Analysis of educational data enabled by deep learning to increase student success

Gautam Kumar| Bulbul Chaudhary | Sachin Choudhary

Abstract A key component of improving educational quality is identifying pupils who are at a high risk of doing poorly academically as early as feasible. To accomplish this, most studies now in existence have used conventional Deep learning (DL) algorithms to forecast students' academic progress based on their behavior data, from which behavior elements are manually identified owing to the professional expertise and knowledge. Nevertheless, it has become increasingly difficult to recognize finely constructed handcrafted traits as a result of a rise in the types and quantities of behavioral data. The Enriched Plant Growth Optimized Artificial Neural Network (EPGO-ANN) technique enabled data analysis of educational data which is a viable tactic that may be used to improve student accomplishment in educational settings as we suggested in this research. The optimization predicts the academic success by autonomously extracting characteristics from student behavior data from several heterogeneous sources. This model's novelty employs recording the in-built time-series data for each kind of activity and uses EPGO-ANN to extract correlation features between various behaviors. The results of the experiments show that the suggested deep model approach outperforms several DL methods. The results of experiments show that the EPGO-ANN technique is superior to other DL methods.

Keywords: deep learning, student success, educational data, ANN, EPGO

1. Introduction

Automated feedback with Deep Learning (DL) capabilities may be an effective tool to help students revise their scientific arguments based on simulation-derived facts. Here are some actions to think about: Establish the learning goals. Before developing the automated feedback system, the learning objectives must be determined. To increase student achievement, Machine Learning (ML) may be used in the following ways: To design a tailored learning route that addresses each student’s unique requirements, DL algorithms may be used to examine a student's learning patterns, strengths, and limitations. DL can help students reach their maximum potential by detecting areas of trouble and customizing their learning experience (Lee et al 2021). The chance that a student would drop out of a course or fail it may be predicted by DL algorithms by examining student data such as attendance, test results, and engagement. The data may be utilized to take early action and provide students who need specialized help (Gilgorea et al 2022). Traditional tests sometimes use a one-size-fits-all methodology, which may be difficult for kids with varying learning preferences and aptitudes. DL algorithms may provide adaptive tests that adapt to a student's level of understanding and offer tailored feedback. Students need to be able to build scientific arguments using the data that the simulation produced. The system needs to evaluate the simulation’s results and provide students feedback on their rationales for the claims they make (Abubakaria et al 2020).

Algorithms based on machine learning (ML) may be used to analyze the arguments and provide each learner with more tailored feedback. Analyze and enhance the feedback system: It is critical to test the feedback system with students to see how effectively it works once it has been developed. The study may gather information on student performance, and that information might then be utilized to enhance the feedback system. Include the curriculum's assessment system: The automated feedback system may also be a part of the curriculum. It is possible to do research through online assignments, in-person activities, and other methods (Manjushree et al 2021). An autonomous evaluation system with ML skills may help students improve scientific claims based on data from simulations. The study may assist students in strengthening their scientific reasoning abilities and achieving their learning objectives by identifying the learning objectives, selecting a suitable simulation, building the feedback system, testing and refining it, and introducing it into the curriculum. The DL method may be used to identify knowledge gaps and provide focused assistance. Writing analysis software (DL) may be used to evaluate student work and provide comments on grammar, sentence construction, and writing style. The strategy may assist students in developing their writing abilities, which are crucial for success in both college and the industry. Intelligent tutoring programs: DL algorithms can provide intelligent tutoring programs that give students individualized advice and assistance.
Student success can be impacted by a variety of factors related to learning. Students who engage in learning for teaching may have a deeper understanding of the material and be better able to apply what they have learned in real-world settings. This can lead to improved academic performance and success which are shown in Figure 1.

