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Performance of Decision Tree and Neural Network Approach in Predicting Students' Performance

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Abstract

Data mining is one of the most popular techniques to analyse and predict students' performance. Hence, this study evaluated two data mining approaches of decision tree and neural network in finding the prediction of students' academic performance. The data used in this study were collected through a self-administered questionnaire distributed to the students. A comparison was made between the two data mining algorithms. Results proved that the decision tree provided the highest accuracy value in the model. Furthermore, it was found that previous certificate results, gender, status of working part-time, time management, parental marital status, study skills, and preparation before attending lectures were significant factors that affected students' performance. Based on the prediction, it can be concluded that the students will get a good result in the next semester with a cumulative grade point average (CGPA) of 3.00 and above if the students know how to manage time, use the right study skills, and do some preparation before the lecture begins.

Keywords: Data Mining, Decision Tree, Neural Network, Predicting, Students' Performance.

Introduction

Recently, student performance has been a major concern for various stakeholders, including educators, administrators, and companies. According to Daud et al (2017), recruiting agencies will consider academic achievement as the main factor to recruit new employees, especially fresh graduates. There are many ways in measuring students' academic performance. One of the measures is grade point average (GPA) which has become a numerical indicator explaining the overall student's academic achievement. According to Alyahyan and Dustegor (2020), early prediction of students' performance may assist decision-makers in making suitable decisive action at that moment and planning suitable mechanism in improving the student's performance. Hence, the deterioration of students' academic performance is a problem that requires a solution. Since academic performance is crucial for university students, improving their academics could somehow help them have a better future, and it became a long-lasting issue. Therefore, predicting students' performance is important in helping the students gain the necessary support in the learning process. Referring to a study by Kolo et al (2015), knowing the possible outcome of the learning process from the prediction of the student's performance can help the institution to make some changes and adjustments towards the factors that contributed to the previous performance. It may also help the educational planners and administrators to think wisely before deciding on any change of direction to the student population. Various factors have been highlighted as the barriers to the students that have significantly affected their study performance. In a study made by Kasantra et al (2013), they discovered that several factors such as teaching methods, attendance, time management, and sleep habits positively influence the academic performance of undergraduates. Another similar research by Daud et al (2017) which predicted students' performance also found that family expenditure and personal information features have a significant impact on the student's performance. Thus, the influential factors that significantly affect the students' performance in this research might help the institution make plans to improve students' performance.

Currently, many techniques have been suggested to evaluate the student's performance. However, data mining is one of the most popular techniques used by the previous researcher in analysing and predicting the student's performance due to its ability to extract new knowledge from a huge volume of students' data (Oyelade et al., 2010; Hamoud & Humadi, 2019). Data mining is the process of discovering the hidden patterns in a large amount of data set, and it is widely used in the educational area. Several data mining techniques have been used in predicting students' performance. However, according to Saa (2016), the appropriate techniques used in predicting students' performance are logistic regression, Naive Bayes, neural networks, support vector machine and decision tree. Previously, several studies have published results that used decision trees and neural networks to predict students' performance (Kolo et al., 2015; Osmanbegovic & Suljic, 2012; Hamoud et al., 2018; Ahmad & Shahzadi, 2018). According to Khalaf et al (2018), the decision tree algorithm is among the best solutions to predict students' performance. The decision tree is also considered the easily understood model in predicting the purpose because it gives simplicity and comprehensibility output (Osmanbegovic & Suljic, 2012). Meanwhile, the neural network approach is also very useful in solving complex problems of classification and prediction that do not have an algorithmic solution. The neural network approach can find complex relations among variables with a high tolerance of data uncertainty. At the same time, it can provide predicted variable patterns in-real time (Bermejo et al., 2019). In summary, various research has been conducted to solve students' performance problems using data mining techniques, specifically using decision tree and neural network approaches. However, these researchers used different scopes and characteristics of students with various factors used in each study. Therefore, this paper aims to fill the gap by extending the study done by previous researchers in investigating the performance of decision tree and neural network approach in predicting the students' performance at a public university in Malaysia. Hence, the specific objectives of this study are; i) to identify the important factors that contribute to students' performance; and ii) to predict students' performance using GPA results depending on the factors that are expected to influence the performance.

