An Internet+ Education Platform for Academic Resource and Status Data Management

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ABSTRACT

The quality education goal is a Sustainable Development Goal (SDG) that the United Nations aim to achieve by 2023. While there is still a long way to go to achieve the goal, information and communications technologies (ICT) provide efficient tools to substantially strengthen and accelerate the process. Thus, in this chapter, the authors design an Internet+ education platform to facilitate all participants conducting quality education effectively and efficiently, providing extensive intelligent quality education tools by exploiting various ICT. Functions provided by the platform can be conveniently used by each user over any kind of end devices, which helps to increase the interests of students and younger teachers in learning and education. In addition, taking the academic success as a case, they study factors influencing the quality education effect by machine learning algorithms on the platform. They propose an LR-based algorithm to predict the academic success of undergraduates to find quality education issues. Experiment results verify the superior performance of the LR-based algorithm.

KEYWORDS

ICT, Quality Education, Sustainable Development Goal

INTRODUCTION

In 2015, 193 member countries of the United Nations (UN) adopted the 2030 Agenda and its 17 interconnected sustainable development goals (SDG) related to social, economic, and environmental growth (United Nations, 2023a). SDG 4, which focuses on quality education, ensures inclusive and equitable education. It also provides lifelong learning opportunities by addressing educational resource imbalance issues, especially for females in low-income developing countries.

Although already halfway to the 2030 Agenda deadline, all the SDG (including SDG 4) are proceeding slowly (United Nations, 2023b). From 2015 to 2021, the primary school completion rate
increased by only two percentage points worldwide, mainly due to COVID-19, an economic downturn, and war (United Nations, 2023b). If all countries maintain the status without acting, only one-sixth of the countries will achieve SDG 4. As a result, an estimated 84 million children and youth will be left out of school (United Nations, 2023b).

In the era of Internet+, information and communication technologies (ICTs) provide efficient ways to share resources and integrate or analyze information. For example, teachers can use online learning platforms or new media like Webcasts to upload teaching resources for students to access at any time and any place. With the aid of artificial intelligence (AI) algorithms, on-demand personalized education or learning schemas can, therefore, be designed for all students (Cope et al., 2021; Smirani et al., 2022). These technologies and platforms can then be used to solve educational resource imbalance issues.

Several studies have exploited ICTs for the analysis of education data, providing reference information for students and teachers to improve the quality of education. The studies assumed that education data are given without consideration for more comprehensive information and various perspectives. In addition, the studies did not provide a platform to effectively share resources and remedy resource imbalance. In fact, only a few of the studies featured personalized education via ICTs.

In the current article, the authors design an Internet+ education platform with comprehensive functions to improve quality education with the help of ICTs. To the best of the authors’ knowledge, this study is the first of its kind. Through the Internet+ platform, users can access services with devices like personal computers, smart phones, or innovative wearable devices. Accessibility can enhance the interest of younger students and teachers.

In addition, the authors take the education effect analysis as a function case of the designed platform to present a prediction algorithm for academic success based on logistic regression. Then, the authors can study the factors affecting academic success, providing important reference information for teachers to understand the impact of quality education on students.

In brief, this study facilitates the achievement of SDG 4 through the following objectives:

1. Provide a method to share educational resources across the globe
2. Provide a valid method for collecting and fusing comprehensive education information
3. Provide personalized learning strategies

This article is organized as follows. The following section analyzes related works. Then, the article discusses the Internet+ platform and proposes the logistic regression-based prediction algorithm for academic success. This is followed by a section that evaluates the performance of the proposed prediction algorithm. Finally, the article presents a conclusion section.

RELATED WORK

Several studies have explored the application of ICTs on analyzing education data. The research has aimed to provide reference information for teachers and students to enhance their teaching abilities and learning outcomes. This section analyzes existing work related to education effect assessment, teaching of quality education, personalized learning design, and academic success prediction, respectively.

