AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 3(2026)

Analysis of Learning Behavior Characteristics and Prediction of Learning Effect for Improving College Students' Information Literacy Based on Machine Learning

KONDA SUKUMAR,
PG Scholar, Department of Computer Applications,
Chaitanya Deemed to be University, Hyderabad,
Telangana, India - 500075.
sukumarkonda09@gmail.com

BOGI MADHU,
PG Scholar, Department of Computer Applications,
Chaitanya Deemed to be University, Hyderabad,
Telangana, India - 500075.
bogimadhu95@gmail.com

AKULA RAHUL,
PG Scholar, Department of Computer Applications,
Chaitanya Deemed to be University, Hyderabad,
Telangana, India - 500075.
rahulakula138@gmail.com

KADAVERUGU SHIVAKUMAR ,
PG Scholar, Department of Computer Applications,
Chaitanya Deemed to be University, Hyderabad,
Telangana, India - 500075.
Shivakumarkadaverugu8195@gmail.com

***Abstract*— In today's rapidly evolving educational landscape, information literacy has become a fundamental skill for college students, enabling them to adapt to the ever-changing demands of society. It is not only a requisite for self-directed learning and lifelong education but also a vital aspect of problem-solving, critical thinking, and cognitive abilities. This paper delves into the mechanisms of information literacy teaching by analyzing the diverse learning behaviors of college students and predicting their learning outcomes. Utilizing data from 320 Chinese university students, the study employs the Pearson algorithm to uncover the correlation between information thinking characteristics and learning outcomes. Further, it constructs a predictive model using various supervised classification algorithms, including Decision Tree, KNN, Naive Bayes, Neural Net, and Random Forest. The outcomes offer differentiated intervention recommendations and decision-making insights for enhancing information literacy teaching, improving educational quality, and nurturing innovative talents. The paper underscores the significance of information literacy for problem-solving skills and, as an extension, introduces the powerful XGBOOST & Voting Classifier algorithm to enhance predictive accuracy in this context.**

Keywords*— *Machine learning, information literacy, learning behavior characteristics, learning effect, innovative talents.

I. INTRODUCTION

In the rapidly evolving landscape of the 21st century, characterized by the ubiquitous presence of information technology, the role of information has become paramount across various societal domains. The proliferation of computers, network technology, and communication platforms has engendered a profound transformation in the way individuals interact, learn, and communicate [1]. As a consequence, information literacy, critical thinking, and creativity have emerged as indispensable skills that college students must master to navigate and thrive in this information-rich environment [1].

Information literacy, constituting the ability to adapt effectively to the demands of the information society, has assumed a central position within the core competencies expected of college students [2], [3]. Its significance lies not only in facilitating personal development but also in contributing to the sustainable cultivation of future talents and innovative thinkers [2], [3]. Recognized as an integral component of cultural literacy and overall quality, the cultivation of information literacy among college students has become a pressing concern for contemporary higher education institutions worldwide.

Information literacy encompasses a spectrum of competencies ranging from foundational knowledge and skills in information technology to the capacity to leverage these tools for learning, collaboration, communication, and problem-solving [2]. Moreover, it encompasses a heightened awareness of information dynamics and ethical considerations in its utilization [2]. Acknowledging its pivotal role, various education departments and libraries across countries such as the United States, the United Kingdom, and Australia have embarked on initiatives to bolster information literacy education [3].

China, too, has recognized the imperative of enhancing digital literacy and skills among its populace. In 2022, the Ministry of Education, alongside other governmental bodies, released strategic guidelines aimed at improving the digital literacy of the entire population [4]. With a specific focus on students, these efforts are expected to catalyze a significant enhancement in information literacy capabilities over the coming years [4].

The advent of online and hybrid teaching modalities, coupled with advancements in artificial intelligence technology, has further underscored the importance of information literacy. Consequently, educational institutions worldwide have intensified their efforts to integrate targeted information literacy education into their curricula [5]. Notable examples include the offerings of information literacy courses by prestigious institutions such as Tsinghua University, Wuhan University, Sun Yat-sen University, and Sichuan Normal University via various platforms like MOOCs [5].

However, despite these concerted efforts, challenges persist in the realm of information literacy education for college students. Addressing these challenges demands a nuanced understanding of the evolving information landscape and a commitment to innovative pedagogical approaches. This paper seeks to delve deeper into the existing issues surrounding information literacy education and explore potential avenues for improvement and refinement. Through a comprehensive analysis, it endeavors to shed light on the multifaceted dimensions of information literacy and its implications for contemporary higher education.