Materials and Methods

This section discusses the methodology used in this study. The main focus of the study is predicting the performance of students with the GPA being used as an indicator measurement. First, a data mining technique was used in developing a classification model for the data under study. Next, the decision tree and neural network were used as a classifier under the cross-validation method. Then, the technique with higher accuracy was used to identify the most influential factor that affects the students' performance and predicts their performance for the upcoming semester. Finally, based on the GPA, the performances of the students from Bachelor of Science (Hons.) Statistics were predicted for their next semester result by considering the important factors that contribute to the students' performance.

Data and Variables Description

This study used the data collected through a questionnaire to all active full-time students in Bachelor of Science (Hons) at Universiti Teknologi MARA (UiTM) who registered for Semester March 2020 – August 2020, which included three branch campuses of UiTM Shah Alam, UiTM Negeri Sembilan (Seremban), and UiTM Kelantan (Bharu & Machang). The respondents involved were undergraduate statistics students registered for the semester of March 2020 - July 2020 session except for the first semester students. Data were collected based on a structured questionnaire as an instrument tool divided into four sections: student demographics profile, academic information, family information, and student's habit. The questionnaire was adapted from (Hamoud et al., 2018; Rabia et al., 2017). There were five variables with nominal scale in demographic profile (Section A), including gender, age, UiTM branch, and part-time working status. Section B was on respondents' academic information with four variables of current CGPA, current GPA, previous certificate result (Matriculation/ Foundation/Diploma), and SPM result for English, Mathematics, and Additional Mathematics subjects. Section C was on family information, while Section D was about the study habits of the respondents based on their time management, behaviour before attending the lecture, behaviour before taking the examination, and study skills. The 7-point Likert scale was used for Section C and Section D. Current GPA was a response variable while demographics profile, academic information, family information, and student habit were input variables.

Data Mining Method

The data mining technique was used to identify the most important factors that contribute to the student's performance by using an appropriate predictive model to predict students' academic performance in their upcoming semesters. The application of data mining technique greatly benefits the prediction of students' performance in tertiary institutions as the academic data come in various types and volumes. Two data mining techniques were used in this study: decision tree and neural network. These techniques were performed using RapidMiner software.

Decision Tree

One of the most popular techniques for predictive modelling is the decision tree. This approach visually and explicitly represents decisions. A decision tree is a tree-like collection of nodes projected in creating a class association decision on an approximation numerical target value (Hamoud et al., 2018). The main goal of the decision tree is to create a training model using simple decision rules inferred from training data (Montella et al., 2019). Then, the model can be used in predicting the value of the target variable. As shown in Figure 1, the decision tree structure starts with the tree's root used in predicting a class label for a record. It represents the whole students and divides this into two or more homogeneous sets. Next, the root is split, in which the process involves dividing a node into two or more sub-nodes. The decision nodes represent a sub-node which is split into further sub-nodes. The nodes that do not split are called leaf or terminal nodes, and the branch or sub-tree is a subsection of the entire tree (Montella et al., 2019). The general procedure in the decision tree starts by retrieving the students' dataset and ends by pruning the decision tree.

The first step is retrieving the students' dataset. Then, the process is followed by splitting the data into two partitions: the testing set and the training set. The data partition is important to develop highly accurate models relevant to data. Next, the training set is implemented to build the model, while the testing set is used to validate the model build. Finally, the decision tree is used in the training set to build the model. The basic algorithm for decision trees keeps growing the tree by splitting nodes as long as the new splits create children that increase purity. However, the fully grown tree is likely to overfit the data, resulting in poor accuracy. Hence, the final step for the decision tree procedure is pruning the decision tree, which removes sub-nodes of a decision node.

In this study, the gain ratio was used for pruning purposes. The gain ratio is a modification of information gain used to minimize error and bias. In pruning, removing the decision tree starts from the leaf node such that the overall accuracy is not disturbed. This technique has been used to predict whether a student might get a good result which is a GPA of more than 3.0.

