Students’ learning habit factors during COVID-19 pandemic using multilayer perceptron (MLP)

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Abstract
Rapid dissemination of coronavirus disease 2019 (COVID-19) across the globe has necessitated the introduction of social distance interventions to slow the spread of the disease. Online learning has become essential, considering the implications of this virus to be spread among the students during physical classes. Hence, educational institutions have shifted the traditional physical classes to online classes. Due to this implementation worldwide, a study on student learning habits is crucial to analyse students learning habits as it is one of the main factors that affecting students’ performance in learning. Fifteen independent variables as inputs to one of the well-known Artificial Neural Network algorithms, Multilayer Perceptron (ANN-MLP) has been used to investigate the student’s learning habit factors during the COVID-19 pandemic. Through analysing original survey data from 420 secondary students (Grade 6-12) in Hanoi shows that the ANN-MLP model is stable for both ANN-MLP optimization algorithms which are for Adjusted Normalized, to be concise. The hours spend for self-learning before COVID-19 is observed to be the most influential factors of student’s learning habit during COVID-19 pandemic. Moreover, the promising Sum of Squares Error (SSE) and Relative Error (RE) values obtained signify that the ANN-MLP model is appropriate in identifying the student's learning habit factors during COVID-19 pandemic.

Keywords
COVID-19, Learning habits factor, Artificial neural network (ANN), Multilayer perceptron (MLP).

1. Introduction
The emerge of the COVID-19 pandemic around the world gave a high impact especially in education sectors where the conventional approach not able to be practice due to this pandemic [1]. There is an urge for the implementation of online learning to cope with the current situation and to avoid the disease from spreading. Online learning is a learning alternative where it provides a synchronous or asynchronous learning experience through the internet with the leveraging of time and place flexibility between both students and instructors [2]. However, the sudden changes in educational content to the digital world may affect student learning habits [3]. In this paper, a factor that contributes towards student learning habits during the COVID-19 pandemic will be analysed.

Students learning habits are very important because they influence the performance and quality of learning [4]. Learning habits are defined as a method of gathering, organizing, the activities related to psychological, cognitive, and affective fields of interaction with learning environments [5]. During the COVID-19 pandemic, online learning influences the student learning habits including personal interests for learning, problem-solving, competencies, and project working skills [6]. The algorithm inspired by the diverse structure of the human brain; the Artificial Neural Network (ANN) has been used in numerous complex problems [7]. It can process a large volume of data, learn from training data, and excellent generalization capability [8]. Due to its capability of self-learning and self-adapting, more research on this algorithm has been successfully implemented to solve real-world problems. It also able to perform more efficient and accurate numerous classification [9-11], prediction [12, 13] and many

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more compared to other classification techniques [14].

The Multi-Layer Perceptron (MLP) is one of the well-known Artificial Neural Networks (ANNs) where data with expected outputs are applied to this network also known as supervised training [15]. MLP outperforms the Linear Regression in the prediction of student performance in the final examination [16]. MLP is also recommended in predicting a student achievement based on motivation, learning, and emotional intelligence where it gives a high number of performance accuracy compared to the Decision Tree algorithm [17]. MLP outperforms Random Forest (RF) in student performance prediction where it able to produce more fine and meticulous results compared to RF. Meanwhile, a comparison between MLP, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Discriminant (DISC) to predict student awareness in ICT and Mobile technology shows a remarkable result. The MLP and SVM also outperform KNN and DISC with no significant differences in performance accuracy. It is recommended to be used for real-time prediction [18].

Due to the positive correlation between both student learning habits and performance, investigation on the factor that contributes to the student learning habits during the COVID-19 pandemic is necessary. Hence, due to the promising results and advantages of MLP in self-learning towards a real-world problem, this research employs MLP in determining the contributory factors of Student’s Learning Habit during COVID-19 pandemic. In this context, the objectives of this paper are as follow:

1. To present a MLP network model in investigating the contributory factor of students’ learning habits during the COVID-19 pandemic
2. To evaluate the performance of the proposed MLP network model using the standard Sum of Squares Error (SSE) and Relative Error (RE).

Following, this research paper contains the Introduction which is presented in Section 1 and followed by Data Background in Section 2. Next, Section 3 and Section 4 discuss the Methods and Results, respectively. Subsequent, Section 5 presented the Discussion and Section 6 deliberated the Conclusion and Future Work.

2. Data background
A dataset on Vietnamese students’ learning habits during the COVID-19 pandemic [3] was retrieved from the ResearchGate open source. This dataset is established from the questionnaires distributed in the period of 7th February 2020 to 28th February 2020. It is composed of three major groups of questions which are (1) student’s demographic, (2) student’s learning habits, and (3) student’s perceptions of self-learning during the school closure. This dataset is composed of 460 responses from the secondary student in grades 6-12. However, only 420 data are valid after the process of data cleaning. There were fifteen covariates used in the network which are fa_job, exam, Self_evaluation, English, Lh_before_Cov, nec_prog, nec_habit, nec_parent, eff_moti, eff_con, eff_supp, eff_env, eff_obj, eff_resource, and eff_friend.