II. RELATED WORK

The literature surrounding college students' information literacy spans a diverse array of topics, methodologies, and findings. This literature survey aims to synthesize key studies from various disciplines and geographic regions to provide a comprehensive overview of the current state of research in this field.

One notable area of inquiry pertains to the research status and trends in college students' information literacy. Yang et al. [11] conducted a bibliometric analysis of Chinese National Knowledge Infrastructure (CNKI) data from 2000 to 2021. Their study identified research hotspots and trends, shedding light on the evolving landscape of information literacy scholarship over the past two decades.

In the realm of educational technology, Li [12] employed machine learning techniques to evaluate the effectiveness of interventions aimed at enhancing college teachers' information literacy. By leveraging advanced computational methods, Li's study offers insights into the efficacy of different instructional approaches and their impact on educators' information literacy proficiency.

Yu et al. [13] explored college students' preferences for smart classroom technologies and their relationship with information literacy. By examining students' attitudes towards technology-enhanced learning environments, the study provides valuable insights into the intersection of technological preferences and information literacy development among contemporary learners.

The integration of big data analytics into information literacy research represents another burgeoning area of inquiry. Ying [14] employed big data methodologies to analyze college students' information literacy levels, shedding light on the multifaceted dimensions of information literacy and its determinants in the era of data-driven decision-making.

The role of online courses, particularly Massive Open Online Courses (MOOCs), in fostering information literacy among college students has also garnered significant attention. Mian et al. [15] investigated the effectiveness of a MOOC-based course on computer and information literacy, highlighting the potential of online platforms in democratizing access to information literacy education.

Beyond traditional educational settings, studies have also explored information literacy among specialized student populations. Haider and Ya [16] examined the information literacy skills and information-seeking behavior of medical students in Pakistan, underscoring the importance of domain-specific competencies in the healthcare sector.

Ouyang et al. [17] delved into the influencing factors and promotion measures of college students' information literacy, offering insights into the complex interplay of individual, institutional, and contextual variables shaping information literacy outcomes.

Geographical variations in information literacy levels have also been a subject of investigation. Nishikawa and Izuta [18] assessed the information technology literacy level of newly enrolled female college students in Japan, highlighting cultural and societal influences on information literacy development.

Collectively, these studies underscore the multifaceted nature of college students' information literacy and the diverse array of factors influencing its acquisition and development. By synthesizing insights from interdisciplinary perspectives and global contexts, this literature survey provides a comprehensive foundation for further inquiry and intervention in the field of information literacy education.

III. MATERIALS AND METHODS

i. Proposed Work:

The proposed system in this study seeks to revolutionize the assessment and prediction of college students' learning behaviors and outcomes through a comprehensive framework. It revolves around the construction of a predictive model based on the rich dataset of information literacy learning behavior characteristics. The system initiates with feature selection utilizing the Pearson Correlation algorithm to extract relevant factors from the dataset. Subsequently, it employs an array of machine learning algorithms, including Decision Tree, Naive Bayes, KNN, Random Forest, and Neural Networks, to forecast student behavior and evaluate each model's performance, measuring accuracy, precision, recall, and FSCORE. Notably, the Random Forest algorithm outperforms the others in terms of accuracy. To further enhance the system, the student behavior dataset is divided into three key indicators: 'Knowledge & Skills,' 'Application & Innovation,' and 'Morality Responsibility.' These are further subcategorized into second-level indicators such as 'IPC,' 'IAC,' 'LLC,' 'ISK,' 'IAS,' 'IT,' 'IB,' 'IE,' and 'ILR,' each representing distinct aspects of a student's problem-solving and critical thinking abilities. For an in-depth understanding of these indicators, readers can refer to the base paper. Each record in the dataset is tagged with a class label, indicating performance as 'Excellent,' 'Medium,' or 'Poor.' An extension concept is introduced to enrich the system's capabilities. While the primary paper explores traditional machine learning algorithms, it recognizes the potential of advanced methods like CNN, LSTM, XGBOOST and Voting Classifier. The extension concept specifically incorporates the XGBOOST & Voting classifier algorithm, which demonstrated superior accuracy during experiments. This addition enhances the predictive capabilities of the system and offers valuable insights for educators and decision-makers in the realm of information literacy teaching and student performance assessment.

ii. System Architecture:

The proposed system architecture comprises feature selection using Pearson Correlation, followed by the application of machine learning algorithms such as Decision Tree, Naive Bayes, KNN, Random Forest, and Neural Networks for predictive modeling of college students' learning behaviors and outcomes. The dataset is divided into three key indicators and further subcategorized into second-level indicators. Records are labeled as 'Excellent,' 'Medium,' or 'Poor.' An extension concept introduces advanced algorithms like XGBOOST and Voting Classifier for enhanced predictive accuracy. This architecture provides a comprehensive framework for assessing and predicting student performance in information literacy, benefiting educators and decision-makers alike.

