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Research Article

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Online addiction analysis and identification of students by applying gd-LSTM algorithm to educational behaviour data

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Abstract: Internet has become the primary source of extracurricular entertainment for college students in today's information age of Internet entertainment. However, excessive Internet addiction (IA) can negatively impact a student's daily life and academic performance. This study used Stochastic models to gather data on campus education behaviour, extract the temporal characteristics of university students' behaviour, and build a Stochastic dropout long short-term memory (LSTM) network by fusing Dropout and LSTM algorithms in order to identify and analyse the degree of IA among university students. The model is then used to locate and forecast the multidimensional vectors gathered, and finally to locate and evaluate the extent of university students' Internet addiction. According to the experiment's findings, there were 4.23% Internet-dependent students among the overall (5,861 university students), and 95.66% of those students were male. The study examined the model using four dimensions, and the experimental findings revealed that the predictive model suggested in the study had much superior predictive performance than other models, scoring 0.73, 0.72, 0.74, and 0.74 on each dimension, respectively. The prediction model outperformed other algorithms overall and in the evaluation of the four dimensions, performing more evenly than other algorithms in the performance comparison test with other similar models. This demonstrated the superiority of the research model.

Keywords: LSTM, Dropout algorithm, internet addiction identification, Stochastic models, time-series features

1 Introduction

Internet addiction (IA) is a word used to describe a user's behaviour who relies excessively on the Internet and exhibits long-term, unchecked addiction to the online world [1]. If a student's IA level is too high, it can negatively impact their ability to interact with others, as well as their physical and mental growth. In extreme circumstances, it can even cause them to waste their education and ruin a great job. As a result, identifying and analysing the IA levels of students in higher education (HE) has also grown to be a crucial topic in the educational field [2]. Numerous international studies have examined the IA level of identification, yet there is still no widely recognised benchmark. Questionnaires are still used to identify Internet addiction (IAI) more frequently [3]. Considering the high labor costs associated with questioning and the inability of questioning surveys to provide broad generalizations [4,5]. In order to evaluate the level of IA, the study used a random model to analyze the academic behavior data. Stochastic models (SM) of college students, and constructed a Gate by integrating LSTM and Dropout algorithms LSTM (Long Short Term Memory and Long Short Term

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Memory, gd LSTM) model. The multidimensional vectors gathered to identify and examine the IA levels of university students are identified and predicted using the gd-LSTM model.

The study is broken up as follows: The IA analysis model employed in the study is derived from the summary and analysis of the present status of international research on LSTM algorithms and IA analysis described in Section 2. Sections 3–5 explain the LSTM method's concepts, the gd-LSTM IA analysis prediction model, which combines the Dropout algorithm with the LSTM algorithm, and the extraction of time-series features (TSF) of university student activity. Section 6 evaluates the gd-LSTM IA analytical prediction model's performance and examines the results of the experiment. The experimental findings are summarised in Section 7, which also identifies the study's flaws.

2 Related works

Internet has been incorporated into every part of people's everyday lives in this era of information explosion, and it has replaced television as the primary form of entertainment on college campuses. Many professionals and academics from across the world have undertaken research on the crucial subject of IAI analysis and have produced some conclusions in order to assist university students utilise the Internet sensibly and prevent IA. To extract spatial and short-term temporal information, Zheng et al. created an attention-based LSTM neural network. By automatically allocating different weights to reflect the trend of traffic flow in the forward and backward directions, the significance of flow sequences at various times was recognised. The efficiency of the algorithm was confirmed by experimental findings [6]. Shrestha et al. have suggested a novel technique based on recursive LSTM and Bi-directional LSTM (Bi-LSTM) network architecture. The results demonstrate that although distance domain data only achieve about 76% accuracy on average, Doppler domain data using Bi-LSTM networks and appropriate learning rates obtain an average accuracy of over 90% [7]. A framework created by Shen et al. that combines Bi-LSTM and data sequencing can be used to forecast the diameter of jet grout columns in soft soils in real time. An example study of jet grouting treatments in soft soils was used to evaluate the model. The efficiency of the method was supported by experimental findings indicating the suggested strategy could successfully estimate the column diameter with depth [8]. By simultaneously modelling behavioural activities at the individual group level, Shu et al. presented an LSTM algorithm with residual connectivity to learn temporal and static properties of person-level residuals to achieve group activity recognition. The usefulness of the approach was confirmed by experimental findings on two open datasets [9]. Convolutional neural networks (CNN) and LSTM algorithms were combined in Sun et al.'s proposed hybrid deep learning technique to estimate the short-term degradation of a 110 kW fuel cell system for commercial vehicles. Sliding windows are used to extract non-linear non-smooth voltage sequences, which are then broken down into modal sequences with various characteristic time scales and fed into the relevant CNN-LSTM [10].

Multivariate analysis of variance (MANOVA) was employed by Jin Jeong et al. to examine the statistical variances among 12 risk factors for addiction. In terms of the differences in addiction risk variables between IA and smartphone addiction, the experimental findings revealed that smartphone addiction was greater than IA [11]. Suresh and Biswas collected and analysed data from 202 respondents over the course of 7 months in Bangalore. The findings revealed that excessive internet shopping was positively correlated with rising IA [12]. In order to investigate the relationship between IA and obesity, Aghasi et al. studied nine cross-sections. By combining 11 effect sizes from the 9 studies, they were able to demonstrate that there was a significantly higher likelihood of being overweight or obese among those who used the Internet the most than those who used it the least [13]. You et al. used the Pittsburgh Sleep Quality Index to measure multiple cross-sectional studies of a sample of college students in order to look into the impact of IA on sleep quality in students. According to the findings, college students with high levels of IA were 2.35 times more likely than those with normal levels to report having poor subjective sleep quality [14].