Table 1 tabulates the description of the covariates used in this study.

| Table 1 Covariates description |
| Input layer | Covariates | Descriptions |
| 1 | fa_job | What is your father’s job? |
| 2 | exam | What subject group are you intend to take for university entrance exam? |
| 3 | Self_evaluation | How do you evaluate your performance, regarding your selected subject group? |
| 4 | English | How do you evaluate your English capability? |
| 5 | Lh_before_Cov | Before COVID-19, how many hours do you spend per day for self-learning? |
| 6 | nec_prog | I can assure my learning progress |
| 7 | nec_habit | I can maintain my learning habit |
| 8 | nec_parent | My parents show me it is necessary |
| 9 | eff_moti | I have motivation for self-learning |
| 10 | eff_con | I have proper concentration skill |
| 11 | eff_supp | I have support from my family |
| 12 | eff_env | I have an effective learning environment |
| 13 | eff_obj | I can define my daily learning objectives |
| 14 | eff_resource | I have various learning resources |
| 15 | eff_friend | I communicate and collaborate with my friends about learning |
3. Methods

This section discusses the methodology used in conducting this study. This study aims to evaluate the performance of the MLP network in investigating the contributory factors of students learning habits during the COVID-19 pandemic. Figure 1 depicts the proposed methodology used in this study.

From Figure 1, the Vietnamese students’ learning habit dataset is used as the input to the model. Next, data normalization and cleaning are performed. Consequently, the process of initialize and train the MLP model is conducted. The model is constructed using SPSS 13. In general, the structure of ANN is composed of an input layer, hidden layers, and the output layer [19]. Next, Figure 2 represents MLP network architecture used in this study. From the architecture, \( x_n \) represents the first layers of the network which is known as the input layer. The prediction result produces by the output layer (third layer) is obtained from a calculation made by the hidden layer (second layer). These three layers consist of a few nodes where each of these nodes connect with one another on each layer. Each of the nodes on each layer is known as a neuron except for the input layer where the nodes \( x_1, x_2, x_3 \) and \( x_n \) are addressed as the input features to the feed to the network.

![Figure 1: Methodology used in this study](image1)

Figure 1 Methodology used in this study

Each neuron consists of three main components which are input signals represented with \( x_1 \) until \( x_n \), multiply by the weight represented by \( w_1 \) until \( w_n \). The input sum is a calculation of weighted input plus a bias (b) in a linear equation as shown in equation (1). Next, the activation functions where determined whether the neuron can be activated or not as output y. The additional of bias to the weighted of sum produces the activation function. Following shows the linear equation for artificial neuron:

\[
y = f(b + \sum_{i=1}^{n} w_i x_i)
\]  

(1)
In general, the data source factor chosen will affect the number of input layer nodes in the network. On the other hand, the number of hidden neurons in the network is determined based on the specified training dataset used. Next, hidden layers are used for the calculation purpose by applying the dedicated function. Each node in the input layer must be connected to all the nodes located in the hidden layer and the nodes at the hidden layer must be connected to all the nodes at the output layer [20].

In this study, the fifteen covariates acted as the input for the MLP network. The activation function used in the network is Softmax and there is one dependent variable which is \( Lh_{in\_Cov} \). To simply the architecture, it can be addressed as 15-7-1. The MLP network architecture as portrayed in Figure 3.

Based on the illustration of the MLP network architecture in Figure 3, this network is composed of 15 input and one hidden layer with seven nodes. Softmax function is used as the hidden layers’ activation function. Hence, the target output of this network is the learning hour in covid (\( Lh_{in\_Cov} \)). Identity (purelin) function is used as the activation function from the hidden layer to the output layer and the default error function applied is the SSE. SSE is the sum of differences between each observation group means, and it is used to indicate the variation within a cluster. Hence, it can be concluded that the smaller the SSE, the lesser the variation between the cluster.

Figure 2 MLP network architecture

4. Results
This section discusses the results obtained from the experiment conducted. The case processing summary for MLP network is portrayed in Table 2. Based on Table 2, the dataset used in this study is divided into two groups which are training and testing. The training set for MLP is 66.7% (280/420) and the testing set is 33.3% (140/420). The overall data from the dataset is \( N = 420 \) and there is no excluded data reported. Next, Figure 4 and Figure 5 portray the standardized residuals and the distribution of standardized residuals respectively. It is concluded that the five most influential factors of students’ learning habit during COVID-19 are \( Lh_{before\_Cov} \) (100), \( eff\_obj \) (54.9), \( eff\_con \) (53.1), English (41.4), and \( eff\_moti \) (34.4) as shown in Table 3.