The systems may support students in learning at their rate, provide targeted criticism, and adjust to their particular requirements. By offering students individualized learning experiences and tailored assistance, DL has the potential to revolutionize education. To help students succeed, instructors may pinpoint the areas where they struggle by analyzing vast volumes of data and using ML algorithms. The following measures must be taken in a methodical and data-driven manner to increase student performance via education data analysis: Definition of what student achievement looks like is the first step. Academic attainment, graduation rates, attendance, conduct, and any other relevant criteria may be used to determine success (Zabriskie et al 2019). Specify the performance measures that will be used to assess the academic success of the pupils. The research may contain indicators like GPA, exam scores, attendance rates, and other pertinent statistics. Select the analytic methods that will best aid in understanding the performance measures under review.

Techniques like regression analysis, clustering, or decision trees might be used in the research (Smith and Lovgren 2018). Make data visualizations that will make it simple to grasp the analysis of the data. Heatmaps, scatterplots, and bar charts might all be used in the research. Once the data has been examined, present the findings in a manner that is clear to all parties involved. The research might include producing dashboards that show important performance indicators or reports that compile the results. Apply the knowledge learned from the analysis to actions to improve the academic achievement of pupils. The research may include putting together tailored treatments for pupils who are having trouble or figuring out where more resources are required. An effective, simple-to-understand, and practical framework for interpreting pupils’ academic achievement is required. The research may provide a framework to aid educators in making decisions that lead to higher student outcomes by following the stages (Yousafzai et al 2021).

Clear and quantifiable objectives are necessary to monitor progress and spot opportunities for growth. The next stage is to gather and evaluate pertinent data to learn more about the behavior and performance of the students. Data from evaluations, attendance logs, demographics, surveys, and other sources may be used in research. Finding trends, patterns, and correlations via data analysis may assist guide decision-making (Ahad et al 2018). After data analysis, it’s critical to pinpoint areas where students are having difficulty and need more assistance. Research may be used to better the design of curricula, identify pupils who are at risk, or assess the quality of education. To increase student achievement, it is crucial to create and put into practice tailored treatments based on the learning from data analysis. Social-emotional learning initiatives, supplementary academic assistance, individualized learning plans, and other evidence-based treatments are all possible research topics. Regular progress monitoring is essential to ensuring that treatments are successful. Data on student performance may be tracked, interventions can be evaluated, and changes can be made as necessary all via research (Xiaoxiao and Dongdai 2020). By using the EPGO-ANN approach to increase student achievement, teachers can better understand student performance, spot areas for development, and provide kids with the individualized assistance they need to reach their full potential. Teachers may make sure interventions are successful and change their strategy as necessary to enhance student results by continuously monitoring and evaluating their work. Anupama and Elayidom (2022) decided which pupils needed to be informed and the research makes predictions about students’ success in a course based on how well they have done in similar courses in the past. In the current cutthroat society, an institution needs to predict student performance, categorize people according to their skills, and work to improve their performance in upcoming exams. Analysis and prediction might benefit from the right patterns. Deshpande et al (2023) examined the academic achievement and failure serve as important stepping stones. The goal of the research is to identify early detection factors that may be used to predict children’s tendency for academic achievement. Dien et al (2020) suggested the goal of the ML approaches used for identifying significant hidden patterns and investigating valuable data from educational contexts. The most crucial elements that may constitute the training dataset for supervised ML algorithms are the standard student characteristics (demographic, academic background, and behavioral aspects). Several supervised ML algorithms, including Decision Tree, Naïve Bayes, Logistic Regression, and Sequential Minimal Optimization were compared in this research for their performance. Pallathadka et al (2021) evaluated the identification of academically underperforming students at an institution is vital, and Educational...
Data Mining and DL aid these students by creating various recommendation systems to improve their performance. By identifying the priceless hidden patterns from their historical knowledge, the technologies guide the pupils toward their plans. Yakubu and Abubakar (2022) determined that Educational Data Mining (EDM) is becoming more significant since it aids in revealing relevant information from educational data sets that may be used for a variety of reasons, including forecasting students’ academic success. Making and implementing various modifications may be beneficial to evaluate the students. ML has been engaged in the majority of recent studies to forecast kids’ academic success using a variety of factors, including family income, student gender, absenteeism, and level, among others. Hashim et al (2020) evaluated in an attempt to determine whether or not performance will be able to complete their degrees, the usefulness of utilizing the more precise CNN version of the DL algorithm to forecast students’ accomplishments. Hussain et al (2019) developed predictive algorithms to predict how well students do in upcoming courses based on their academic scores. Akour et al (2020) analyzed the information gathered from two courses held on the Massive Open Online Courses (MOOCs) platform at National Tsing Hua University. According to their learning habits, the first model effectively assessed student performance. The solutions allow instructors to quickly identify underachievers and provide them with further support. Vijayalakshmi and Venkatachalopathy (2021) examined the forecast aids students in making informed course choices and self-designed study schedules. Furthermore, by using student performance prediction, lecturers and educational management may identify which students need to be watched over and helped to finish their programs with the greatest outcomes. By providing these resources, colleges may issue formal warnings less often and even expel students who do poorly. Nabil et al (2021) suggested a strategy for forecasting student performance using several DL methods. A Vietnamese interdisciplinary university’s student information system was used to acquire four million samples for the experiments, which were constructed on 16 datasets connected to a wide range of various disciplines. Results indicate that the suggested strategy, particularly when employing data modification, produces accurate prediction results. The conclusions apply to real-world situations. Rickles et al (2021) reported that raising students’ test scores in the future depends on instructors’ ability to effectively forecast students’ subsequent learning impacts through techniques, based on their present and investigates the degree to which students are mastering future-related courses now. Researchers haven’t given the use of DL approaches to forecast academic success and provide the best learning strategies much thought. Tao et al (2022) explored by using clustering algorithms to find comparable learning circumstances and predicting course grades based on student’s prior experiences, the study can help students perform better in the classroom. Neha et al (2021) assessed the early detection of student performance in the classroom using DL and identified the students with an early warning; the algorithm performs a comparable category grouping.