In conclusion, even though many experts have suggested numerous techniques and forecasting models for the detection and analysis of IAI, they have rarely started investigations into the behavioural traits of university students. In order to develop an IAI analysis model based on the LSTM algorithm combined with the Dropout algorithm, the study combines educational behavioural data in order to extract behavioural TSFs using SM. As a result, the study introduces fresh perspectives and references to the IAI field.

3 Applying the gd-LSTM algorithm to construct a student IA analysis recognition model

To identify and analyse students' IA levels more efficiently and accurately, the study adopts a statistical approach to classify the TSF of university students during their school years into multi-dimensional vectors for inductive analysis, and uses the LSTM algorithm combined with the Dropout algorithm to build an IA analysis model, so as to complete the identification and analysis of IA risks of university students.

3.1 Student IA analysis under educational behaviour data

To quantitatively analyse the IA level of university students, the study used big data techniques combined with statistical methods to refer educational behaviour data to the SM and to assess the overall data using the central limit theorem. The SM is a model made according to a combination of random variables, which are independent of each other and can faithfully reflect the relationship between the random parameters in the system, and well characterise the real-life. The sample mean probability statistics of SM is shown in Figure 1.

σ in Figure 1 indicates the SM standard error. The probability of a sample falling within the range of $\pm 1\sigma$ is 68%, i.e. the confidence level is 68%. As can be seen from Figure 1, the SM satisfies the central limit theorem, i.e. the sample mean is infinitely close to the overall mean and any sample will always be normally distributed around the overall mean [15,16]. Therefore, the mean value and standard deviation of the sample can be used to estimate the overall mean value and standard deviation, and thus analyse the level of IA of college students. The next step is to construct a TSF of college students from their behavioural data during their school years. The study starts from four dimensions, namely, behavioural patterns, consumption behaviour, academic performance, and gender, and the TSF system of college students obtained is shown in Figure 2.

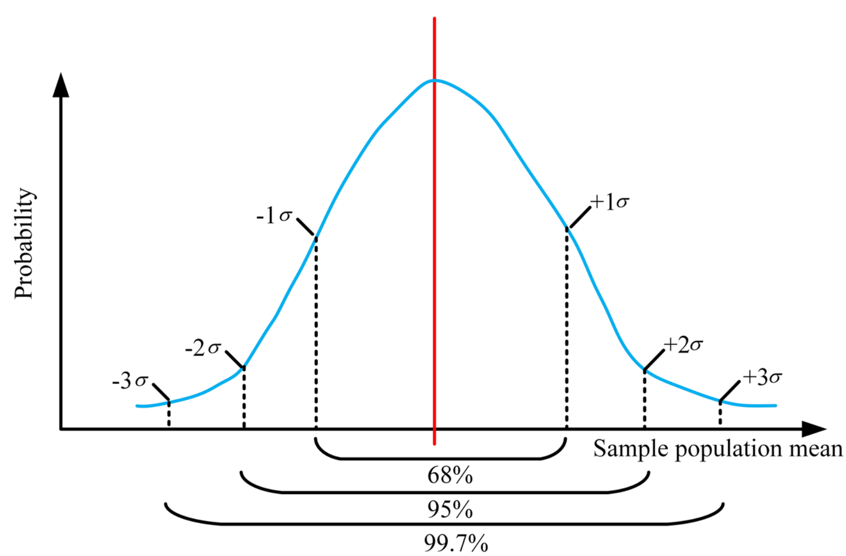

Figure 1: Sample mean probability statistical chart.