Following, Figure 6 portrays the normalized importance independence variables in a different representation. All the 15 covariates are presented according to it normalize importance.

As mentioned previously, the performance evaluation was conducted on the developed MLP network model using the SSE and RE. Table 4 and Table 5 demonstrate the SSE and RE for the MLP network model, respectively. Further elaboration on both Table 4 and Table 5 are deliberated in Section 5 Discussion accordingly.
Figure 3 MLP network architecture

Table 2 Case processing summary for RBF model

|          | N   | Percent |
|----------|-----|---------|
| Sample   | 280 | 66.7%   |
| Testing  | 140 | 33.3%   |
| Valid    | 420 | 100.0%  |
| Excluded | 0   |         |
| Total    | 420 |         |
Figure 4 Standardized residuals

Figure 5 Distribution of standardized residuals

Table 3 Independent variables’ importance

| Variables                                         | Importance | Normalized importance |
|---------------------------------------------------|------------|-----------------------|
| What is your father’s job?                        | .032       | 19.8%                 |
| What subject groups do you intend to take for the university entrance exam? | .063       | 38.9%                 |
| How do you evaluate your performance regarding your selected subject group? | .065       | 40.5%                 |
| How do you evaluate your English capability?      | .065       | 40.7%                 |
| Before COVID-19, how many hours did you spend per day for self-learning? | .161       | 100.0%                |
| I can assure my learning progress                 | .064       | 39.8%                 |
| I can maintain my learning habit                  | .072       | 44.7%                 |
| My parents show me it is necessary                | .044       | 27.7%                 |
| I am motivated for self-learning                  | .088       | 54.9%                 |
| I have proper concentration skills                | .081       | 50.5%                 |
| I have support from my family                     | .045       | 28.1%                 |
| I have an effective learning environment           | .058       | 36.4%                 |
Variables | Importance | Normalized importance
--- | --- | ---
I can define my daily learning objectives | .064 | 39.5%
I have various learning resources | .059 | 36.8%
I communicate and collaborate with my friends about learning | .038 | 23.4%

**Figure 6 Normalized importance**

**Table 4 SSE of ANN-MLP model**

| Rescaling of covariates | Optimization algorithm | Scaled conjugate gradient | Gradient descent |
| --- | --- | --- | --- |
| Standardized | 102.813 | 97.762 |
| Normalized | 95.731 | 96.218 |
| Adjusted Normalized | 85.564 | 88.562 |
| None | 97.848 | 102.669 |

**Table 5 RE of ANN MLP model**

| Rescaling of covariates | Optimization algorithm | Scaled conjugate gradient | Gradient descent |
| --- | --- | --- | --- |
| Standardized | 0.679 | 0.650 |
| Normalized | 0.674 | 0.666 |
| Adjusted Normalized | 0.613 | 0.602 |
| None | 0.677 | 0.696 |

**5. Discussion**

Referring to the SSE results tabulated in Table 4, it can be observed that the Adjusted Normalized produced the lowest SSE rate for both Scaled Conjugate Gradient and Gradient Descent which are 85.564 and 88.562 respectively. The None rescaling on the other hand returned the highest SSE in Gradient Descent which is 102.669. Also, the Standardized by Scaled Conjugate Gradient is monitored to be the least efficient by returning the highest SSE rate at 102.813.

Next, similar for RE, the Adjusted Normalized recurrently yield the lowest rate for both Scaled Conjugate Gradient and Gradient Descent which are 0.613 and 0.602 correspondingly in Table 5. Therefore, it can be concluded that the MLP model is stable for both MLP optimization algorithms which is for Adjusted Normalized, to be particular. These promising SSE and RE values obtained signify that the MLP model is appropriate in identifying the Students’ Learning Habit Factors during COVID-19 pandemic.
6. Conclusion and future work
This study investigates the contributory factor on students learning habits during the COVID-19 pandemic using the Artificial Neural Network of Multilayer Perceptron (ANN-MLP) model. The proposed model was implemented on a Vietnamese dataset. Fifteen covariates were used in this research which is based on a 15-7-1 structure. The major contribution to students’ learning habits is English capability, motivation for self-learn, concentration skill, daily learning objective, and the most major contribution is hours spend for self-learning before COVID-19 with 100% normalized importance. From the result obtained, it shows that ANN-MLP is an appropriate model to identify the contributory factors for the students’ learning habits with a promising rate of SSE and RE. By understanding the contribution factors, it could improve teaching and learning processes, and overcome the unprecedented challenges in teaching and learning during COVID-19 pandemic.

In a nutshell, this study implements the original MLP network. The hybridization of the existing MLP model with any AI techniques in future is believed to offers expansion of knowledge in this technique. In addition, the use of other statistical approaches despite SSE and RE will provides deeper insights in understanding the model performance.

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Conflicts of interest
The authors have no conflicts of interest to declare.

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