The following is the paper’s key contributions:

1. A whole chain based on students’ multi-source daily behavior data, EPGO-ANN is suggested for the prediction of academic achievement. It can automatically extract characteristics without depending on specialized knowledge.
2. By combining ANN with an embedding layer, the time-series characteristics of each kind of behavior data are effectively recovered.
3. ANN is used to find the correlation characteristics between different sorts of behaviors.
4. The trials are performed using a sizable actual data set, and the results demonstrate that our suggested technique works better than the conventional DL methods.

The remainder of the document is structured as follows: In section 2, the research methodology and techniques used to collect and evaluate the data are described along with recommendations for future research based on the findings. Before presenting the research results concisely and systematically, analyzing and explaining them in light of the study aims or objectives, we go through the Discussion and results in section 3 first. Section 4 provides an overview of the Study’s main elements, as well as its relevance and contributions, potential ramifications for practice or policy, and potential future study areas.

2. Materials and Methods

2.1. Data set

The majority of undergraduate students attend colleges in Asia where they reside on campus, take many courses each semester, and are given grades or scores for each subject they pass. On campus, many kinds of behavior data are generated, including information on canteen intake and web page viewing.

2.2. Data elucidation

The data set for this research was obtained from Beijing University over 145 days in the spring semester. Using extract, transform, and load (ETL) techniques, 9000 students’ campus behaviors (Li et al 2022) were gathered from several databases. Data, time, place, and consumption quantity are the additional four characteristics of consumer behavior. Consumption behavior was among them, and it was further divided into breakfast, lunch, supper, and shopping activities. These behavioral
statistics accurately reflect the actions of students on campus in a variety of ways. All student IDs were permanently anonymized throughout the gathering procedure to safeguard students' privacy. The objective of this study is to forecast academic achievement using student behavior data from the university; hence, the student samples with the fewest behavioral records were eliminated. The exact conditions were that there should be a minimum of 20 behavior recordings every semester for each of the following: breakfast, lunch, dinner, and gateway login; and a minimum of 1000 behavior data for online browsing. The filtered dataset included 8228 student samples.

