Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

An Artificial Intelligence Approach to Monitor and Predict Student Academic Performance

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ARTICLE INFO

Article history:
Received 29 March 2023
Received in revised form 17 September 2023
Accepted 7 April 2024
Available online 25 April 2024

Keywords:
Prediction Model; Artificial Intelligence; Student's Performance; System Architecture; Education

ABSTRACT

Recent progress in technology has altered the learning behaviours of students. It can easily be said that the improvements in technologies especially from the area of artificial intelligence and data mining can empower students to learn more efficiently, effectively, and contentedly. The purpose of this paper is aimed at developing a prediction model that gives a guide to the stakeholders likes university, student's sponsor and parents that can monitor and interpret the on-going student's performance. The proposed system will help the user to identify students who have a high risk or low risk to ending the semester with unsatisfactory results through discovering the essential features that can influence student's academic performance. The methodology used were mixed method approach which is qualitative and quantitative. For the part of quantitative technique, the data set for this research will be collected from the academic records section. Meanwhile, the part of qualitative will go through a few main stages which are focused on developmental phase. The prediction model used in this research are RepTree, k-NN and Naïve Bayes. The finding states that RepTree had the highest accuracy compared to k-NN and Naïve Bayes techniques. It also suggests that the RepTree algorithm would be the best prediction model which has focused the research in term of developing the system of monitoring students' academic performance at UPTM.

1. Introduction

Students are the main product of any educational institutions. Thus, the students' academic performance is very critical to the most institutions. The capability of educational institution plays an important role in producing high and acceptable quality graduates. Naturally, most educational institutions are trying to maintain high standard of teaching and learning to maintain high quality of graduates and becomes the first choice of new prospective students. Some institutes are more concerned about their prestige as compared to the quality of education [1]. However, most

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https://doi.org/10.37934/araset.44.1.105119

governments have established accreditation agencies to monitor the educational institutes follow strict and high standard of procedures or quality assurance as to maintain high quality learning environment.

The main objective of the institution is to produce high quality graduates. To achieve this objective, the institution must monitor the students' academic performance, by knowing as much as possible information about the student and providing recommended measures to maintain good performance and preventive measure to the problematic students [2]. The instructor may not be able to distinguish the level of students at the start of the course. However, if the struggling students are identified by some means then the instructor can design preventive measures to deal with them. Therefore, sophisticated prediction models are imperative to forecast the performance track of the student and make it possible for the instructor to take care of the struggling students.

From the previous studies, it is determined that machine learning algorithms proved as efficient and productive tools for developing models to monitor and predict the student's academic performance. Different machine-learning types of algorithms such as Naïve Bayes, decision tree, neural networks, detections by outliers and sophisticated statistics have in recent years been used [3]. The existing models are mostly targeted to specific local institution and produce efficient results for a single course. Therefore, the research is going to develop an AI based approach which is a monitoring and prediction model for an academic program taught at UPTM and the branches of MARA poly-techs. It would also to test the accuracy of prediction of the system's prototype to meet the acceptable performance. The purpose of this research is not only to monitor and interpret the on-going student performance, but to develop a prediction model that can guide to the stakeholders to take appropriate measures to counter students' problems.

2. Literature review

2.1 Educational Data Mining

Educational data mining (EDM) was well-known area of research where data will be extracted from the various sources and later to be analysed according to the pattern that user want in educational institution. EDM is concerned with developing methods and analysing educational content to enable better understanding of students' performance [4]. Besides that, the main objective of EDM is to discover new knowledge and hidden pattern exists in student data [3]. Numerous models or techniques have been proposed under the different educational context to address the student performance prediction. According to Asiah *et al.,* [4] in order to build the predictive modelling, there are several tasks used, which are classification, regression and clustering. Among the algorithms used are Bayesian Network (BN), Decision Tree (DT), Artificial Neural Networks (ANN), Naive Bayes (NB), K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) and others [4].

In the recent study, Kausar *et al*., [5], made use of ensemble techniques to examine the relationship between students' semester course and final results. The experimental evaluation concludes Random Forest and Stacking Classifiers with achieving the highest accuracy. Furthermore, Chen and Ward [6] built models with decision tree and linear regression with a set of features extorted from the institution's auto-grading system. The research assists the institution to recognize the struggling students and assign teaching hours automatically in a smart way.