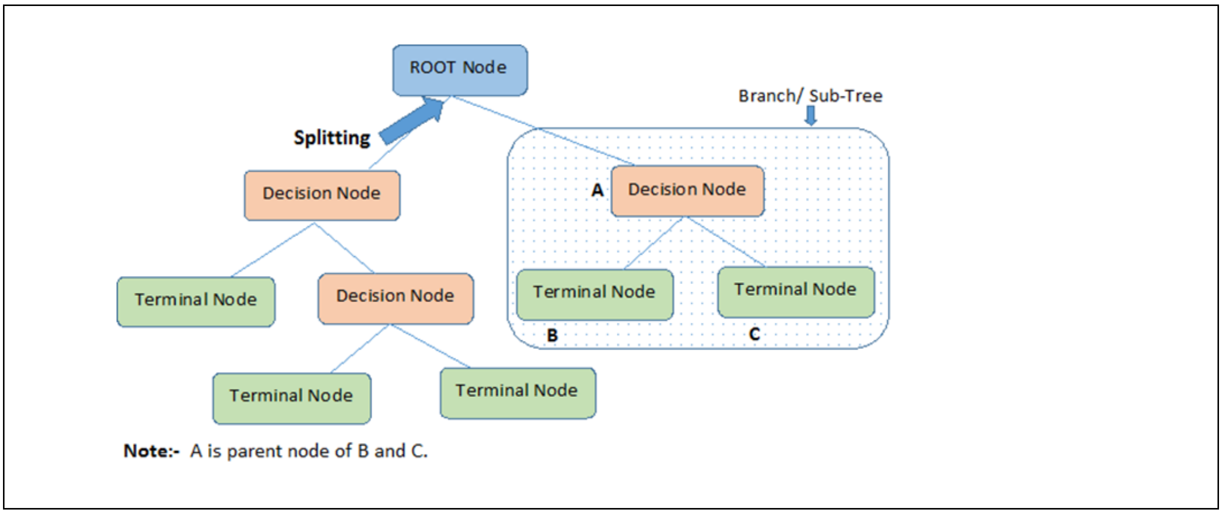

Figure 1. Summary of Decision Tree structure

Neural Network

The neural network is a technology based on the structure of the neurons inside a human brain. Typically, the neural networks are organized in layers consisting of interconnected nodes with an activation function. The network starts its pattern through an input layer connected to one or more hidden layers where the actual processing is carried out from a weighted connection system. The hidden layers then link to the output layer, which indicates the neural network's output. The neural network was used in this study to predict next semester's students' performance based on the data from students' last semester's performance of Bachelor of Science (Hons.) Statistics at three UiTM branch campuses. The neural network aims to learn how to recognize patterns in student data and achieve this study's objective, which is the prediction of students' performance. Typically, a neural network is organized in layers of interconnected nodes with an activation function, as shown in Figure 2. The network starts its pattern through an input layer connected to one or more hidden layers where the actual processing is carried out from a weighted connection system (Lau et al., 2019). The hidden layers are then linked to the output layer, which indicates the neural network's output.