Education Effect Assessment

Mo et al. (2022) used the extended triple helix model combined with the fuzzy evaluation method to convert scores by experts (in higher education, industry, and government) into one value for grading the effect of curriculum ideology and politics. Lin et al. (2022) proposed the use of classroom performance data for the effect evaluation in which the evaluated value is the weighted sum of scores collected in Rain Classroom teaching (an online teaching platform developed by XuetangX and Tsinghua
University). Wang et al. (2023) presented an effect assessment metric for curriculum ideology and politics according to student achievement and fluctuations over time. Li and Luzi (2022) presented 14 evaluation indicators for the integration of ideology and politics into sports aerobics. Then, they employed the back propagation neural network to evaluate the effect of curriculum ideology and politics education.

These works helped design an education effect assessment method by reducing multiple numbers scored by teachers into one number to achieve the grading effect. By using only the subjective rate scores, the result lacks objectivity. In addition, the education data quality is decided by teachers, which can be poor, especially in low-income countries. This article presents an education platform that can collect comprehensive education data from various perspectives, employing ICTs to analyze the data for various purposes.

**Teaching Quality Evaluation**

Liu and Cheng (2022) designed a sampling plan based on Brewer’s method to evaluate the teaching effect of curriculum ideology and politics (CIP) and to judge the implementation effect of CIP in higher education or secondary colleges. Then, the authors proposed a survey and analysis procedure by stratified random sampling for the teaching effect evaluation of CIP. Finally, the authors tested their proposed approach by the Monte Carlo simulation method, verifying the effectiveness of the effect evaluation approach.

Li and Qi (2021) used the fuzzy method to build a mathematical model to study the competency of teachers under the background of CIP. First, the work consulted 12 experts to construct the competency index system. Then, based on the evaluation indices with various weights, the authors built the fuzzy competency model for evaluating the CIP education competency of a university teacher.

Lv (2021) exploited Aprior, an association rule mining algorithm, to analyze affecting factors and evaluate the teaching quality of the curriculum ideology and politics. This was based on traditional teaching evaluation data.

Zhong (2022) used convolutional neural networks (CNN) to overcome strong subjectivity and unrepresentative results in the quality evaluation of culture and CIP teaching by traditional methods. CNN was used to introduce facial expression recognition into the teaching process, aiming to grasp the actual teaching effect. To have a full understanding of the current teaching situation, the author used a questionnaire to ask students about their understanding of curriculum ideology and politics, satisfaction related to teaching, and expectations of the teaching method.

Like education effect assessment works, these works evaluate teaching quality based on subjectivity data.

**Personalized Learning Design**

Zhao et al. (2020) proposed a personalized learning framework for online ideological and political educations. The framework exploits knowledge graphs and data mining techniques to mine the ideological and political elements of a course. It then develops personalized ideological and political learning programs based on education data collected through the network, database, and mobile platforms.

Fan and Meng (2021) presented a personalized algorithm to recommend curriculum ideology and political teaching resources to students according to students’ knowledge structure, learning preferences, and course knowledge structure. Students’ knowledge structure and learning preferences are achieved by their test answers. Course knowledge structure includes the sequence of knowledge points and difficulty of learning resources, which is achieved by analyzing students’ learning data. This work aimed to meet the needs of students at different learning levels through improved efficiency, enhanced quality, and support for social education.

Zhao (2021) proposed that curriculum ideology and political resources should be explored. In addition, the study promoted the construction of multiple means of teaching and improvement surrounding teachers’ curriculum ideology and political abilities. These efforts would effectively combine curriculum ideology and politics into management communication courses. The author
proposed the use of cluster technology to understand the similarities of students based on learning behavior data collected from the classroom and intelligent learning environments. The information could then be used for the implementation of personalized education.

These studies often used data mining algorithms to understand the similarity of students based on learning data. In turn, the researchers could recommend resources based on the similarities. However, in the real world, the education effect is decided by learning resources, students’ behaviors, and factors like learning method, learning environment, and family. Real-world impacts can lead to poor recommendation performance. Thus, an adaptive learning path (rather than only learning resources) must be designed and recommended for every student according to their current learning status.

**Academic Success Prediction**

Mai et al. (2022) exploited the random matrix theory, community detection algorithm, and statistical hypothesis tests to identify groups of students with similar learning behaviors and outcomes. The detected groups could also be applied to classification techniques for predicting outcomes at early study stages. Sreenivasulu et al. (2022) proposed the use of CNN to predict students’ course success. Kanetaki et al. (2022) built a generalized linear autoregressive (GLAR) model to predict students’ grades in online learning scenarios within a hybrid learning environment. These works focused on the outcome prediction for courses or early grades instead of the final grade.