2.3. Data preprocessing

The date and time must thus be preprocessed. By using the university calendar, the value of the date property was changed into an integer beginning at 1, where 1 denotes the date that corresponds to the first day of the calendar, and so on. The students may visit the same website several times in a short period; the duration of the experiment for web page browsing behavior was set at 4 hours. The behavior information may have been unnecessary if the value had been less. The other three categories of behaviors were set to 15 minutes. On gateway login behavior data, the same merge process is also carried out, and a new record's network traffic and online time are set to match the total of the merged records' values. The duplication-elimination process was done for both the behavior of entering libraries and browsing websites.

2.4. Intellectual performance evaluation

The academic success of students is often evaluated by their cumulative GPAs. Predicting whether a student's performance will be excellent, good, or poor is how this research defines the classification job of academic performance prediction. The authors of pertinent research often artificially establish the thresholds since differing thresholds might provide different grading outcomes and restrict the comparison of model performance. The study established four thresholds—5%, 10%, 15%, and 20% to assess academic attainment to evaluate the model's performance as thoroughly as feasible. Table 1 displays the results of the grading and the number of students in each grade that fell within each range of GPA.

<table>
<thead>
<tr>
<th>Academic</th>
<th>5%</th>
<th>10%</th>
<th>15%</th>
<th>20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>GPA</td>
<td>(4,4)</td>
<td>GPA</td>
<td>(3.92,4)</td>
</tr>
<tr>
<td>Excellent</td>
<td>[0, 2.5]</td>
<td>515</td>
<td>[0, 2.8]</td>
<td>828</td>
</tr>
</tbody>
</table>

2.5. Deep learning techniques

Studies using DL algorithms often characterize the challenge of forecasting academic accomplishment as a classification or regression job, to determine the degree or ranking of students’ achievement. Data on students' behavior, as well as demographic data, were used to derive characteristics that confirm a good association between regular living habits and academic success. In addition, the method used two characteristics (orderliness and diligence) from student behavior data related to eating, taking a shower, going to the library, and getting water on campus and added attributes related to sleep patterns to orderliness and diligence. They developed a multitask academic performance prediction framework utilizing learning to rank algorithm based on the three attributes and used social influence theory to investigate the link between the student's academic success and comparable behaviors. From Internet connection records, the research derived the frequency and length of student visits to various websites. These studies use DL algorithms to forecast pupils' academic achievement. The DL classification task is performed by using EPGO-ANN technique.

2.5.1. Enriched Plant Growth Optimized Artificial Neural Network (EPGO-ANN)

Enhanced plant growth optimized artificial neural network (EPGO-ANN)-enabled data analysis of educational data is a potential strategy that may be utilized to increase student achievement in educational environments. The goal of this strategy is to improve student learning outcomes by analyzing educational data, seeing patterns and trends, and optimizing instructional tactics. The following are some strategies for using the study of educational data made possible by EPGO-ANN to improve student achievement:

- **Personized Learning**: By analyzing educational data, EPGO-ANN can determine the best learning environments for certain students. To suit the unique requirements of each student, this may be utilized to tailor learning methodologies and lesson programs.
- **Predictive Analytics**: Using prior educational data analysis, EPGO-ANN can forecast future performance. This may assist educators in identifying pupils who are at risk and helping them succeed via focused interventions.

https://www.malque.pub/ojs/index.php/msj
• **Curriculum Development**: The most efficient teaching methods and lesson plans for certain subjects may be found by analyzing educational data using EPGO-ANN. This may help with curriculum planning and guarantee that the best possible learning opportunities are given to the kids.

• **Student Engagement**: The most efficient teaching methods and lesson plans for certain subjects may be found by analyzing educational data using EPGO-ANN.

### 2.5.2. Enriched Plant Growth Optimization

Specify performance indicators that will be used to gauge how well the optimization procedure has worked. These might consist of parameters like plant height, yield, or quality which includes:

• **Identify Optimal Conditions**: Use data analysis tools and techniques, such as machine learning algorithms, to identify the optimal combination of environmental conditions for plant growth.

• **Monitor Performance**: Follow the development of the plant and the surrounding environment over time to make sure the optimization process is yielding the expected outcomes. This can include gathering more information and, if necessary, modifying the optimization strategy.