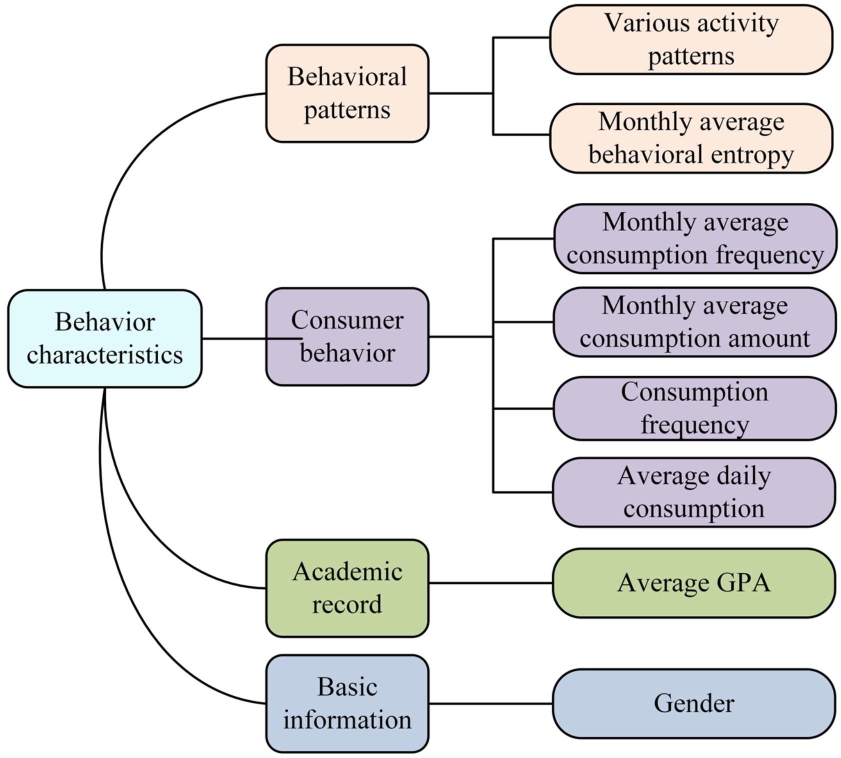

Figure 2: Time series characteristic system diagram of college students.

The behavioural patterns of students in HE are mostly chaotic but repetitive, and the concept of Information Entropy (IE) is used to characterise behavioural patterns. It is possible to calculate the likelihood that a random event will occur in terms of the likelihood that an uncertain event will occur. The greater the uncertainty, the greater the IE [17]. By specifying the frequency of different behaviours of university students per unit of time and calculating the entropy of student behaviour, the behavioural patterns of university students can be quantified.

A time interval of 1 h is specified, and a day is divided into a 24-dimensional time vector. The frequency of behaviour v in each time period per person per month is counted and the frequency of occurrence of the event is calculated. The equation for calculating frequency p is shown in equation (1).

$$p_v(T = t_i) = \frac{n_v(t_i)}{\sum_{i=1}^{n} n_v(t_i)}, \tag{1}$$

where T is the time interval, t_i denotes the i th time interval of the day, v is the various behaviours of the student, and $n_v(t_i)$ denotes the total number of times behaviour v occurs during time interval t_i. Further calculations lead to the expression for the behavioural entropy of behaviour v in a month as in equation (2).

$$E_v = -\sum_{i=1}^{n} p_v(T = t_i) \log p_v(T = t_i). \tag{2}$$

By solving equation (2), the entropy of behaviour regarding behaviour v for each month is obtained. Next taking the whole semester as a unit, the mean value of behavioural entropy for each month within each semester is calculated, and the result obtained is the behavioural entropy of the student's behaviour v. The larger the behavioural entropy value, the more the time periods in which the student's behaviour v occurs, proving that the student's behaviour v is more irregular. Following the above method to conduct behavioural entropy analysis on the consumption behaviour of college students, the behavioural entropy about college students regarding their consumption behaviour can be determined. By solving the behavioural entropy, the TSF of each dimension can be extracted from the huge amount of educational behaviour data.

4 TSF analysis based on LSTM algorithm

To better analyse the TSF of university students in each dimension, the study uses the LSTM algorithm to build a predictive model for student IA level recognition analysis. The LSTM prediction model is a recurrent neural network (RNN)-based temporal RNN that can remember both long- and short-term information. Figure 3 depicts the RNN's structural layout.

In Figure 3, h_t is the hidden layer state, x_t is the input vector at the moment of t, and Tanh is the activation function (AF). According to Figure 3, the RNN, as a feed-forward neural network, has a directed graph at its core, and the directed graphs are linked in a chain-like manner to form recurrent units [18]. Many identical recurrent units connected in a chained fashion make up the RNN. And the state expression of an RNN is given in equation (3).

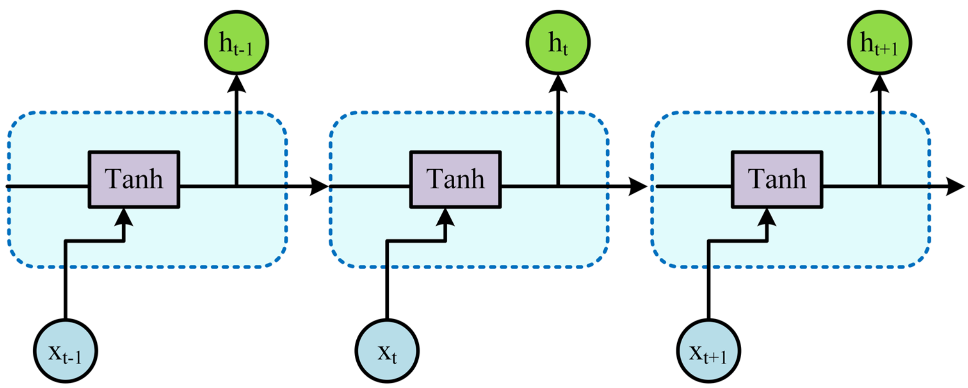

Figure 3: RNN structure diagram.

$$x_t = F(x_{t-1}, \mu_t, \theta), \tag{3}$$

where x_t is the system state of the RNN at the moment t, μ is the system input, and θ is the weight coefficient inside the recurrent unit. In addition to the recurrent unit, the RNN is generally set up with another output node and defined as a linear function. The expression of the function of the output node o_t is shown in equation (4).

$$o_t = vx_t + c, \tag{4}$$

where v and t are the different weighting coefficients. For an RNN with specified parameters, it is generally expressed in terms of weights, and the weight expression of an RNN is as in equation (5).

$$x_t = W_{\text{rec}}\sigma(x_{t-1}) + W_{\text{in}}\mu_t + b, \tag{5}$$

where W_{rec} denotes the weight of the recurrence matrix of the neural network, W_{in} denotes the input weight, b is the bias of the neural network, and σ is the AF. RNN, as a chain-structured neural network, has a variable length of the input sequence it processes [19]. In comparison, the LSTM neural network has the same chain structure but four network layers inside the recurrent cell. Through these three gates – the input gate, output gate, and forgetting gate – it is able to control the amount of information sent about the cell state. The cell structure of LSTM neural network is schematically shown in Figure 4.