Segura et al. (2022) recommended using data that corresponds to dropout candidates after their first year for the early detection of students likely to drop out. Ajibade et al. (2022) used bagging, boosting, and voting techniques to combine Naive Bayes (NB), decision tree (ID3), support vector machine (SVM), and K-nearest neighbor (KNN) to predict students’ academic performance. These approaches assumed that educational data used by machine learning algorithms are known without considering the collection of data. Besides, these works only exploited a few of the students’ features, resulting in a partial picture of the educational status.

**Our Novelty**

Prior studies have explored ways to improve quality education through ICTs in the era of Internet+. However, there are no studies that design an Internet+ platform to provide convenient and comprehensive tools for participants of quality education with the help of ICTs. In addition, the current study looks at the academic success of undergraduates, which can directly reflect the effect of quality education. It then proposes the LR-based algorithm to study influence factors for academic success.

**INTERNET+ EDUCATION PLATFORM**

As shown in Figure 1, the authors design an Internet+ education platform to facilitate the three-all education for various populations (e.g., students, teachers, school support personnel, students’ families, enterprises, and the public). In the platform, students can exploit traditional computers, smartphones, wearable devices, and virtual reality/augmented reality (VR/AR) for independent study at any time and any place. Using these devices and sensors, the platform can collect students’ behaviors and additional information to analyze interests, education effects, and mental health (Garcia-Ceja et al., 2018).

Teachers can use the platform to assign take-home exercises or exams that will train and assess the learning effects of students. Based on the features analysis, teachers can then provide targeted learning advice and education plans to students. Teachers can also share their resources with colleagues around the world.

The ministry of education released new policies as schools adapt to international situations. The policies should be put into effect as soon as possible to achieve the benefits. With the Internet+ platform, policies can be communicated from top policymakers to bottom executors. The impact of their practices can be relayed in an efficient and effective manner. By employing the platform, teachers can communicate their needs with support personnel, which also promotes responsive and efficient work processes.
Students’ families, enterprises, and the public should also be involved in quality education. Students’ general views and world views are impacted by their families, which influences mental health and quality education. Families need to understand the students’ education and mental state, offering support as needed.

A problem in higher education is the gap between education and enterprise needs. Most undergraduates do not have professional practices due to individual conditions and school resources. Enterprises can share their practice resources to help schools educate high-quality talent. Thus, some learning abilities like students’ effective communication depend on social circumstances. The public must understand their role in educating students, offering resources, and helping to filter negative information. The platform provides efficient and effective ways to meet these needs.

The Internet+ platform provides the following functions for users based on the goals of quality education (see layer three in Figure 1).

1. Using recommendation algorithms, education and learning resources shared in the platform can be retrieved for teachers and students. These resources can be personalized with respect to specialties.
2. Deep learning technologies can generate efficient and effective personalized strategies for learning or teaching. This, in turn, can enhance quality education.
3. Educational resources can be shared through various devices at any time and any place.
4. Students’ mental state can be analyzed through affective computing. This is based on data collected through user devices and sensors. A corresponding remedy can be carried out in a timely manner if mental problems are identified.
5. The effect of quality education strategies must be assessed to provide evidence for updating or designing strategies. This can be achieved through the Internet+ platform. Using big data analysis,

Figure 1. Internet+ education platform for applying ICTs to education resource management

<table>
<thead>
<tr>
<th>Users</th>
<th>Devices for service access and data collection</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student</td>
<td>Computer</td>
<td>Educational and learning resource recommendation</td>
</tr>
<tr>
<td>Teacher</td>
<td>Smart phone</td>
<td>Educational and learning Resource sharing</td>
</tr>
<tr>
<td>Support personnel</td>
<td>Laptop</td>
<td>Education effect analysis</td>
</tr>
<tr>
<td>Students’ family</td>
<td>Tablet</td>
<td>Live streaming</td>
</tr>
<tr>
<td>Enterprise</td>
<td>Wearable device</td>
<td>Information filtering</td>
</tr>
<tr>
<td>The public</td>
<td>VR/AR</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sensors</td>
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<table>
<thead>
<tr>
<th>Infrastructures</th>
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<tbody>
<tr>
<td>Data Center</td>
<td></td>
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<tr>
<td>Cloud Computing</td>
<td></td>
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<tr>
<td>Crowd Computing</td>
<td></td>
</tr>
<tr>
<td>Edge Computing</td>
<td></td>
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</tbody>
</table>
contributing factors can be identified in an accurate manner. The quantitative model can be used to study the education effect. In turn, we can better understand the learning effect of students and the education ability of teachers.