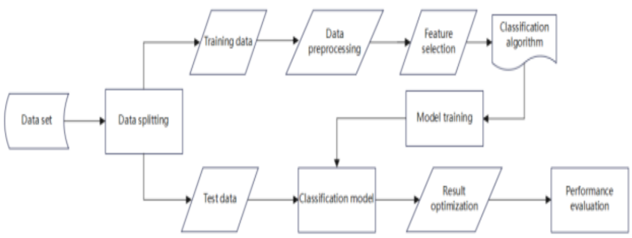

Fig. 1. Proposed Architecture

iii. Dataset:

The Student Learning Behavior dataset encompasses a rich repository of information capturing various facets of college students' engagement and performance in information literacy activities. It comprises data points reflecting students' interactions with learning materials, participation in collaborative activities, and problem-solving approaches. Key attributes include indicators of knowledge acquisition, skill development, critical thinking, and ethical responsibility. Additionally, the dataset includes demographic information such as age, gender, and academic background to provide context for analyzing learning behaviors. Each record in the dataset is labeled with performance indicators ranging from 'Excellent' to 'Poor,' enabling the classification of students based on their proficiency levels. This comprehensive dataset serves as the foundation for constructing predictive models aimed at assessing and predicting students' learning outcomes in the domain of information literacy.

	IPC1	IPC2	IPC3	IAC1	IAC2	LLC1	LLC2	ISK1	ISK2	ISK3	ISK4	IAS1	IT1	IT2	IT3	IB1	IE1	IE2	ILR1	label
0	69	63	78	87	94	94	87	84	61	4	4	7.9	A	1.0	0.0	0.0	0.0	0.0	no	excellent
1	78	62	73	60	71	70	73	84	91	7	2	5.4	B	2.0	0.0	0.0	0.0	0.0	no	medium
2	71	86	91	87	61	81	72	72	94	1	1	5.2	B	7.0	0.0	0.0	0.0	0.0	no	excellent
3	76	87	60	84	89	73	62	88	69	1	2	8.5	C	10.0	0.0	0.0	0.0	0.0	yes	excellent
4	92	62	90	67	71	89	73	71	73	5	6	8.8	C	6.0	0.0	0.0	0.0	0.0	no	excellent
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1008	88	85	68	84	88	66	86	76	82	2	2	7.6	A	1.0	0.0	0.0	0.0	0.0	no	excellent
1009	76	63	92	74	76	81	76	87	81	8	7	7.4	C	7.0	0.0	0.0	0.0	0.0	yes	excellent
1010	74	94	94	82	64	92	84	67	80	4	6	7.7	C	5.0	0.0	0.0	0.0	0.0	no	poor
1011	60	84	84	70	80	78	64	83	60	8	6	7.6	D	8.0	0.0	0.0	0.0	0.0	yes	excellent
1012	91	61	83	80	88	62	88	76	86	9	1	7.4	D	5.0	0.0	0.0	0.0	0.0	no	excellent

Fig. 2. Dataset

iv. Data processing:

In the data processing stage, the first step involves importing the dataset into a pandas dataframe, a powerful data manipulation tool in Python. Once imported, any unwanted columns irrelevant to the predictive modeling task are dropped from the dataframe, streamlining the dataset for further analysis.

Following this, normalization techniques are applied to standardize the range of numerical features within the dataset. Normalization ensures that all numerical attributes contribute equally to the modeling process, preventing biases stemming from differences in scale.

Subsequently, the processed data is visualized using libraries such as seaborn and matplotlib. These visualization tools offer a comprehensive view of the dataset's characteristics, enabling analysts to identify patterns, trends, and potential outliers. Visualizations aid in gaining insights into the relationships between variables and can inform feature selection and modeling decisions.

Finally, label encoding is performed to convert categorical variables into numerical format, facilitating their inclusion in machine learning algorithms. Label encoding assigns a unique numerical label to each category within a categorical variable, enabling algorithms to process and analyze categorical data effectively.