In Figure 4, each yellow box indicates a neural network layer, each pink circle indicates an element-level operation, and C_t indicates the cell state. This results in a selective screening of information within the cell state. The study proposes the LSTM-based gated Dropout algorithm, referred to as gd-LSTM algorithm, which is to make the three gates of LSTM not functioning randomly with a certain probability. The algorithm realises the application of dropout to the hidden layer, and in LSTM, W denotes the weight matrix, and the expression of the oblivious gate f_t is shown in equation (6).

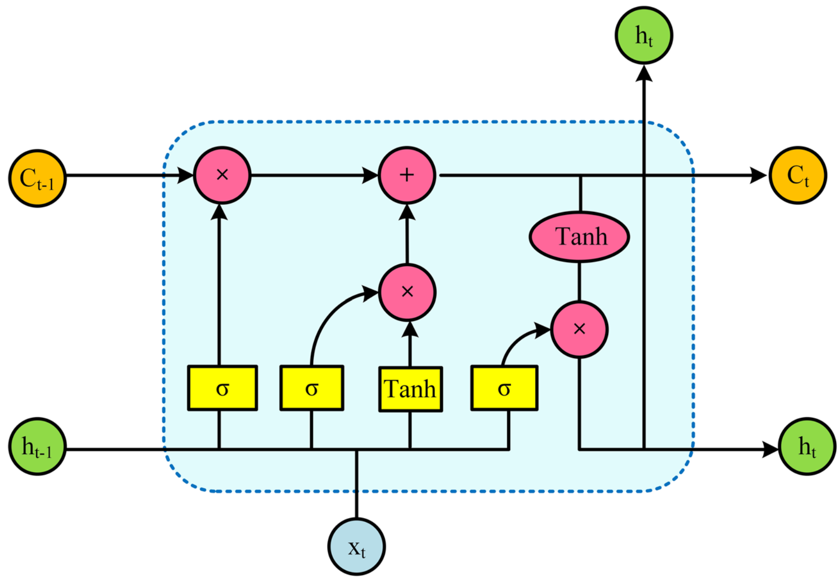

Figure 4: Schematic diagram of cell structure of LSTM neural network.

$$f_t = \sigma(b_f + w_f \cdot [h_{t-1}, x_t]), \tag{6}$$

where $[h_{t-1}, x_t]$ represents the information connecting the hidden layer to the input, and b_f is the bias vector of the forgetting gate. The information allowed to pass through is sent to the input gate for data update. The expression for the input gate i is given in equation (7).

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i), \tag{7}$$

where b_i is the bias vector of the input gate. The input gate determines which information is added to the cell state. The candidate cell information $\tilde{C}_t$ is obtained by filtering the information from the hidden state h_{t-1} and the input vector x_t. The candidate cell information $\tilde{C}_t$ is calculated as shown in equation (8).

$$\tilde{C}_t = \tanh(b_c + W_c \cdot [h_{t-1}, x_t]), \tag{8}$$

where W_c represents the cell state matrix and b_c is the cell state bias vector. The input gate updates the candidate information $\tilde{C}_t$ into the cell state via the tanh AF to obtain the updated cell information C_t. the equation for the updated cell information C_t is given in equation (9).

$$C_t = i_t \times \tilde{C}_t + f_t \times C_{t-1}, \tag{9}$$

where C_{t-1} in equation (9) represents the old cell information. The data in the updated cell information C_t are delivered to the output gate, where the state characteristics of the output cell are determined by the tanh AF. The expression of the output gate o is shown in equation (10).

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o), \tag{10}$$

where b_o in equation (10) is the bias vector of the output gate. The cell state characteristics of the output gate are passed through the tanh layer to obtain a vector of [−1,1]. The expression for the output h_t of the loop cell is given in equation (11).

$$h_t = o_t \times \tanh(C_t). \tag{11}$$

In the model, the value of the parameter gate_dropout is specified to make the gd-LSTM algorithm work, i.e. to make the three gates of LSTM randomly non-functional with probability value of gate_dropout. gate_dropout takes a value between 0 and 1, when it takes 0, it means that no gate_dropout is added, and when it takes 1, it means that it is not functional with probability 1, i.e. the cell fails. Generally, the value of gate_dropout is 0.2 or 0.4.