6. A student may have questions that need to be addressed by schoolmates or teachers. The platform provides both asynchronous and synchronous communication approaches for its users.

7. Live streaming allows users to engage in real-time communication, breaking through space limitations found in traditional education modes. Individuals from across the globe can gain knowledge through a low-cost device.

8. As a complement to live streaming, students can review lectures with on-demand video.

9. Online users and shared information varies. Therefore, some useless or wrong information may be posted. Information filters through intelligence algorithms allow platform users the ability to avoid exposure to misinformation.

10. The Internet+ platform provides many conveniences for users with ICT skills. For instance, they can develop individual data analysis models or AI algorithms.

These functions require significant computing and storage resources for data analysis, especially with numerous users. Therefore, the user of servers must be considered as we build the infrastructure for the implementation of the Internet+ platform. Solutions include traditional data centers, cloud computing, and more advanced computing paradigms like edge computing, mobile computing, and crowd computing.

ACADEMIC SUCCESS PREDICTION ALGORITHM

Academic success can best reflect the learning effect for a student. This article uses data analysis to analyze the factors influencing academic success. The study proposes an LR-based prediction approach to foresee students’ academic success. Teachers can assist students when problems are found based on predicted results. LR is employed because of its strong performance in classification. It has been applied with low overhead in fields like clinical studies (Zabor et al., 2022), geology (Kaya & Başayiğit, 2021), and breast tumor deterioration (Wang et al., 2022).

Academic Success Prediction Problem

For the prediction of academic success, several types of data (features) related to academic success are collected from areas like student status or family background (during school time). It can be represented as \( X = [x_{i,j}]_{N \times M} \), where \( x_{i,j} \) is \( j \)th feature of \( i \)th student. \( M \) and \( N \) are numbers of features and students, respectively. \( Y = [y_i]_{N \times 1} \) represents the academic success status of students. In \( y_i \in \{0,1,2\} \), values represent dropout, enrolled, and graduate, respectively.

An academic success prediction approach aims to find a function mapping \( \mathcal{F} : X \to Y \) for undergraduates using data of dropout, enrolled, and graduate. The main optimization objective of the prediction approach is to maximize the prediction accuracy rate or/and other performance metrics. The prediction accuracy rate is formulated as:

\[
ACC = \frac{\sum_{i=1}^{N} \{y_i == \hat{y}_i\}}{N} \tag{1}
\]

where \( \hat{y}_i \) is the predicted value of \( y_i \) and \( \{y_i == \hat{y}_i\} \) is 1 when the predicted value is right for \( y_i \).
LR-Based Prediction Algorithm

LR-based prediction algorithm is to learn a $F$ to minimize the loss $L(Y, \hat{Y})$ by gradient descent with collected academic success data of former graduates and use learned $F$ to predict the academic success status of undergraduates.

LR-based prediction uses the logistic function as the activation function that maps the linear regression into a probability space (see equation 2). Where $P(y_i = 1 \mid X_i)$ is the probability that the academic success of $i$th student with feature $X_i = [x_{i,j}]_{j=1}^J$ is type 1 and $P(y_i = 0 \mid X_i) = 1 - P(y_i = 1 \mid X_i)$ is the probability of type 0. There are three types (dropout, enrolled, and graduate) for the academic success status of a student. Then, two logistic functions are used for the three-type classification problem by one-vs.-rest approach. Where with the first logistic function, $y = 0$ and 1, are respectively representing no graduate and graduate. The second logistic function, $y = 0$ and 1, are respectively representing dropout and enrolled. $W = [w_j]_{j=1}^M$ and $b$ are the parameters needed to be learned for the classification or prediction model.