Overall, through data processing techniques such as column dropping, normalization, visualization, and label encoding, the raw dataset is transformed into a structured and prepared format suitable for training machine learning models to predict college students' learning behaviors and outcomes in information literacy.

v. Feature Selection:

Feature selection is a crucial step in the data preprocessing pipeline, aimed at identifying and retaining only the most relevant attributes that contribute significantly to the predictive modeling task. In this case, feature selection is based on high correlation values between different features in the dataset. The Pearson correlation coefficient is commonly utilized for this purpose, quantifying the strength and direction of the linear relationship between two variables.

By calculating the correlation matrix, features with high correlation values are identified and retained, while redundant or irrelevant attributes are discarded. This process ensures that only the most informative and non-redundant features are included in the subsequent modeling steps, thereby improving model performance, reducing computational complexity, and enhancing interpretability.

Feature selection based on high correlation values enables the construction of more parsimonious and efficient predictive models, leading to better insights and decision-making in the realm of information literacy assessment and prediction.

vi. Training & Testing:

The data is split into training and testing sets using an 80:20 ratio, with 80% of the data allocated for training and 20% for testing. The training set comprises a majority of the data and is utilized to train the predictive model, enabling it to learn patterns and relationships within the dataset. Conversely, the testing set serves as an independent validation set, allowing for the evaluation of the model's performance on unseen data.

During training, the model utilizes the training set to optimize its parameters and learn from the patterns present in the data. Once trained, the model is evaluated using the testing set to assess its generalization ability and performance on new, unseen instances. This process helps to gauge the model's accuracy, precision, recall, and F-score, providing insights into its effectiveness in predicting college students' learning behaviors and outcomes in information literacy.

vii. Algorithms:

Decision Tree: A decision tree algorithm is a machine learning algorithm that uses a decision tree to make predictions. It follows a tree-like model of decisions and their possible consequences. The algorithm works by recursively splitting the data into subsets based on the most significant feature at each node of the tree.

KNN: The k-nearest neighbors algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point.

Naive Bayes: The Naïve Bayes classifier is a supervised machine learning algorithm, which is used for classification tasks, like text classification. It is also part of a family of generative learning algorithms, meaning that it seeks to model the distribution of inputs of a given class or category.

Neural Network – MLP: The Multilayer Perceptron (MLP) neural network algorithm is a feedforward artificial neural network. Comprising an input layer, hidden layers, and an output layer, it processes information through interconnected nodes with weighted connections. Employing backpropagation for training, it learns complex patterns and is widely used for various machine learning tasks.

Random Forest: Random forest is a commonly-used machine learning algorithm trademarked by Leo Breiman and Adele Cutler, which combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fueled its adoption, as it handles both classification and regression problems.

XGBoost: XgBoost is a gradient boosting algorithm for supervised learning. It's a highly efficient and scalable implementation of the boosting algorithm, with performance comparable to that of other state-of-the-art machine learning algorithms in most cases.

Voting Classifier: A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on their highest probability of chosen class as the output.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

