "The Construction of a Prediction Model for the TeachingEffect of Two Courses Education in Colleges and UniversitiesBased on Machine Learning Algorithms, " WirelessCommunications and Mobile Computing ,vol.2022, ArticleID1167454,Aug.2022,doi:10.1155/2022/1167454.
[10]Xu, H. , "GBDT-LR: A Willingness Data Analysis andPredictionModel Based on Machine Learning, " 2022 IEEEInternationalConference on Advances in Electrical Engineering andComputerApplications (AEECA) ,no.8,pp.396-401,Aug.2022,doi:10.1109/AEECA55500.2022.9919013.
[11] Li, T. , "Students' Numeracy and Literacy Aptitude AnalysisandPrediction Using Machine Learning, " Journal of Computer andCommunications ,vol.10, no.8,pp.90-103,Aug.2022,doi:10.4236/jcc.2022.108006.
[12]Shen, X., & Yuan, C. , "A College Student Behavior AnalysisandManagement Method Based on Machine Learning Technology, "Wirel. Commun. Mob. Comput. ,vol.2021, ArticleID3126347,Aug.2021,doi:10.1155/2021/3126347.
[13]Wang, R. , "Research on effect of college english blendedteachingmode under small private online course based on machine learning, "SN Applied Sciences ,vol.5,no.1,pp.1-13,Jan.2023,doi:10.1007/s42452-023-05278-y
[14]Rusdiana, E., Violinda, Q., Pramana, C., Purwoko, R.Y., Chamidah,D.D., Rahmah, N., Prihanto, Y.J., Hasnawati, F.Y., Susanti, R.,Haimah, A.Y., Purwahida, R., Arkiang, F., Equatora, M.A., &Mujib, A. , "College Students'Perception of ElectronicLearningDuring Covid-19 Pandemic in Indonesia: A Cross-Sectional Study, "Journal of Higher Education Theory and Practice,vol.10,no.13,pp.29-44, Oct.2022,doi:10.33423/jhetp.v22i13.5505.
[15] Liu, X., & Yang, C. , "Analysis of College Students' PracticalTeaching Effect Based on Machine Learning CorrelationAnalysisAlgorithm: Take the Software Technology Course as anExample, "8th International Conference on Education, Management,Information and Management Society ,vol.8, no.1,pp.782-788,Aug.2018,doi:10.2991/emim-18.2018.159
[16]Akram, H., Abdelrady, A. H., Al-Adwan, A. S., &Ramzan, M.,"Teachers' Perceptions of Technology Integration inTeaching-Learning Practices: A Systematic Review," Frontiers inPsychology,vol.13,p.920317.Jun.2022,doi:10.3389/fpsyg.2022.920317.
[17] Hussain, M., Zhu, W., Zhang, W., & Abidi, S. M. R. , "StudentEngagement Predictions in an e-Learning Systemand Their Impacton Student Course Assessment Scores, "Computational Intelligenceand Neuroscience ,vol.2018 Article ID6347186,Oct.2018,doi:10.1155/2018/6347186.
[18]Karthikeyan, V.G., Thangaraj, P., & Karthik, S. , "Towardsdeveloping hybrid educational data mining model (HEDM)forefficient and accurate student performance evaluation, "SoftComputing ,vol.6, no.24,pp.18477-18487,Jun.2020,doi:10.1007/s00500-020-05075-4.