$$P(y_i = 1 \mid X_i) = \frac{1}{1 + e^{-(W X_i + b)}}$$

The loss function is defined in equation 3, where the first part in the right side is the cross-entropy between collected data $Y$ and predicted values $\hat{Y}$. The second is $L_2$ regularization, which is used for avoiding over-fitting of the learned model. $\hat{y}_i = 1 / \left(1 + e^{-(W X_i + b)}\right)$

$$L(Y, \hat{Y}) = -\frac{1}{N} \sum_{i=1}^{N} \left( y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i) \right) + \lambda \cdot \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

Then, by gradient descent, $L(Y, \hat{Y})$ can be minimized with updating parameters $W$ and $b$ iteratively by collected data of graduates. When parameters $W$ and $b$ are obtained, we can calculate the probability of each academic success status for every student using equation 2. We can also predict the status as the one with the maximum probability.

To avoid the weight skew of different features due to varied feasible ranges, we employ $Z$-score normalization to scale each feature into a standard normal distribution. For the $j$th feature ($X_j = [x_{i,j}]_{i=1}^N$), the values are scaled by equation 4. $EX_j = \sum_{i=0}^{N} x_{i,j} / N$ is the average of all values in the $j$th feature. $\sigma_j = \sqrt{\sum_{i=0}^{N} (x_{i,j} - EX_j) / N}$ is the variance.

$$x_{i,j}^s = \frac{x_{i,j} - EX_j}{\sigma_j}$$

The main work to be done by the LR-based prediction algorithm is the training of the prediction model with a labeled dataset. Via the trained model, one can predict the academic success status by feature values for each student. LR-based prediction algorithm learns model parameters ($W$ and $b$) using a labeled training dataset. This includes $X$ with known $Y$ by the gradient descent algorithm (GDA) to minimize loss. The basic steps of the training phase are first randomly initializing parameters (each with a small number). Then, it iteratively updates parameters with equation 5 until the iteration
number reaches the maximum \((T)\) or the accuracy of trained model reaches a predefined threshold \((A)\). \(\theta = [W \cdot b]\) is the parameters needed to be learned. \(\frac{\partial L(\theta)}{\partial \theta}\) is the gradient of the loss function in the direction of \(\theta\), which is the maximum descent direction. This is deduced in equation 6 with known \(X\) and \(Y\), arguments of \(\theta\), and dependent variables of \(\hat{Y}\). \(\alpha\) is the learning rate, which affects the convergence and speed. Then, the detailed steps of the prediction model training are shown in Table 1 (Algorithm 1), where subscript \(t\) represents the iteration number.

\[
\theta = \theta + \alpha \cdot \frac{\partial L(\theta)}{\partial \theta}
\]  

\[
\frac{\partial L(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta} \left( \frac{1}{N} \sum_{i=1}^{N} \left( y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i) \right) + \lambda \cdot \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \right)
\]

\[
= \frac{1}{N} \sum_{i=1}^{N} \frac{1}{y_i} \frac{\partial \hat{y}_i}{\partial \theta} + \frac{1}{1 - y_i} \left( -\frac{\partial \hat{y}_i}{\partial \theta} \right) + 2\lambda \cdot \left( y_i - \hat{y}_i \right) \left( -\frac{\partial \hat{y}_i}{\partial \theta} \right)
\]

\[
= \frac{\hat{y}_i}{N y_i \left( 1 - \hat{y}_i \right)} \frac{y_i - \hat{y}_i}{1 - \hat{y}_i} - 2\lambda \cdot \left( y_i - \hat{y}_i \right) \left( -\frac{\partial \hat{y}_i}{\partial \theta} \right)
\]

\[
= \frac{\hat{y}_i \left( 1 - \hat{y}_i \right)}{N y_i \left( 1 - \hat{y}_i \right)} \frac{y_i - \hat{y}_i}{1 - \hat{y}_i} - 2\lambda \cdot \left( y_i - \hat{y}_i \right) \left( -\frac{\partial \hat{y}_i}{\partial \theta} \right)
\]

\[
= \frac{\hat{y}_i \left( 1 - \hat{y}_i \right)}{N} - 2\lambda \cdot \hat{y}_i \left( 1 - \hat{y}_i \right)
\]  