• **Evaluate Results**: Utilize the efficiency measures outlined in step 2 to assess the outcomes of the optimization process. This will assist in determining if the procedure was effective and pointing out any areas that may need more attention.

• **Continuously Improve**: By gathering more data, improving analytical tools and models, and discovering fresh areas for improvement which may gradually enhance the optimization process. Enriched plant growth optimization is a useful strategy for enhancing plant growth and raising agricultural output overall. Farmers and other stakeholders may optimize plant development and boost agricultural yields by determining the ideal set of environmental factors and making adjustments appropriately.

### 2.5.3. Artificial Neural Network

Artificial neural networks (ANNs) with numerous layers are used in the deep learning discipline of machine learning to model complicated connections in data. A machine learning model called an ANN is created to mimic the form and operation of biological neural networks. Neurons, which are layers of linked nodes in an ANN, process, and transfer information. Each neuron takes data, processes it, and then sends the results to the layer of neurons below it. An artificial neural network (ANN) has layers of neurons, with the input layer accepting input data and the output layer creating output data. The input data are transformed into the output data via intermediary processing carried out by the hidden layers.

### 3. Results

In this part, we go through the training and performance evaluation of the EPGO-ANN. Three significant issues, including the class imbalance issue, overfitting, and assessing the EPGO-ANN approach, are resolved.

#### 3.1. The generalized function of loss to address the issue of class imbalance

The accomplishment prediction task has a class imbalance issue, as can be demonstrated by looking at the dataset in Table 1. The three main kinds of solutions to this issue are weighted loss function, under-sampling technology, and over-sampling technology. To balance the three groups of students, the second kind of strategy involves creating fresh samples of individuals with both low and good test results. The traditional over-sampling EPGO-ANN technique is computationally inefficient when synthesizing high-dimensional student samples indicated by different behaviors. The third kind just gives students’ low and high test scores greater weight when calculating the loss function, so enhancing the influence of these samples on the loss function. Neither samples are created nor removed. Since it requires fewer processing resources than over-sampling methods, we decided to employ the weighted loss function in this study to address the class imbalance problem. We employed the weighted loss function to resolve the class imbalance issue since it uses less processing power than over-sampling techniques, which is why we chose to do so in this research. In Equations 1 and 2, the weighted cross entropy loss function is shown, where \( u_j \) shows the importance of class \( i \), \( M \) is the quantity of all student samples, \( M_j \) is the proportion of class-specific student samples \( j \), \( N \) is the number of lessons, together with the actual score level, \( z_j \) student samples belonging to class \( i \), and \( o_j^i \) is the predicted score level probability.

\[
    u_j = \frac{M}{N + M_j} \quad (1)
\]

\[
    \text{loss} = \frac{1}{M} \sum_{i=1}^{M} \sum_{j=1}^{N} u_j o_j^i \log(o_j^i). \quad (2)
\]

#### 3.2. Evaluation metrics
The three-way classification accomplishment prediction task was established by equations 3 and 4, \( O_j \) and \( Q_j \) represent the subclasses of bad, good, and outstanding results, accordingly. Equation 5 represents \( E^j_\beta \) which is a trade-off metric between \( O_j \) and \( Q_j \). \( O \) indicates the class’s accuracy rate. \( j, Q \) indicates the recall rate of class \( i \) captured by a model which is represented in equation 6 and 7, and the proportional weights of accuracy and recall in \( E^j_\beta \) metric is adjusted by setting \( \beta \) value which was shown in equation 8.

\[
O_j = \frac{SO_j}{SO_j + EO_j} \quad (3)
\]

\[
Q_j = \frac{SO_j}{SO_j + EM_j} \quad (4)
\]

\[
E^j_\beta = \frac{(1+\beta^2)O_j + Q_j}{(\beta^2 \times O_j) + Q_j} \quad (5)
\]

\[
O = \frac{1}{3} \sum_{j=1}^{3} O_j \quad (6)
\]

\[
Q = \frac{1}{3} \sum_{j=1}^{3} Q_j \quad (7)
\]

\[
E^\beta = \frac{(1+\beta^2)O + Q}{(\beta^2 \times O) + Q} \quad (8)
\]