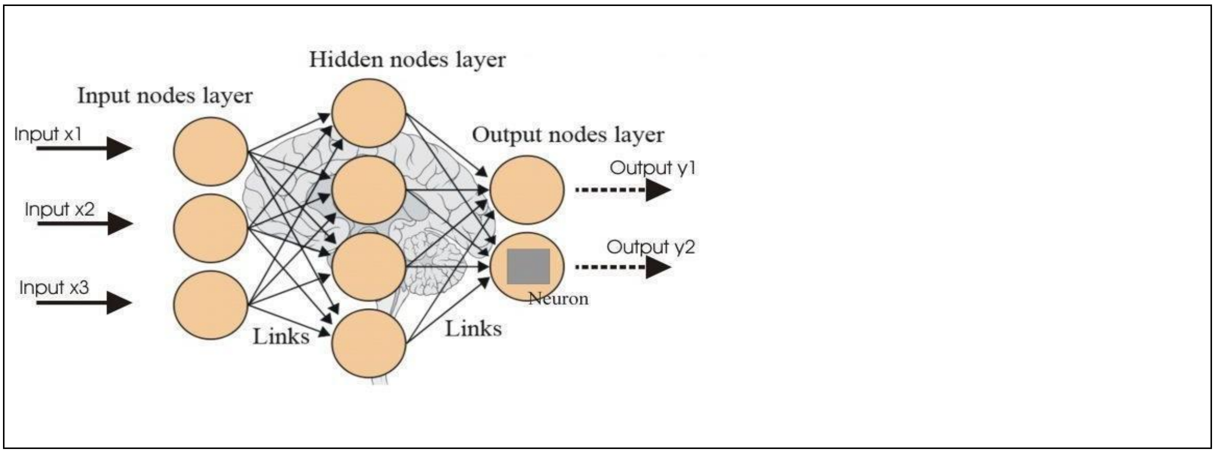

Figure 2. General Model of Neural Network

The first step of the neural network is similar to the decision tree when the retrieving and splitting processes are applied. The next step is data partition; in the training of neural networks, the k-NN operator is applied. Finally, the iterative process works in forwarding propagation and backpropagation of the information used by the layers of neurons. The first phase, forward propagation, occurs when the network is exposed to the training data and the prediction to be calculated. The next backward propagation phase is divided into two phases; propagation and weight update. With this information, the algorithm changes the weights of each connection to reduce the value by a small amount of error function. Usually, after repeating this process for a sufficiently large number of training cycles, the network is converted to a certain point where the calculation error is small. The neural network has learned to make more precise predictions after the iterations by adapting its parameters to the students' data. This study was conducted to determine a model capable of predicting students' performance in their upcoming semester.

Measure of Performance

In this study, the accuracy of the data mining technique was tested using the confusion matrix to describe the performance of those models. The confusion matrix summarises the prediction results on the classification problem by giving insight into the errors being made by the classifier and, most importantly, the types of errors that are made. Figure 3 shows a confusion matrix for a binary classification table with two rows and two columns. This classification table includes true positive (TP) rate, false positive (FP) rate, true negative (TN) rate and false-negative (FN) rate where TP rate is the number of correct predictions that the value is positive and is correctly identified as positive, FP rate is the number of incorrect predictions that the value is positive which is incorrectly identified as positive, TN rate is the number of correct predictions that the value is negative which indicates that it is correctly identified as negative. At the same time, FN is the number of incorrect predictions that the value is negative, which means it is incorrectly identified as negative (Mani et al., 2018). The performance and accuracy of these classifications are tested and validated using sensitivity and specificity. Sensitivity is referred to as TP rate, which is related to the model's ability to identify the positive targets. Specificity or TN rate is related to the model's ability to identify the negative targets. Accuracy is the proportion of the total number of correct predictions. The accuracy value is always between 0 to 100%. The higher the value of accuracy, the better the model's performance.

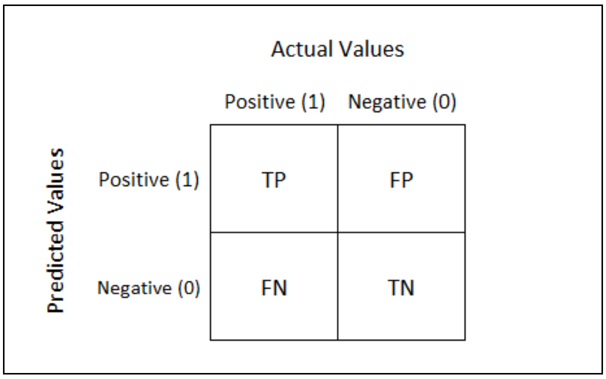

Figure 3. Confusion Matrix for Binary Classification

Besides that, this study also measured precision and recall measurement in measuring the effectiveness of the models. Having better effectiveness could produce a better model performance that can be used for prediction. Precision can be explained as the number of TPs divided by the number of TPs plus FPs. Meanwhile, recall is the ratio of the relevant instances in the dataset by knowing how much it can be predicted correctly and having the same formula as sensitivity. The recall value should be as high as possible, which is close to 1. The effectiveness model can be used when the recall value is very high; it means the model has correctly classified all the values as positive, leading to the decision that the model has low precision. The followings are the formula for calculating sensitivity, specificity, accuracy, recall and precision (Mani et al., 2018).