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

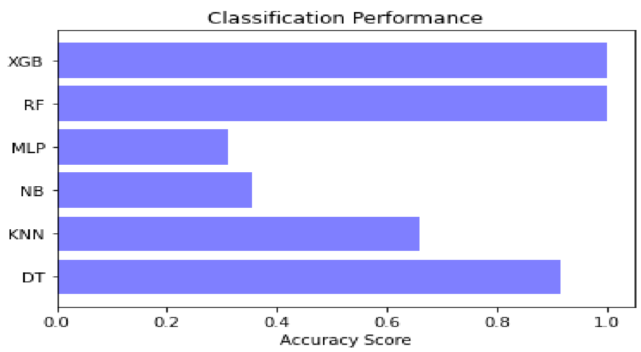

Fig 3 Accuracy Comparison graph

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

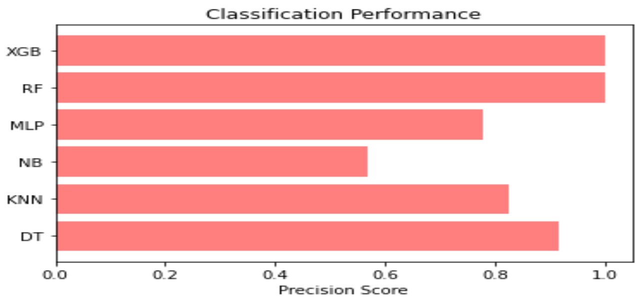

Fig 4 Precision Comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

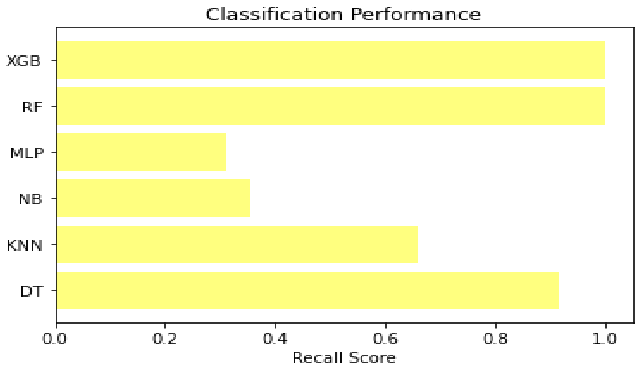

Fig 5 Recall Comparison graph

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

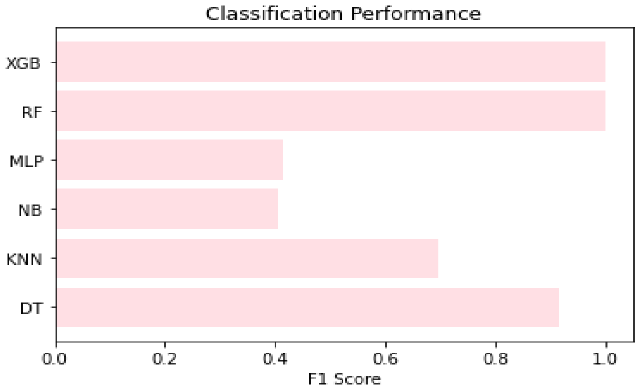

Fig 6 F1-Score Comparison graph

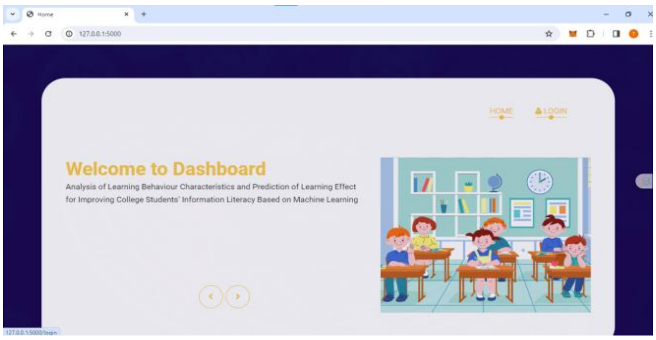

Fig 7 Home Page

Fig 8 Signup Page

Received: 12-08-2026 | Accepted: 18-09-2026 | Published: 22-09-2026 | www.ajaccm.com