3.3. Evaluation of the performance of the EPGO-ANN model using various behavioral information

The four assessment metrics of prediction performance based on EPGO-ANN and multi-source behavior which are all greater than those of any kind of single behavior data, notably in the macro recall meter according to the observation of Figures 2, 3, 4, and 5. Although there are considerable variances in macro F1-score, precision, accuracy, and recall, there are very few differences in prediction results based on a single behavior. Overall, gateway login and shopping activity come in second and third, with lunch coming in last. Prediction performance based on breakfast and dinner behavior is best overall. The worst actions include entering libraries and surfing websites.

![Figure 2](https://www.malque.pub/ojs/index.php/msj) Comparison of accuracy based on different behavior data.

![Figure 3](https://www.malque.pub/ojs/index.php/msj) Comparison of precision based on different behavior data.
3.3.1. Accuracy

In the context of machine learning models like the EPGO-ANN, accuracy refers to the percentage of examples that are properly identified or predicted out of all occurrences. To put it another way, accuracy assesses how effectively the model can recognize or forecast the desired output based on the input data. The accuracy would be determined by dividing the total number of cases in the test set by the number of instances that were properly categorized. A high accuracy shows that the model can correctly predict the outcome variable from the input variables, while a low accuracy indicates that the model may need to be improved or that other factors may need to be included to increase its ability to predict the future.

Accuracy takes into consideration all of the model’s predictions since it assesses how effectively the model can distinguish between positive and negative scenarios. When equation 9’s positive and negative instances are not significantly out of balance, this measure is helpful. Accuracy may not provide a comprehensive view of the model’s performance in circumstances when the dataset is unbalanced; instead, supplementary measures like precision and recall may be more useful.

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

(9)

Table 2 displays the proposed procedure’s precision and accuracy. A percentage of the total is often used to represent precision levels. The suggested factor, multi-source has a 28% precision rate compared to Breakfast, Lunch, Dinner, Shopping, Library entry, gateway login, and web browsing, multi-source which has 7%, 14%, 16%, 17%, 13%, 21%, 18%. The suggested factor, multi-source has a 25% accuracy rate compared to Breakfast, Lunch, Dinner, Shopping, Library entry, gateway login, and web browsing, multi-source which has 6%, 13%, 14%, 16%, 12%, 20%, 17%.
### Table 2 Numerical outcomes of Precision and accuracy based on different behavior data.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Precision (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakfast</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Lunch</td>
<td>14</td>
<td>13</td>
</tr>
<tr>
<td>Dinner</td>
<td>16</td>
<td>14</td>
</tr>
<tr>
<td>Shopping</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td>Library Entry</td>
<td>13</td>
<td>12</td>
</tr>
<tr>
<td>Gateway Login</td>
<td>21</td>
<td>20</td>
</tr>
<tr>
<td>Web Browsing</td>
<td>18</td>
<td>17</td>
</tr>
<tr>
<td>Multi-source</td>
<td>28</td>
<td>25</td>
</tr>
</tbody>
</table>

#### 3.3.2. Precision

Precision is a statistic that assesses the percentage of accurate positive predictions among all positive predictions generated by a machine learning model, such as the EPGO-ANN. In other words, precision describes the accuracy or precision of the model’s optimistic forecasts. When false positives (identifying someone as having a specific behavior when they don’t) are expensive or have substantial repercussions, precision is a crucial statistic. Equation 10 displays the high accuracy score, which demonstrates that the model has a low rate of false positives and makes accurate positive predictions. High accuracy may often be paired with poor recall, which indicates that a significant portion of real positives may be missed by the model. Therefore, to assess the total performance of the model, precision should be used in combination with other metrics like recall and accuracy.

\[
\text{precision} = \frac{TP}{TP + FP} \quad (10)
\]