$$\text{Sensitivity} = \text{Recall} = \frac{TP}{(TP+FN)} \quad (1)$$

$$\text{Specificity} = \frac{TN}{(TP+FN)} \quad (2)$$

$$\text{Accuracy} = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (3)$$

$$\text{Precision} = \frac{TP}{(TP+\rightleftarrows FP)} \quad (4)$$

where TP is the true positive rate, FP is the false positive rate, TN is the true negative rate, and FN is the false-negative rate.

Results and Discussion

This study focused on all UiTM full-time Statistics degree students from UiTM Kelantan, UiTM Negeri Sembilan and UiTM Shah Alam. The majority of the statistics students were female and belonged to the group age of around 18 to 24 years old and above. The highest-grade percentage for English and Additional Mathematics subjects was B+ while grade A recorded the highest grade for Mathematics subjects. For the previous result of SPM, most of the students recorded their current GPA and previous certificate result as between 3.00 and 3.49, with the second-highest academic performance achievement of above 3.50. Most of the students have good background of family information and living as a happy family.

In this study, the prediction of the students' performance was performed using two data mining predictive models: decision tree and neural network. The performance of these two techniques was then compared using the data under study. The accuracy measure was computed for classification tasks with the confusion matrix. A confusion matrix obtained is used to describe the performance of the classification performance, which is to count the number of correctly classified values. From the confusion matrix, precision and recall are obtained. Precision is a measure of exactness, whereas recall is a measure of completeness. Since the confusion matrix has a multi-class classification, precision is calculated as the sum of true positives across all classes divided by the sum of true positives and false positives across all classes. At the same time, recall (also known as sensitivity) is the proportion of actual positives identified correctly. Table 1 shows the precision and recall of the confusion matrix for the decision tree and a neural network consisting of classes from the target variable, GPA.

Table 1
Class Recall and Class Precision of Confusion Matrix

GPA	Decision Tree		Neural Network	
	Class recall	Class precision	Class recall	Class precision
3.00 - 3.49	82.65%	72.97%	60.20%	57.84%
2.50 - 2.99	76.92%	85.71%	28.21	57.89%
Above 3.50	66.67%	74.58%	67.70%	51.69%
Below 2.49	71.43%	100.00%	0.00%	0.00%

The first precision of the decision tree for GPA 3.00 to 3.49 showed that 72.97% was correctly predicted. The class precision for students with GPA 2.50 to 2.99 and above 3.5 was also true with 85.71% and 74.58%, respectively. The last precision showed that the students with GPA below 2.49 were 100% correctly predicted. On the other hand, the class recall for GPA between 3.00 and 3.49 was correctly predicted with 82.65%. The recall value for students predicted to get a GPA between 2.50 and 2.99 was 76.92%, while the recall value for GPA above 3.5 was 66.67%. The last class recall showed that 71.43% of the students were predicted to get a GPA below 2.49. Based on the class precision, the value in the range of 72.97% to 100.00% was considered a high precision value, which means there were very few false positives. The classifier was very strict in classifying the students' GPAs as positive. Overall, the accuracy tells how often the model is in making a correct prediction. Accuracy is calculated based on the confusion matrix as the sum of correct classifications which is divided by the total number of classifications. The best accuracy is 1.0, whereas the worst is 0.0. Since the result showed that the accuracy for the test decision tree was 0.7619, the score of 76.19% for the test set indicated the percentage of the model that is correctly predicted.