Table 1. Algorithm 1: Training of the LR-based prediction model

<table>
<thead>
<tr>
<th>Input:</th>
<th>X; Y; (\alpha); (T); (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>(W; b)</td>
</tr>
<tr>
<td>1</td>
<td>Initialize (W) and (b) with small random numbers;</td>
</tr>
<tr>
<td>2</td>
<td>while iteration number does not reach (T) do:</td>
</tr>
<tr>
<td>3</td>
<td>for each (X) with (Y) do:</td>
</tr>
<tr>
<td>4</td>
<td>Calculate gradients by Eq. (6);</td>
</tr>
<tr>
<td>5</td>
<td>Update (W) and (b) by Eq. (5);</td>
</tr>
<tr>
<td>6</td>
<td>Calculate the loss by Eq. (3);</td>
</tr>
<tr>
<td>7</td>
<td>if the loss change is smaller than (A) do:</td>
</tr>
<tr>
<td>8</td>
<td>break;</td>
</tr>
<tr>
<td>9</td>
<td>return (W) and (b);</td>
</tr>
</tbody>
</table>
PERFORMANCE EVALUATION

In this section, the authors evaluate the performance of their proposed LR-based academic success prediction algorithm using a dataset created from a higher education institution related to students enrolled in undergraduate degrees (Realinho et al., 2021). There are 36 features for the students, including academic path, demographics, and social-economic factors, and academic performance at the end of the first and second semesters. The academic successes for students include dropout, enrolled, and graduate, respectively. The dataset includes 4,424 instances.

The authors compare their LR-based academic success prediction approaches with four classification algorithms: (1) k-nearest neighbor (KNN); (2) support vector classification (SVC); (3) decision-making tree (TREE); and (4) NB classifier. Accuracy is measured by K-fold cross-validation with K = 6 for each algorithm. Its mean value is then reported. K-fold cross-validation first divides the total dataset into K parts. Next, it evaluates the performance of an algorithm K times and reports the average performance value. In each of the performance evaluations, K-fold cross-validation uses one part of the dataset as the test set and others as the training set. The approach excludes the effect of randomness, ensuring that the evaluation results can be reproduced. The time is the whole process of the K-fold cross-validation for each algorithm in seconds. This consists of K training phases and K testing phases. The performance metrics used for the comparison include accuracy, F1 score, precision, recall, and ROC_AUC. The values of accuracy, F1 score, precision, and recall can be achieved by equations 1, 7, 8, and 9, respectively. Where TP (True Positive) is the number of positive samples predicted correctly (i.e., \( y = \hat{y} = 1 \)). FN (False Negative) is the number of positive samples predicted incorrectly (i.e., \( y = 1 \) but \( \hat{y} = 0 \)). FP (False Positive) is the number of negative samples predicted incorrectly (i.e., \( y = 0 \) but \( \hat{y} = 1 \)). TN (True Negative) is the number of negative samples predicted correctly (i.e., \( y = \hat{y} = 0 \)). ROC_AUC is the area under the curve (AUC) of the receiver operating characteristic (ROC). ROC is the curve plotted by a false positive rate (FPR) on the horizontal axis and true positive rate (TPR) on the vertical in two dimensions. TPR = TP / (TP+FN), which is identical to recall. FPR = FP / (FP+TN).

\[
\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)
\]

\[
\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (8)
\]

\[
\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (9)
\]

The metrics range from 0.5 to 1 and improve as they near 1. The results, shown in Table 2, illustrate that bold values are best. According to the table, the LR-based algorithm has the best accuracy, F1 score, Precision, Recall, and ROC_AUC in predicting academic success. LR achieves 6.06% to 21.3%, 7.15% to 28.7%, 2.49% to 62.8%, and 10.1% to 65.1% better performance than others in accuracy, F1 score, Precision, Recall, and ROC_AUC, respectively. This verifies the performance superiority of the authors’ proposed algorithm. SVC has the worst performance in accuracy, F1 score, Precision, Recall, and ROC_AUC. However, it has the best recall. This is because SVC achieves the minimum value of TP, TN, and FN with the maximum value of TP. Thus, it has the highest recall but lowest metric values.