#### 3.3.3. Recall

A recall is a statistic that assesses the percentage of accurate positive predictions among all real positive instances in the dataset, and it is used in machine learning models like the EPGO-ANN. Recall, then, measures the model’s accuracy in properly identifying positive instances. When false negatives identify someone as not exhibiting a certain behavior when research is expensive or has major repercussions, recall becomes a crucial measurement. Equation 11 displays the high recall score, which demonstrates that the model has a low incidence of false negatives and can properly identify a large percentage of real positive events. However, poor accuracy may coexist with high recall, which increases the likelihood of false positives in the model. Recall should, therefore, be used in combination with other measures, such as precision and accuracy, to assess the model’s overall performance.

\[
\text{Recall} = \frac{FN}{FN + TP} \quad (11)
\]

Table 3 displays the proposed procedure’s recall and F1-Score. The suggested factor, multi-source has a 21% recall rate compared to Breakfast, Lunch, Dinner, Shopping, Library entry, gateway login, and web browsing which has 9%, 16%, 15%, 19%, 14%, 23%, 20%, and suggested factor, multi-source has a 24% F1-score rate compared to Breakfast, Lunch, Dinner, Shopping, Library entry, gateway login, web browsing, multi-source which has 8%, 15%, 17%, 18%, 13%, 22%, 19%.

### Table 3 Numerical outcomes of Recall and F1-score and accuracy based on different behavior data.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Recall (%)</th>
<th>F1-score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakfast</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>Lunch</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td>Dinner</td>
<td>15</td>
<td>17</td>
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<tr>
<td>Shopping</td>
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<tr>
<td>Library Entry</td>
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<td>13</td>
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<tr>
<td>Gateway Login</td>
<td>23</td>
<td>22</td>
</tr>
<tr>
<td>Web Browsing</td>
<td>20</td>
<td>19</td>
</tr>
<tr>
<td>Multi-source</td>
<td>21</td>
<td>24</td>
</tr>
</tbody>
</table>

#### 3.3.4. F1-score

F1-score is a statistic that combines accuracy and recall to provide an overall assessment of the performance of machine learning models like the EPGO-ANN. The harmonic mean of accuracy and recall, which gives both measures equal weight, is used to generate the F1 score. When the dataset is unbalanced—that is, when there are more instances of one class (such as non-smokers) than another (such as smokers), the F1-score is a helpful indicator. Equation 12 illustrates how uneven accuracy and recall may be distorted, while the F1-score offers a fair evaluation of the model’s performance. A high
F1 score means that the model is doing well in terms of accuracy and recall, while a low F1 score indicates that the model may need to be improved or that more variables may need to be added to the model.

\[
F1 - score = \frac{(\text{precision}) \times (\text{recall}) \times 2}{\text{precision} + \text{recall}}
\]  

(12)

4. Conclusions

A potential strategy that may be utilized to increase student achievement in educational settings is the study of educational data made possible by deep learning. To improve learning outcomes and student achievement, educators may take well-informed choices by using machine learning algorithms to evaluate educational data and spot patterns and trends. Data from the educational sector lends itself especially well to deep learning algorithms, such as EPGO-ANN. EPGO-ANN may be used in education for a variety of purposes, such as individualized learning, predictive analytics, curriculum building, and student engagement. It can model complicated interactions between input and output data. We draw the conclusion that educators can learn more about the precise elements that lead to student achievement via the analysis of educational data and may create interventions that are specifically tailored to help students who may be having trouble. Informing the creation of curriculum that are tailored for student learning, deep learning algorithms may also be used to determine the best teaching methods and subject matter. The study of educational data made possible by deep learning has the potential to transform education and enhance student results in a variety of contexts. Educators may make data-driven choices that result in improved learning outcomes and more student achievement by using the power of machine learning algorithms. An EPGO-ANN model for forecasting students’ academic achievement using data on their on-campus daily activities is suggested in this work. Our approach tackles the difficulties of manually collecting characteristics from data on several sources of varied behavior.

Ethical considerations

Not applicable.

Declaration of interest

The authors declare no conflicts of interest.

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