Meanwhile, for the neural network, the precision results for GPA between 3.00 and 3.49, between 2.50 and 2.99, above 3.50, and below 2.49 were 57.8%, 57.89%, 51.69% and 0%, respectively. The recall value is calculated as the sum of TP across all classes divided by the sum of TP and FN across all classes. The result of class recall showed that GPA above 3.50 had the highest value with 69.70%, followed by GPA between 3.00 and 3.49 (60.20 %), between 2.50 and 2.99 (28.21%), and below 2.49 with 0%. After running the process and moving to the result perspective, it produced the performance vector with details on the created model performance obtained from RapidMiner. It showed that the model's accuracy by using k-NN with a default on the value of k equal to one was 55.24%.

Table 2 shows the model accuracy checking for decision tree and neural network. The decision tree obtained 0.7619 while the neural network obtained 0.5524 from both confusion matrices. The accuracy value showed how often the model is making a correct prediction; if it obtains the highest value of accuracy, it is the best model. Based on the result, the decision tree showed the model had the best accuracy of 76.1% per cent compared to the neural network, which had 55.24% accuracy. Thus, the decision tree was the most appropriate data mining technique in predicting students' performance for their next semester, March-July 2020.

Table 2
Summary of Model Accuracy Checking for Decision Tree and Neural Network

Data Mining Technique	Accuracy
Decision Tree	76.19%
Neural Network	55.24%

In building the predictive decision tree, the current GPA of the students was used as the response variable. This implies that the study is concerned with predicting the students' upcoming GPA using the existing (current) GPA. Figure 4 shows that the decision tree is overfitted as it becomes incredibly large and complex, making it significantly difficult for the decision tree to be interpreted. From Figure 4, 31 nodes classified the students based on the variables used in this study. This happened because of excessive dependence on irrelevant training data features, which resulted in poor prediction of unseen instances. Overfitting results may cause poor performance in the decision tree. The learning algorithm continues to develop hypotheses that reduce training set error at the cost of an increased test set error. Pruning can reduce the size of decision trees by removing parts of the tree that do not provide power for classifying instances. After a decision tree has been induced, post-pruning can be bought into play by assessing the tree's ability to differentiate classification accurately.

Figure 5 shows the decision tree structure after the pruning process in predicting students' performance. In this study, pre-pruning and post-pruning were applied in performing a pruned decision tree to get better accuracy. Pre-pruning is an alternative method to prevent overfitting by stopping the tree-building process early before it produces leaves with very small samples. Post-pruning is a pruning process that involves cutting back the tree. Based on Figure 5, the important factors in predicting students' performance were identified. It showed that the root node was a previous certificate result known as a predictor variable where it was used for the primary split. It predicted that the students who had previous certificate results between 3.00 to 3.49 did not work as part-timers. In addition, their parental marital status was married and did not prepare well before attending the lecture would get the upcoming GPA between 3.00 3.49. This result contradicted with the students who had better preparation before entering the class as they were predicted to get the upcoming GPA of above 3.50.