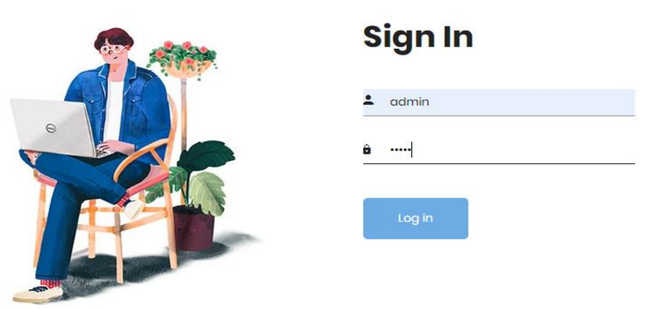

Fig 9 Signin Page

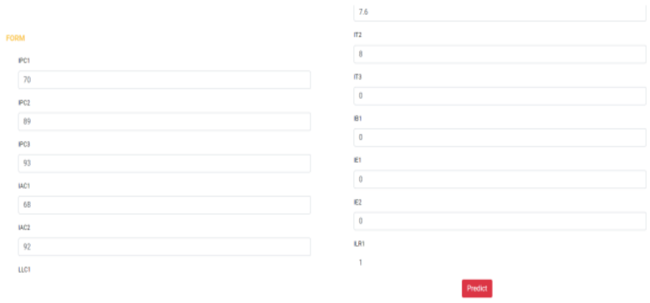

Fig 10 Upload Input values

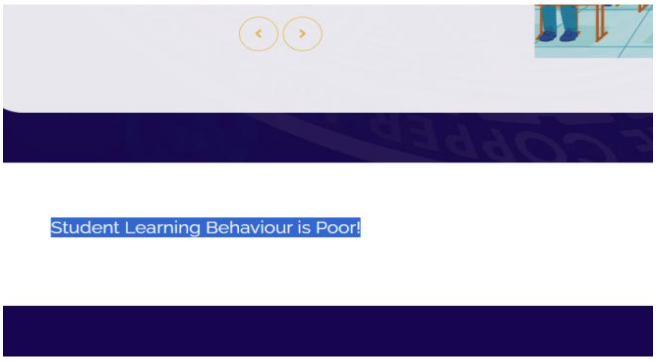

Fig 11 Predict result as student learning behaviour is poor

Fig 12 Upload another input values

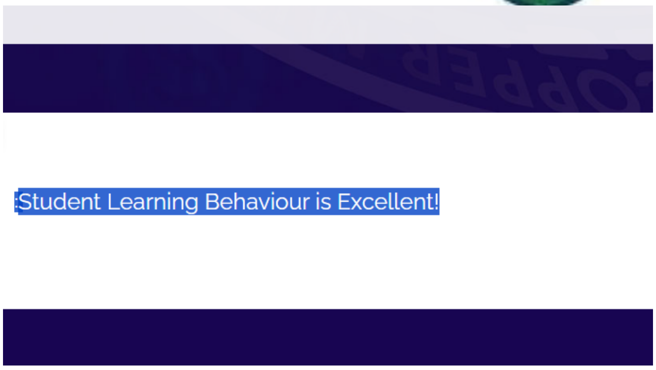

Fig 13 Final outcome as student learning behaviour is excellent

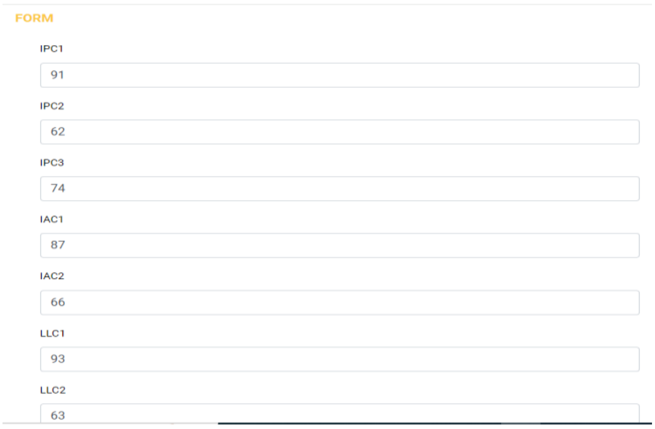

Fig 14 Upload another input values

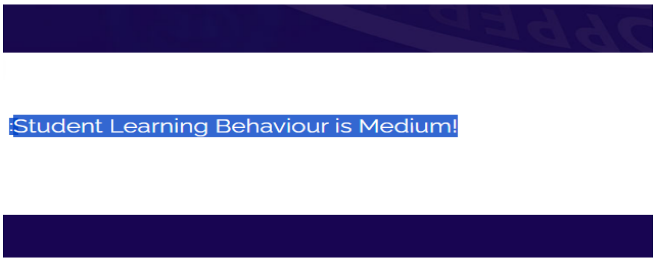

Fig 20 Predict result as student learning behaviour is medium

V. CONCLUSION

The results prove that the prediction model proposed in this paper has a significant effect on the cultivation of information literacy of college students. On the one hand, Algorithmic analysis of the learning behaviour characteristics of college students' information literacy reveals a more significant correlation between information thinking, information application skills and learning effect. Emphasis should be placed on the cultivation of information thinking, while not neglecting the cultivation of information acquisition ability. Universities should understand the importance and urgency of information literacy education for college students from the height of sustainable development of talents and cultivation of high-quality and innovative talents. It is necessary to make full use of network and multimedia technologies to provide intelligent learning tools and learning environments conducive to independent, cooperative and research learning, to incorporate critical thinking methods into the information literacy education system, to establish a longterm assessment mechanism oriented to the cultivation of critical thinking, and to actively promote the critical thinking cognition and knowledge creation skills of college students. On the other hand, it is necessary to further optimize the learning methods in such aspects as information laws and regulations, streamline the learning contents in such aspects as information perception awareness, and continuously instill and guide college students to establish the concept of lifelong learning. This study provides a more reliable data base for educational administrators to analyze the potential connections between information literacy education phenomena and outcomes, thereby increasing the success rate of educational decisions. In conclusion, this study proposes an effective machine learning approach to characterize the learning behaviors and predict the learning effects of information literacy among college students. This study uses a data-driven thinking to promote teachers and students to optimize their learning paths and improve the effectiveness of information literacy instruction. It also strongly supports the implementation of differentiated teaching decision-making [59] and the construction of a long-term mechanism for differentiated educational decisions through a data-driven approach. Although this study has conducted some exploration, there are still limitations. While machine learning approaches work to some extent, the study suggests that technological tools need to be applied according to the specific teaching and learning situation.

vi. REFERENCE

Further research is proposed in the following areas at a later stage.(1)Learning effect prediction has not been able to cover other possible factors in learning scenarios, which puts higher demands on the quality of the learning behavior trait scale. We will explore the learning behavior characteristics in more scenarios, evolve the learning behavior characteristics scale, improve the universality, and form a closed loop of textbook development of teaching experiment, teaching research, and teaching practice.(2)In this study, only five supervised classification algorithms are used, such as Decision Tree, KNN, Naive Bayes, Neural Net, and Random Forest. In subsequent studies, the adopted algorithms can be collectively improved to achieve better prediction results.