5 Predictive model for IA analysis combining Dropout algorithm and LSTM algorithm

Although LSTM prediction models have shown strong computational performance when analysing student TSF data, they are prone to overfitting [20]. The reason for this phenomenon is that the LSTM prediction model is more complex compared to the dataset, making the algorithm too stringent in its judgement criteria and lack of regularisation when dealing with simple data. The study therefore regularises the LSTM at the hidden layer by placing the Dropout algorithm, with the probability of randomly discarding one of the three gates from functioning, thus greatly improving the level of regularisation of the model. Research using the gd-LSTM algorithm to construct a prediction model and adding an attention mechanism after the output of the hidden layer to enhance the influence of important features and improve model performance. Among them, the model is a bidirectional LSTM structure with 71 input units and n outputs – Classes use binary classification, with 60 neurons per hidden layer. AF is ReLU, optimisation method is Adam algorithm, for gate, the dropout parameter is set to 0.3 to prevent overfitting. During the training process of the model, a 10-fold cross validation is used to randomly divide the training set into 3:7 validation data and training data. The number of iterations is 5, and the batch size is 50. Adjust the hyperparameters to optimise the model. Figure 5 depicts the final structure of the gd-LSTM IA analysis model.

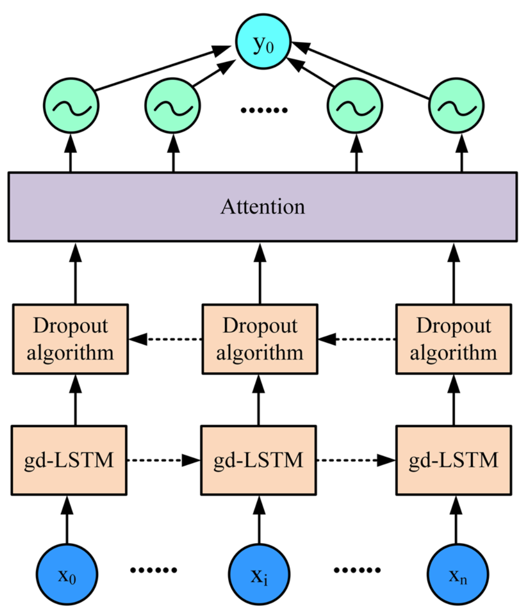

Figure 5: Structure diagram of gd-LSTM IA analysis model.

As shown in Figure 5, x_0 is the current amount of cell state and y_0 is the updated cell state information. In order to prevent the loss of important information due to the excessive length of the model sequence, the study added the Attention mechanism after the output of the hidden layer of the model, using the correlation between IA risk and each feature as the attention weight to enhance the influence of important features on IA level. The study builds the confusion matrix by dichotomous classification, which yields prediction accuracy for the difference between the actual class and the prediction class, in hopes to assess the performance of the model. Figure 6 provides a schematic illustration of the confusion matrix's elements.

According to Figure 6, it can be seen that the confusion matrix ultimately yields four components, where TP is denoted as a sample of positive cases with correct predictions, FP is a sample of negative cases with incorrect predictions, TN is a sample of negative cases with correct predictions, and FN is a sample of positive cases with incorrect predictions. In order to avoid the data imbalance that may be brought about by evaluating

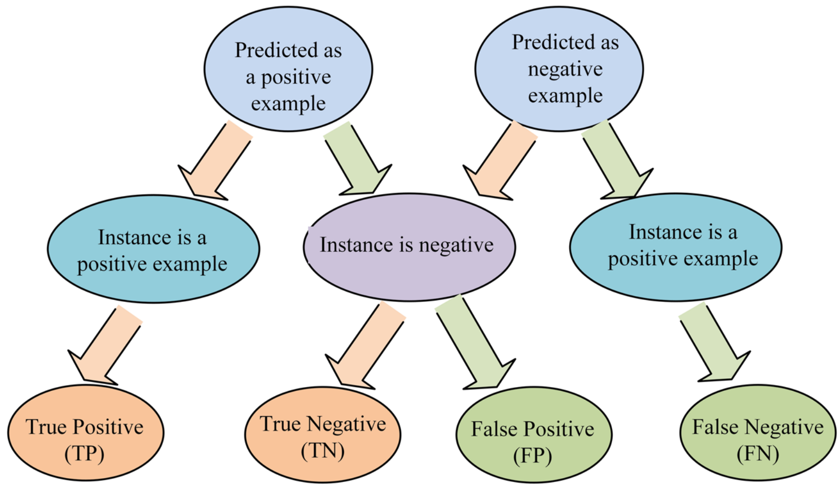

Figure 6: Component diagram of confusion matrix.

data of a single dimension, the study evaluates the prediction results of the model in four dimensions: accuracy, recall, precision, and reconciled mean. The expression is shown in equation (12).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}}, \tag{12}$$

where Accuracy is the performance measure of the learning algorithm, i.e. the proportion of correct samples. When the sample data are unbalanced, the accuracy can still be high, so to avoid distortion of the results, the study introduces other dimensions for a comprehensive evaluation of the model. In equation (13), the Recall is provided.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{13}$$

whereRecall denotes the number of samples that were correctly predicted in the sample of positive examples. The expression for the accuracy rate of the model is given in equation (14).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{14}$$

where Precision indicates the percentage of samples with positive cases among all samples with positive cases predicted. Finally, the precision and recall rates are reconciled, and the final reconciled mean expression is obtained as in equation (15).

$$F_1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}, \tag{15}$$

where the harmonic mean F_1 reconciles the relationship between precision and recall, and a smaller value of either component results in a smaller harmonic mean F_1, thus avoiding imbalance in the sample data.