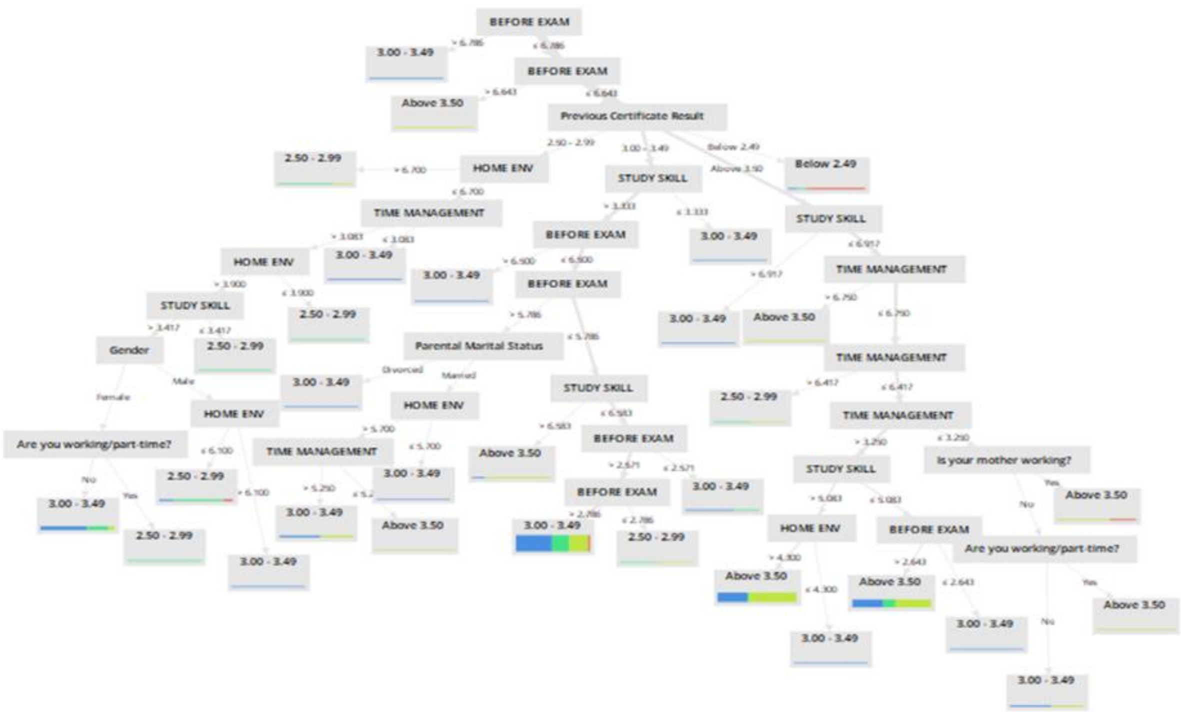

Figure 4. Decision Tree Structure before Pruning Process in Predicting Students' Performance

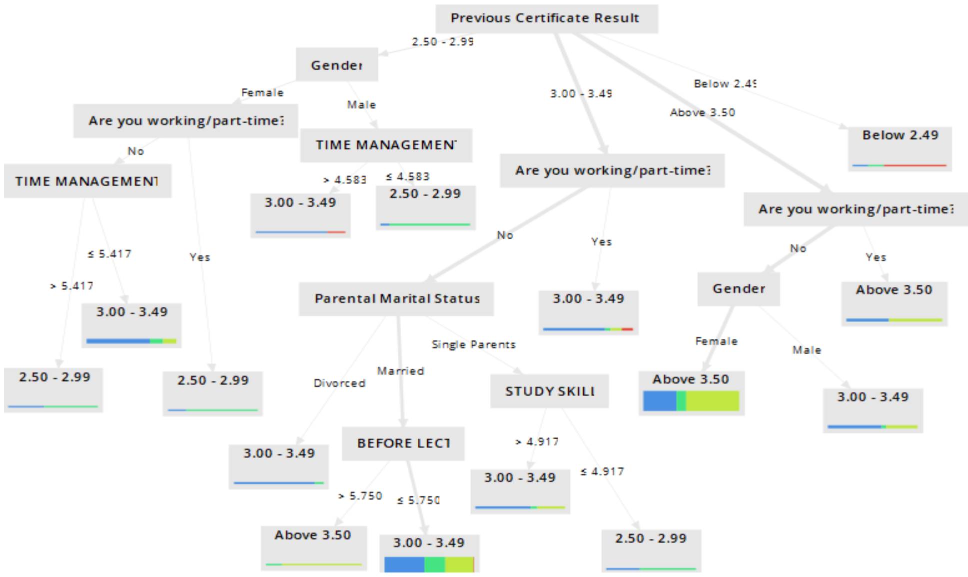

Figure 5. Decision Tree Structure after Pruning Process in Predicting Students' Performance

Next, the students who had previous certificate results of above 3.50 did not work as part timer and female students were predicted to get a good GPA of above 3.50, but male students would get a GPA between 3.00 and 3.49. In addition, students who got GPA below 2.49 for their previous certificate result were predicted to get the same result in their upcoming GPA. However, male students who had previous certificate results between 2.50 and 2.99 could improve their GPA from 3.00 to 3.49 if they have good time management. Pruning reduces the size of the decision tree, reduces the training accuracy and improves the accuracy of the test data. Table 3 shows that the model accuracy improved from 76.19% to 80.95%. Since it had the highest accuracy value, it was the best model to use for prediction. This indicated that the pruned decision tree had 80.94% accuracy in classifying the students. Thus, this clearly showed that the accuracy of the data increased after the decision tree was pruned.