REFERENCES

[1] Z. Changhai, ‘‘Research on the information literacy education model of Chinese college students based on critical thinking and creativity,’’ J. China Library, vol. 4, no. 15, pp. 15–16, Aug. 2016, doi: 10.13530/j.cnki.jlis.164008.

[2] S. Hui, ‘‘Information literacy education for college students,’’ Educ. Theory Pract., vol. 30, no. 10, pp. 38–39, Oct. 2008.

[3] D. Yan and G. Li, ‘‘A heterogeneity study on the effect of digital education technology on the sustainability of cognitive ability for middle school students,’’ Sustainability, vol. 15, no. 3, pp. 2784–2786, Feb. 2023, doi: 10.3390/su15032784.

[4] Y. Xiaohong, Z. Xin, and Z. Jing, ‘‘Research on the Chinese experience of the ‘epidemic’ of the education war—Online education perspective,’’ China Distance Educ., vol. 43, no. 1, pp. 1–11, Jan. 2023, doi: 10.13541/j.cnki.chinade.2023.01.002.

[5] G. Shan and F. Shan, ‘‘Digital literacy practice and enlightenment of the University of Queensland library in Australia,’’ Library Sci. Res., vol. 7, no. 10, pp. 95–101, Jul. 2019, doi: 10.15941/j.cnki.issn1001-0424.2019.10.015.

[6] T. H. Wufati, ‘‘Mining the characteristics of meaningful learning behavior: A framework for predicting learning outcomes,’’ Open Educ. Res., vol. 25, no. 6, pp. 75–82, Jan. 2019, doi: 10.13966/j.cnki.kfjyyj.2019.06.008.

[7] H. Hang, L. Yaxin, L. Qi’e, Y. Hairu, Z. Qiuhua, and C. Yifan, ‘‘The occurrence process, design model and mechanism explanation of deep learning,’’ China’s Distance Educ., vol. 5, no. 1, pp. 54–61, Mar. 2020, doi: 10.13541/j.cnki.chinade.2020.01.005.

[8] I. A. AlShammari, M. Aldhafiri, and Z. Al-Shammari, ‘‘A meta-analysis of educational data mining on improvements in learning outcomes,’’ College student J., vol. 47, no. 2, pp. 326–333, Jun. 2013.

[9] W. Gaihua and F. Gangshan, ‘‘Prediction of online learning behavior and achievement and design of learning intervention model,’’ China’s Distance Educ., vol. 2, no. 2, pp. 39–48, Mar. 2019, doi: 10.13541/j.cnki.chinade.20181214.007.

[10] UNESCO. Accessed: Apr. 1, 2023. [Online]. Available: https://www.unesco.org/en/articles/challenges-and-opportunities-artificialintelligence-education

[11] G. Yang, B. Wen, and W. Lin, ‘‘Research status, hot spots and enlightenment of college students’ information literacy: Based on bibliometric analysis of CNKI from 2000 to 2021,’’ in Proc. 4th World Symp. Softw. Eng., Sep. 2022, pp. 161–166, doi: 10.1145/3568364.3568389.

[12] J. Li, ‘‘Machine learning-based evaluation of information literacy enhancement among college teachers,’’ Int. J. Emerg. Technol. Learn., vol. 17, no. 22, pp. 116–131, Nov. 2022, doi: 10.3991/ijet.v17i22.35117.

[13] L. Yu, D. Wu, H. H. Yang, and S. Zhu, ‘‘Smart classroom preferences and information literacy among college students,’’ Australas. J. Educ. Technol., vol. 38, no. 2, pp. 144–163, Feb. 2022, doi: 10.14742/ajet.7081.

[14] Y. Ying, ‘‘Research on college students’ information literacy based on big data,’’ Cluster Comput., vol. 22, no. S2, pp. 3463–3470, Mar. 2019, doi: 10.1007/s10586-018-2193-0.

[15] 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,’’ in Proc. IEEE 3rd Int. Conf. Comput. Sci. Educ. Inf. (CSEI), Jun. 2021, vol. 6, no. 7, pp. 300–306, doi: 10.1109/CSEI51395.2021.9477751.