Time overhead is a key factor affecting the application for a prediction algorithm, especially in cases of large-scale systems with numerous users. The authors test the time consumed by algorithms in a computer with an Intel Core i7-7500U CPU @ 2.70GHz computing core and 8GB RAM. Each algorithm is tested more than 10 times. The mean value is also reported. The authors then perform a t-test for the mean equality between LR and other algorithms. The \( p \)-values achieved are shown in Table 3. According to the table, LR is significantly different from the others (all \( p \)-values are much
The results in Figure 2 show that LR consumes 41.5% and 95.0% less time than KNN and SVC, respectively. Although LR needs more time than TREE and NB, LR consumes only about 0.35 seconds. Thus, it is less than 0.06 (0.35/6) seconds for a training phase with 737 instances (4424/6). This magnitude of time consumption leads to a range of applications of the authors’ algorithm as time consumption can be very little, even in a personal computer.

KNN and SVC perform poorly because they have not normalized their features prior to training. It, in turn, leads to features with large values instead of placing importance on weight. Therefore, this study adds the Z-score normalization on each of the algorithms, evaluating performance of the improved algorithms. The accuracies of each algorithm (with and without normalization) are shown in Figure 3. As shown in the figure, normalization can improve the performance of KNN, SVC, and LR. The three algorithms measure the similarity between two instances by the Euclidean distance, whose reliability is affected by the relative difference of value ranges between features. For TREE and NB, data is trained based on the classification of each feature. Thus, TREE and NB have performance variations by normalization. Even with normalization, the LR-based algorithm performs better than any other algorithm, further confirming the performance superiority of the algorithm.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>F1 Score</th>
<th>Precision</th>
<th>Recall</th>
<th>ROC_AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>KNN</td>
<td>0.694616</td>
<td>0.711195</td>
<td>0.674158</td>
<td>0.75418</td>
<td>0.756027</td>
</tr>
<tr>
<td>SVC</td>
<td>0.506779</td>
<td>0.65934</td>
<td>0.503193</td>
<td>0.956084</td>
<td>0.558526</td>
</tr>
<tr>
<td>TREE</td>
<td>0.794759</td>
<td>0.791823</td>
<td>0.799201</td>
<td>0.788134</td>
<td>0.793854</td>
</tr>
<tr>
<td>NB</td>
<td>0.742315</td>
<td>0.772327</td>
<td>0.691693</td>
<td>0.875061</td>
<td>0.837649</td>
</tr>
<tr>
<td>LR</td>
<td>0.842905</td>
<td>0.848447</td>
<td>0.819134</td>
<td>0.880479</td>
<td>0.922089</td>
</tr>
</tbody>
</table>

Table 3. p-Values of testing mean equality between LR and others in time consumption

<table>
<thead>
<tr>
<th></th>
<th>KNN</th>
<th>SVC</th>
<th>TREE</th>
<th>NB</th>
</tr>
</thead>
<tbody>
<tr>
<td>p-value</td>
<td>$4.6 \times 10^{-18}$</td>
<td>$9.5 \times 10^{-21}$</td>
<td>$2.3 \times 10^{-11}$</td>
<td>$1.15 \times 10^{-13}$</td>
</tr>
</tbody>
</table>

Figure 2. Time consumed by algorithms in predicting academic success
CONCLUSION

This article studies quality education improvements via ICTs in the era of Internet+. First, the authors design an Internet+ education platform to support all learners in achieving an effective and efficient quality education. The platform provides extensive intelligent CIP education tools by exploiting various forms of ICTs. The functions provided by the platform can be used on various devices, increasing the use of younger users for both CIP learning and education.

Regarding academic success, the authors study the education effect of quality education by machine learning algorithms on the platform. The study proposes a LR-based prediction algorithm to understand the factors that influence the quality education effect. The experiment results verify the performance superiority of the authors’ proposed prediction algorithm on prediction accuracy and time consumption.

Work must still be done to improve the application of the authors’ work. For example, teachers, schools, and countries must communicate and cooperate to share high-quality resources. The availability and use of rich resources and data will allow users to take full advantage of the authors’ platform and decrease learning costs for low-income individuals. In addition, many hardware infrastructures are expensive, which limits accessibility for low-income individuals. A practical solution is that higher income countries build several infrastructures and, in turn, provide services for low-income countries through idle resources at a considerably lower cost. In general, each country has individual education request loads related to time differences and other factors.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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