Table 3
Model Accuracy Checking for Decision Tree after Pruning Process

	Accuracy
Unpruned tree	76.19%
Pruned tree	80.95%

Finally, the prediction of GPA for the upcoming semester of September 2020 – February 2021 was conducted using the variables in the decision tree rule. The prediction was made for five randomly selected students, and the results are shown in Table 4. All students except student number 5 were predicted to have changes in their current GPA result for the semester March-July 2020. There was no increase or decrease result for student number 5 as she remained her GPA result with above 3.5 for the upcoming semester. This student's previous certificate result was between 3.00 and 3.49 with married parental marital status and high mean values for time management, prepared before lecture and conducted study skills (between 5.5 and

6.7). Students number 3 and 4 were predicted to improve their GPA, while students 1 and 2 were predicted to worsen their GPA results. Student number 3 was predicted to increase his GPA result for the semester March-July from the current GPA below 2.49 to above 3.50. This student's previous certificate result was above 3.50 with a divorced parent, a high average of prepared before the lecture (6.8) and a low average of time management and study skill. The same case was found for student number 4, where she was predicted to improve her GPA from between 3.00 and 3.49 to above 3.50. Her previous certificate result was between 3.00 and 3.49, divorced parental marital status, a medium average of time management and study skill (between 4.0 and 4.4), and a low average of preparation before the lecture (2.1). However, for student number 1, she was predicted to worsen her GPA from a current GPA of above 3.5 to a GPA below 2.49. This student's previous certificate was below 2.49, with a divorced parent, medium time management and average study skill (between 4.7 and 5.2) and a low average for prepared before the lecture (2.0). The same case was found for student number 2, where he was predicted to get a GPA between 2.50 and 2.99 from his current GPA between 3.00 and 3.49. The student obtained precious certificate results between 2.50 and 2.99, married parental marital status, medium time management, average prepared before the lecture (between 5.1 and 5.3), and low average for study skills.

Table 4
Students' Prediction for GPA result in semester March-July 2020

No	Gender	Status of Working Part-Time	Previous Certificate Result	Parental Marital Status	Time Management	Before Lecture	Study Skill	Current GPA	Prediction GPA
1	Female	No	Below 2.49	Divorced	5.2	2.0	4.7	Above 3.50	Below 2.49
2	Male	Yes	2.50 - 2.99	Married	5.1	5.3	2.0	3.00 - 3.49	2.50 - 2.99
3	Male	No	Above 3.50	Divorced	2.8	6.8	2.1	Below 2.49	Above 3.50
4	Female	Yes	Above 3.50	Divorced	4.0	2.1	4.4	3.00 - 3.49	Above 3.50
5	Female	No	3.00 - 3.49	Married	5.8	5.5	6.7	Above 3.50	Above 3.50

Conclusions

This study used two data mining algorithms on the assessment to predict students' performance and measure a higher performance of accurate model created to evaluate the predictive accuracy model. It was found that the decision tree approach was more accurate compared to the neural network. By applying the decision tree predictive model with the data collected from the questionnaire distributed to the students, it can be concluded that previous certificate results, gender, the status of working part-time, time management, parental marital status, study skills and preparation before lecture were found to affect the students' performance significantly. Thus, based on these significant factors, the prediction of students' academic performance in the upcoming semester was generated, and it can be concluded that the statistics students will get a good result for their next semester with a GPA of 3.00 and above if they know how to manage time, use the right study skills, and prepare before the lecture begins. Besides that, students who do part-time job with parental marital status will affect the GPA result for the next semester. Therefore, the students and the university management should plan a wise strategy by looking at the factors that may influence the students' performance to produce good student results and improve the institution's success.

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