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Predicting Student Performance in Beginning ComputerProgramming Classes with Deep Learning Models

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ABSTRACT: This study predicted student performance in beginning computer programming classes using deep learning algorithms and log data from Moodle. This study specifically aims to use prediction results to identify possible low- performing pupils who could require teacher support. According to the findings, deep learning models show promise in predicting student performance and identifying underachievers in the context of the study. This paper also explored the ways in which the models' prediction results can help teachers in educational contexts.

KEYWORDS: **Educational** data mining; deep learning; student performance prediction; time-series data; Moodle

I. INTRODUCTION

The initial findings of a project that is now underway to investigate students' learning habits recorded by the learning management system Moodle in beginning computer programming classes using deep learning techniques were presented in this paper.

Despite the fact that the courses that served as the basis for this study were taught in traditional classroom settings, the instructor made extensive use of Moodle's affordances and features. For instance, the course materials are available on Moodle for students to access, preview, and study. Additionally, they submitted their tasks using Moodle. Additionally, they can use Moodle to communicate the outcomes of group discussions or start text discussions. Due to the fact that the majority of the learning activities in the courses required students to use the Moodle platform, Moodle's log files sufficiently documented and tracked students' learning throughout the semester. This makes it possible to gather and examine the Moodle log data in order to investigate how students learn.

Educational data mining is brought to light when it comes to evaluating vast amounts of log data that are received from a learning management system. "Educational Data Mining is an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students and the settings which they learn in," according to the International Educational Data Mining Society [1]. This definition states that the data used in education data mining (EDM) must have something to do with education and human learning, and that the purpose of EDM is to improve teaching and learning by gaining insight from an understanding of students and learning environments. While data features and EDM's ultimate objective may not change much in this discipline, EDM techniques can be borrowed from a variety of fields, including statistics, data mining, machine learning, psychometrics, information visualization, and computational modeling [2]. Predictive, clustering, relationship mining, model-based discovery, and data distillation for human judgment are more categories into which the technologies can be divided based on their intended use [3]. More advanced techniques, like deep learning approaches, are now possible for conducting EDM thanks to recent improvements in digital storage technology and processing performance [4]. The four EDM tasks that were the main focus of recent empirical studies in EDM using deep learning techniques are (1) predicting student performance, (2) identifying undesired student behaviours, (3) generating recommendations on how to assist students, and (4) automatic evaluation [4]. The first

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task—predicting student performance—would be the main focus of this investigation.

Long Short-Term Memory (LSTM) was the most often utilized deep learning technique to predict student performance, and the majority of previous studies found that deep learning techniques outperformed typical machine learning techniques [5]. The three deep learning models that can handle time-series data to predict student performance—the Recurrent Neural Network (RNN) [6], Long Short-Term Memory (LSTM) [7], and Gated

Recurrent Units (GRU) models [8]—were compared by the authors of this study because the data used to predict student performance was time-series data.

Apart from evaluating how well three popular deep learning models predicted student performance, the authors also tried to use the prediction results to pinpoint possible underachievers in the classroom. By doing this, teachers can focus more on and prepare help for potential low-performing children ahead of time. Additionally, in order to support the previously indicated objective of educational data mining, the authors would like to consider the educational implications of applying such prediction results using deep learning techniques.
Thus, the following research issues were intended to be addressed by this study:
(1) Which deep learning models are more accurate at forecasting how well students will fare when studyingcomputer programming?
(2) How can low-achieving students who require assistance in learning computer programming be identified usingdeep learning techniques?
(3) How can teachers identify children who perform poorly in learning environments based on the results above?

II. METHOD

A. Dataset and Research Site
The study was conducted at a Northern Taiwanese institution in an undergraduate general education course called "programming 101." Students with little to no prior programming experience and majors unrelated to computer technology were enrolled in this course. The purpose of the course wasto instruct pupils in Python. The spring and fall semesters of 2020 and the spring semester of 2021 saw the availability of the courses that served as the foundation for this investigation. The log data of the courses that were obtained from Moodle served as the dataset for this investigation.

B. Data Analysis
The data analysis procedure is shown in Fig. 1. The first ten weeks of the courses' log data were used to extract the feature data. In order to forecast students' performance, nine features were chosen for this study, including (1) the number of assignments in a week and (2) the amount of time in minutes for the first assignment submission. (3) The amount of time in minutes for the final assignment submission Numbers of submissions (4) and clicks on the course materials (5) during class Six (6) clicks on the course materials following class. (7) in the event that students are posting in group discussion forums, (8)in the event that students are viewing their posts, and (9) in the event that students are not participating inthe group discussion forums.

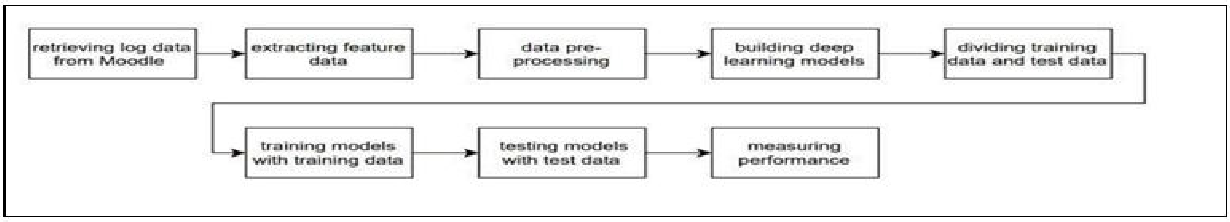

Fig. 1. Process of data analysis

In order to address the missing values of features (2), (3), and (4), this study employed k-nearest neighbors imputation

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(kNN) [9] for data pre-processing. To lessen the effect of extreme values or outliers, normalization with mean 0 and standard deviation 1 was applied to features (2)–(6).