In fact, Hamsa *et al.,* [7] had proposed a decision tree model and fuzzy logic algorithm to discover the essential features which influence students' academic performance. The data related to students' demographic, academic and social behaviour was collected through a survey. Latrellis e*t al.,* [8] also proposed a machine learning approach wherein K-Means algorithm generates a set of coherent clusters and afterward supervised machine learning algorithms are used to train prediction models for predicting students' performance. Other than that, Yaacob *et al*., [9] develop predictive models using classification algorithm to predict student's performance into excellent or non-excellent students depending on the results of their academic performance via educational data mining.

Siddique *et al*., [10] in his research intended to determine the critical factors that affect the performance of students at the secondary level and to build an efficient classification model through the fusion of single and ensemble-based classifiers for the prediction of academic performance. Previously, Kaunang and Rotikan [11] produced several models based on decision tree algorithm over a data containing student's demographics, academic and family background features collected through questionnaires. It is because the roles of features related to demographics, personality traits, socio-economic, and environmental may affect students' performance [12-14].

2.2 Attributes and Methods for Predicting Student's Performance in AI

According to Vijayalakshmi *et al.,* [14] attributes and methods are the factors for predicting student's performance. Figure 1 shows the important attributes used in predicting student's performance. There are ten (10) attributes are formed by grouping common classes. This figure is designed after reviewing literature from various article related to student performance model using data mining technique.

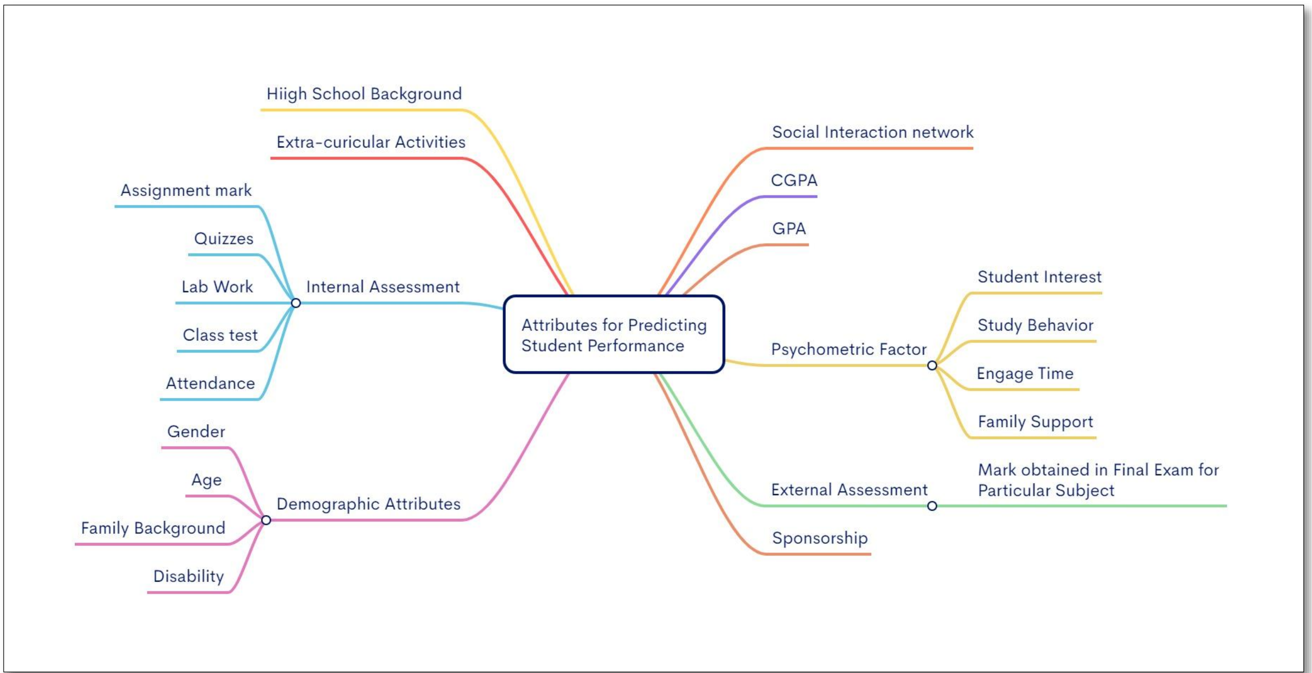

Fig. 1. Classification of Attributes

Based on the graphical representation for classification of attributes above, the research had been conducted by choosing the four (4) common list of attributes which are CGPA, GPA (GPASem1 until GPASem4), demographic attribute (gender) and sponsorship. The result of systematic review had shown that Cumulative Grade Point Average (CGPA) is the attribute that have been frequently used in predicting student performance [24]. While the Grade Point Average (GPA) is a widely used indicator of academic success. Many universities have a minimum GPA requirement that must be met. Consequently, GPA continues to be the most typical element that academic planners consider while assessing students' academic development. Many things could prevent a student from achieving and maintaining a high GPA during their time in college, which measures their overall academic performance. GPA also already being chosen as one of the attributes to monitor and predict student performance in this research.