6 Performance testing of IA analysis models based on gd-LSTM algorithm

The study used the educational behaviour data of a university's class of 2020 college students as the training set to train the model, and obtained multidimensional TSF data of 5,861 college students for four semesters, of which 214 were IA high-risk students, noted as the positive class sample, and 5,647 were IA low-risk students, noted as the negative class sample, and randomly assigned the training set data in a 7:3 ratio using 10-fold cross-validation into training data and validation data. The IA analysis model was created in the following study using the gd-LSTM method, with the parameters A set to 0.3, 85 input units, 73 neurons per hidden layer, and the ReLU function for AF. The output was binary classification. 50 batches were created with 5 iterations per iteration.

The study computed the total amount of time each student spent online in minutes based on their starting and stopping timings to determine how many hours each student spent online while enrolled in HE. Then, each individual's daily online time was summed up to obtain the final sum of each student's online time for each month. The statistical results were applied to the SM, and the final histogram of the sample mean frequency of Internet access hours of university students was obtained as shown in Figure 7.

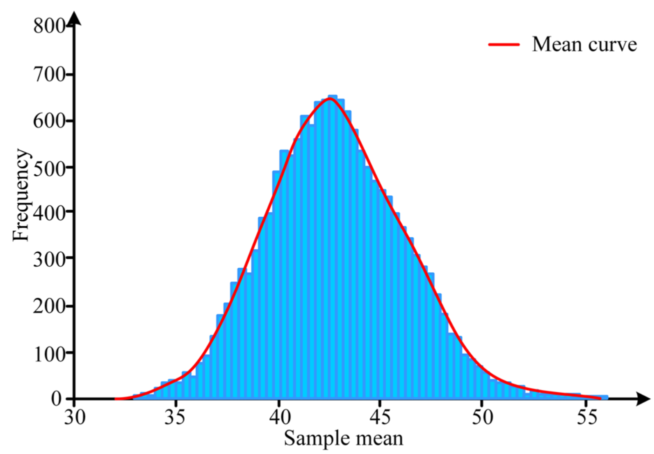

Figure 7: Sample mean frequency histogram.

As shown in Figure 7, the sample data basically show a normal distribution, and the mean value of the sample mean was 43.742. The study used the two standard error ranges as the criteria for distinguishing the level of IA among college students, and after further calculations, the corresponding length of time spent online was 274.692. Therefore, the study used 275 min as the criterion for judging IA, and students who spent more than 275 min on the Internet in a single day were regarded as IA students. According to the data in Figure 7, the number of IA students accounted for 4.23% of the total number of students. The next step was to analyse the behavioural TSF of HE students, and the annual behavioural entropy change of HE students was obtained as shown in Figure 8.

Figure 8 displays the change in behavioural entropy of college students in the stadium, canteen, library, and bathing facility, respectively. Figure 8 shows that the behavioural entropy in each subplot in February and August is almost zero, which is due to the fact that these months correspond to the college and university's winter and summer breaks, respectively, when the vast majority of students have left for the holidays and the minority of students are still enrolled. Figure 8a shows that the behavioural entropy of IA students spiked in May. It was determined that this spike was caused by the need for the school's PE classes to be held in the gymnasium, which increased the number of times IA students visited the facility, despite the fact that they did so infrequently on average. Figure 8 demonstrates that the behavioural entropy of non-IA students is less and more stable than that of IA students, indicating that non-IA students have a more predictable routine. The following phase involved comparing the grades of college students for each semester in 2020, calculating the grades and the resulting GPA, and using those numbers as the grade attributes for each topic. Figure 9 depicts the final box plot of the grade characteristics for each semester.

Figure 9 illustrates a box plot with upper and lower horizontal lines denoting the upper and lower limits of the data, a blue box in the middle denoting the 25–75% of the data distribution, or the data between the upper and lower quartiles, a green horizontal line in the middle denoting the median data, and outlier values