[16] M. S. Haider and C. Ya, ‘‘Assessment of information literacy skills and information-seeking behavior of medical students in the age of technology: A study of Pakistan,’’ Inf. Discovery Del., vol. 49, no. 1, pp. 84–94, Feb. 2021, doi: 10.1108/IDD-07-2020-0083.

[17] X. Ouyang, Y. Xiao, and J. Zhong, ‘‘Research on the influencing factors and the promotion measures of college students’ information literacy,’’ in Proc.

8th Int. Conf. Inf. Technol. Med. Educ. (ITME), Dec. 2016, vol. 12, no. 12, pp. 728–732, doi: 10.1109/ITME.2016.0169.
[18] T. Nishikawa and G. Izuta, ''The information technology literacy level of newly enrolled female college students in Japan,'' Hum. Social Sci. Rev., vol. 7, no. 1, pp. 1–10, Mar. 2019, doi: 10.18510/hssr.2019.711.
[19] R. Diani, A. Susanti, N. Lestari, M. Saputri, and D. Fujiani, ''The influence of connecting, organizing, reflecting, and extending (CORE) learning model toward metacognitive abilities viewed from students' information literacy in physics learning,'' J. Phys., Conf. Ser., vol. 1796, no. 1, pp. 1–9, Feb. 2021, doi: 10.1088/1742-6596/1796/1/012073.
[20] F. Liu and Q. Zhang, ''A new reciprocal teaching approach for information literacy education under the background of big data,'' Int. J. Emerg. Technol. Learn, vol. 16, no. 3, pp. 246–260, Feb. 2021, doi: 10.3991/ijet.v16i03.20459.
[21] M. K. Masko, K. Thormodson, and K. Borysewicz, ''Using case-based learning to teach information literacy and critical thinking skills in undergraduate music therapy education: A cohort study,'' Music Therapy Perspect., vol. 38, no. 2, pp. 143–149, Oct. 2020, doi: 10.1093/mtp/miz025.
[22] R. Xu, C. Wang, Y. Hsu, and X. Wang, ''Research on the influence of DNNbased cross-media data analysis on college students' new media literacy,'' Comput. Intell. Neurosci., vol. 2022, Aug. 2022, Art. no. 9224834, doi: 10.1155/2022/9224834.
[23] M. Aydın, ''A multilevel modeling approach to investigating factors impacting computer and information literacy: ICILS Korea and Finland sample,'' Educ. Inf. Technol., vol. 27, no. 2, pp. 1675–1703, Aug. 2021, doi: 10.1007/s10639-021-10690-1.
[24] Y. Sun, Z. Tan, Z. Li, and S. Long, ''Predicting and analyzing college students' performance based on multifaceted data using machine learning,'' in Proc. 4th Int. Conf. Adv. Comput. Technol., Inf. Sci. Commun. (CTISC), Apr. 2022, pp. 1–6, doi: 10.1109/CTISC54888.2022.9849815.
[25] J. Guo and T. Xu, ''IT monitoring and management of learning quality of online courses for college students based on machine learning,'' Mobile Inf. Syst., vol. 2022, Sep. 2022, Art. no. 5501322, doi: 10.1155/2022/5501322.
[26] 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,'' in Proc. 2nd Int. Conf. Inf. Sci. Educ. (ICISE-IE), Nov. 2021, pp. 484–487, doi: 10.1109/ICISEIE53922.2021.00117.
[27] C. Pei, ''The construction of a prediction model for the teaching effect of two courses education in colleges and universities based on machine learning algorithms,'' Wireless Commun. Mobile Comput., vol. 2022, Aug. 2022, Art. no. 1167454, doi: 10.1155/2022/1167454.
[28] H. Xu, ''GBDT-LR: A willingness data analysis and prediction model based on machine learning,'' in Proc. IEEE Int. Conf. Adv. Electr. Eng. Comput. Appl. (AEECA), no. 8, Aug. 2022, pp. 396–401, doi: 10.1109/AEECA55500.2022.9919013.
[29] T. Li, ''students' numeracy and literacy aptitude analysis and prediction using machine learning,'' J. Comput. Commun., vol. 10, no. 8, pp. 90–103, Aug. 2022, doi: 10.4236/jcc.2022.108006.
[30] X. Shen and C. Yuan, ''A college student behavior analysis and management method based on machine learning technology,'' Wireless Commun. Mobile Comput., vol. 2021, Aug. 2021, Art. no. 3126347, doi: 10.1155/2021/3126347.