597 students who enrolled in the courses during the spring and fall semesters of 2020 provided the training data, which was separated from the exam data. Test data came from 269 students enrolled in the courses during the spring semester of 2021. The final grades of the pupils in the training data were divided into three groups based on their performance: 174 students were classified as low performers, 244 asaverage performers, and 179 as good performers. The following paragraph will provide a description of the LSTM model used in this investigation.

C. Modeling

The models in this study were constructed using the Keras deep learning framework. The model utilized for this investigation is shown in Fig. 2. This neural network model consisted of four layers: masking, LSTM, dropout, and dense layers. The cross-entropy approach [10] was employed as the loss function during model training. The optimizer was set to Nadam [11].

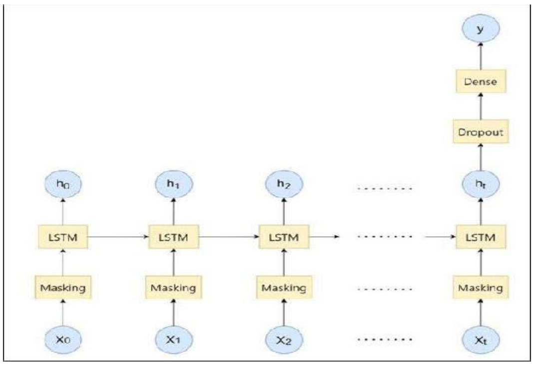

Fig. 2 Deep learning models

Filtering missing values from data from multiple semesters and courses with partially equivalent learning activities was the goal of the masking layer. The LSTM layer received the filtered data as input. Each cell's input data from ten time points, cell state, and hidden state were processed one after the other using input, output, and forget gates. The LSTM layer's output from the most recent time point was sent to the Dropout layer to avoid overfitting [12]. Finally, the output was sent to the Dense layer, which computed the likelihood of three classes (i.e., low-performing, average-performing, and high-performing) using softmax as the activation function. The outcome of categorization was the highest possibility.

D. Measurements

The performance of the trained models was evaluated in this study using Accuracy, Precision, and Recall. The definitions of these three metrics are compiled in Fig. 3.

	Predicted Positive	Predicted Negative
Actual Positive	TP（True Positive）	FN（False Negative）
Actual Negative	FP（False Positive）	TN（True Negative）

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

$$Precision = \frac{TP}{TP + FP}$$

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

Fig. 3. Definitions of measurements

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III. RESULTS

Table 1 contrasts the RNN, LSTM, and GRU performances in order to answer the first research question. In the three tests, LSTM outperformed RNN and GRU, as seen in Table 1. The accuracy of theLSTM model was 0.578, indicating that about 60% of predictions were accurate.

TABLE I.
RESULTS FOR MODEL PERFORMANCE

	Accuracy	Precision	Recall
RNN	0.524	0.541	0.515
LSTM	0.578	0.595	0.570
GRU	0.563	0.578	0.558

The precision and recall of the three models for identifying underachievers are compiled in Table 2 in order to respond to the second research question. The model that predicted a student to be low-performing had the highest precision (i.e., 0.649), meaning that around 65% of the students were truly low-performing. However, the GRU modelhad the highest recall (i.e., 0.563), meaning that, out of all the real low-performing students, the GRU model predictedthat they would do poorly in about 56% of cases, while the LSTM model projected that they would perform poorly around 55% of cases.

TABLE II.
RESULTS FOR MODEL PERFORMANCE IN PREDICTING LOW-PERFORMING STUDENTS

	Precision	Recall
RNN	0.629	0.506
LSTM	0.649	0.552
GRU	0.641	0.563

Regarding the third research question, the results can help instructors understand that only 56% of the real low-performing kids who could require help can be predicted by the model; 44% still require teachers' efforts to find and help.

IV. DISCUSSION AND CONCLUSION

In order to identify possible low-performing students who could require extra attention and guidance from teachers, this study combined deep learning algorithms with Moodle log data to predict student performance inbeginning computer programming classes. The findings revealed found when compared to RNN and GRU models, LSTM overall outperformed them in forecasting student performance, which was consistent with the results of earlier pertinent studies [5, 13]. The results indicated that the GRU performed best in Recall while theLSTM model performed best in Precision, especially when it came to predicting low-performing pupils.

The authors would like to draw attention to a concern regarding the use of deep learning techniques in educational data mining, in addition to enhancing the effectiveness of deep learning models in forecasting student performance as the future direction of this ongoing study. According to this study, deep learning approaches hold promise for assisting educators in identifying children who might require assistance. Teachersmust, however, interpret the models' prediction results in light of the learning environments when they employthese strategies to comprehend students' learning.

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