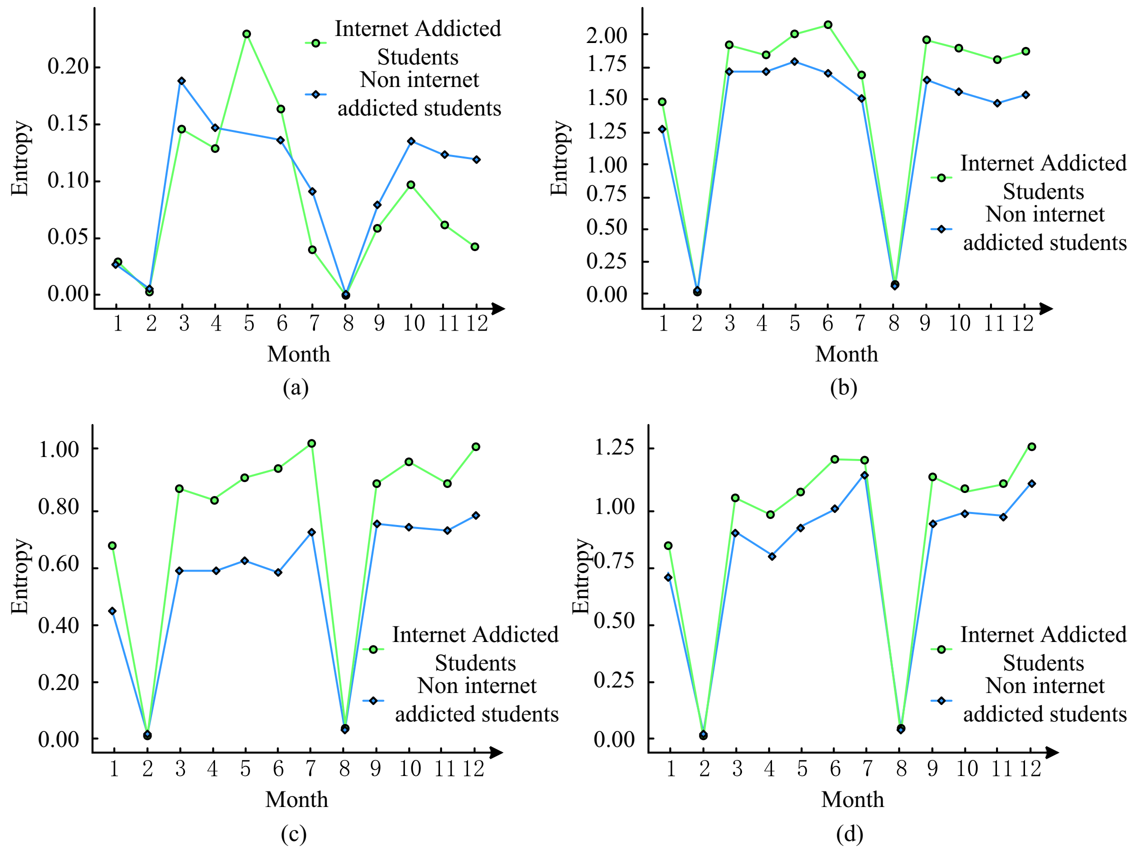

Figure 8: Annual behaviour entropy change chart. (a) Entropy changes in gymnasium from January to December, (b) Entrophy changes in the cafeteria from January to December, (c) Library entropy changes from January to December, and (d) Entropy changes in bathing centers from January to December.

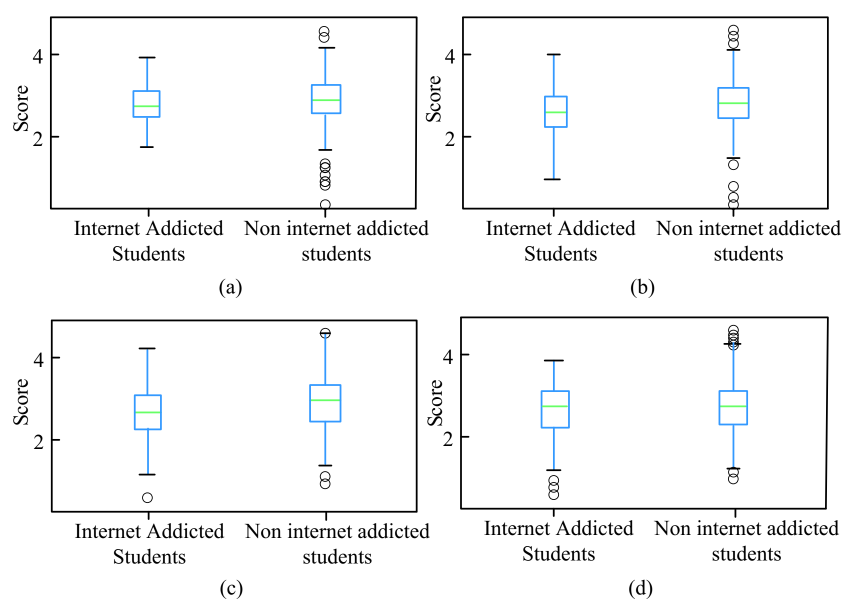

Figure 9: Characteristic maps of grades for each semester. (a) First semester, (b) second semester, (c) third semester, and (d) fourth semester.

denoting values that fall outside the upper and lower limits. Looking at Figure 9, it can be seen that IA students have a lower mean GPA and low lower limit values than non-IA students, while non-IA students generally have higher upper limit values than IA students and somewhat higher outlier values than IA students. This suggests

Table 1: Student sex ratio table

Dataset	Proportion	
Raw data	Male	68.37%
	Female	31.63%
Non-IA students	Male	70.23%
	Female	29.77%
IA students	Male	95.66%
	Female	4.34%

that non-IA students generally perform better academically and confirms the negative impact of IA on academic performance. Finally, the relationship between gender and IA was verified for students in HE, and the final student gender ratios obtained are displayed in Table 1.

As can be seen from Table 1, the proportions of male and female students in the original data were 68.37 and 31.36%, respectively. Among the students without IA, the proportions of male and female students were 70.23 and 29.77%, which basically matched the original data. Among IA students, the proportions of male and female students were 95.66 and 4.34%, which differed greatly from the original data on the proportions of male and female, indicating that the vast majority of IA students are male and female students are even less likely to become IA students.

The next study conducted a comprehensive evaluation of the prediction results of the gd-LSTM IA analysis model in four dimensions: accuracy, recall, precision, and harmonic mean. The LSTM algorithm, gd-LSTM algorithm, and CNN algorithm were used for performance comparison, and the graphs of the three algorithms obtained are shown in Figure 10.

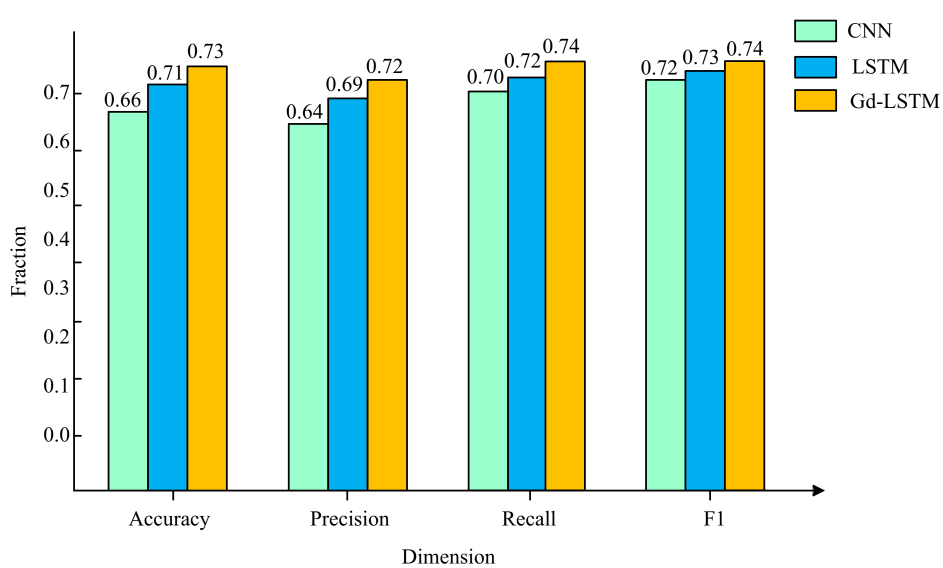

Figure 10: Performance comparison chart of three algorithms.

According to Figure 10, the gd-LSTM algorithm scores 0.73, 0.72, 0.74, and 0.74 in each dimension, which are significantly higher than the scores of the other two algorithms in the same dimension. This indicates that the gd-LSTM algorithm has the best performance and stability among the three algorithms, thus proving the

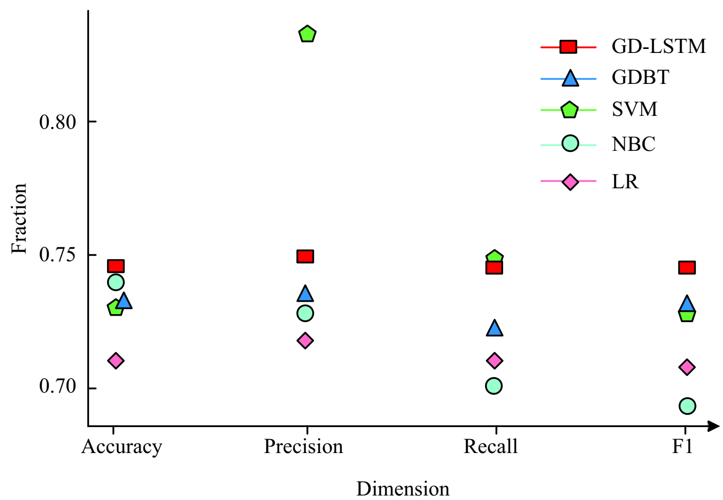

Figure 11: Comparison of performance of common algorithm models.

effectiveness of the optimisation algorithm. The study compared the performance of several commonly used international algorithmic models with the gd-LSTM algorithm, and the final performance comparison graph is shown in Figure 11.

In Figure 11, GDBT stands for Gradient Boosting Decision Tree (GDBT), LR stands for Logistic regression (LR), SVM stands for Support Vector Machine (SVM), and NBC stands for Naive Bayesian Model (NBC). The scores of the gd-LSTM algorithm were 0.746, 0.749, 0.745, and 0.746 in each dimension, which were the highest values in the accuracy and F1 dimensions, indicating that the prediction results of the research algorithm were more accurate. Although the SVM model scored the highest in the accuracy dimension with a score of 0.875, it still did not perform as well as the gd-LSTM algorithm in the other dimensions. Therefore, when looking at all dimensions together, the gd-LSTM algorithm performs better, thus demonstrating the superiority of the model.

7 Conclusion

The study used SM to extract the student behavioural feature vector from educational behaviour data, applied the gated dropout technique to the LSTM model, and then developed the IAI analysis model to identify and analyse the level of IA among university students. As a consequence of the trial, it was discovered that 5,861 university students were IA students, making up 4.23% of the overall student body. Additionally, the percentage of male and female students in the IA students was 95.66 and 4.34%, respectively, showing that male students made up the majority of the IA students. The multidimensional behavioural TSF calculation reveals that IA students lead more erratic lives and have more behavioural entropy. IA pupils typically performed worse than non-IA students across all academic performance parameters. The gd-LSTM algorithm proposed in the study receives scores of 0.73, 0.72, 0.74, and 0.74 in each dimension, respectively, which are higher than those of the LSTM algorithm and CNN algorithm in the same dimension, demonstrating the effectiveness of the optimisation algorithm. The gd-LSTM algorithm scored 0.746, 0.749, 0.745, and 0.746 in each dimension, with a more balanced performance in each dimension and the highest values of the model in the accuracy and *F*1 dimensions, proving the accuracy of the algorithm's prediction. These results were obtained from performance comparison tests with other models of the same type. There is still no globally recognised diagnostic technique for IA, hence the study can only be used as a method of evaluating and appraising the riskiness of IA and not as a medical tool for IA diagnosis.

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Conflict of interest: The authors report there are no competing interests to declare.

Data availability statement: The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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