The next attribute that is used most frequently is student demographic. Gender, age, family history, and disability are all factors in student demographics. While sponsorship also one of the attributes that will become factors for predicting student performance. All those attributes had been chosen based on the raw data that were collected from University Poly Tech Malaysia in Faculty of Computing and Multimedia (FCOM) specifically after considering the pattern that should be valid, novel, potentially useful and understandable.

2.3 Methods

Many algorithms for classification techniques have been used in educational data mining to forecast student achievement. Decision Tree, Naive Bayes, K-Nearest Neighbour, Neural Network and Support Vector Machine are some of the techniques that are most frequently utilized. This research entitled An Artificial Intelligence Approach to Monitor and Predict Student Academic Performance decided to used only three (3) different type of methods or algorithm after doing the systematic literature review regarding the same topic related student performance which are Decision Tree, Naïve Bayes and K-Nearest Neighbour.

2.3.1 Decision Tree

Decision Trees are a well-liked method of prediction. Due to this technique's ease of use and readability, most academics have utilized it to identify tiny or big data structures and forecast values [14]. Furthermore, due to their simple logic and ability to be directly translated into a set of IF-THEN rules, decision tree models are simple to understand [15]. A decision tree was employed as the strategy. Previous research employing the Decision Tree method has been used to predict academic dropout characteristics in student data [15], identify the best career for a student based on their behavioural patterns [15], and forecast MCA students' performance in the third semester.

Besides, decision trees using a top-down, recursive divide-and-conquer method. Due to their functioning properties and growing use as a prediction method in data science, these algorithms utility in identifying useful models. This method has been chosen by several researchers due to its simplicity and adaptability to all sizes of data structures for value estimation. Decision trees can be easily understood because of their tree-like form, which applies classification principles to actual human reasoning [15].

2.3.2 Naïve-Bayes

Naive Bayes is a classification algorithm. It is known as Naive Bayes because the probabilities for each class are calculated in a straightforward manner. The foundation of Naive Bayes classifiers is Bayesian classification techniques. These rely on Bayes' theorem, an equation defining the relationship between conditional probabilities of statistical quantities [16].

2.3.3 IBK (K-Nearest Neighbour)

IBK is a classifier for K-Nearest Neighbour. The development of the classifier requires only minimal effort, and is typically completed concurrently with the classification process, earning it the nickname "lazy learning" technique [17]. To make locating the closest neighbours easier, different search algorithm combinations might be used. In general, linear search is the most widely utilised method, however KD-trees, ball trees, and cover trees are additional viable methods. The distance from the test instance can be used to weight predictions made by taking into account several neighbours, and two separate formulas are then used to translate the distance into the weight [17].

2.3.4 Neural networks

Al Shibli *et al*., [15] mentioned that another well-liked method for data mining in education is neural networks. The fundamental benefit of neural networks is that they can identify all potential interactions between predictor variables [17]. Even in complex nonlinear relationships between dependent and independent variables, neural networks were still able to make a comprehensive detection without a doubt.

The input layer, hidden layer, and output layer are the three layers of a basic neural network. There are various numbers of neurons in each layer. There is no fundamental research on how many hidden layers are sufficient for a network of this type, therefore the hidden layer could be made up of one or two layers. The hidden layers actually define the network's size, which suggests that the larger the network, the longer it will take to train.

The output of one layer serves as the input for the subsequent layer in hidden layers. The transfer function of a neuron transforms the input into the neuron's output. Comparatively speaking to single layer neural networks, multilayer neural networks are much more potent instruments utilised to solve a variety of problems [17].

2.3.5 Support vector machine

Lyn *et al.,* [16] states that support vector machines are supervised machine learning approaches with associated learning methodologies that can be used for regression and classification tasks. With a determined separating hyperplane, it can also be stated to be a discriminative classifier. SVM's ability to simultaneously minimise the empirical classification error and maximise the geometric margin is a key characteristic.

As a result, SVM is sometimes referred to as a maximum margin classifier. The Structural Risk Minimization is the foundation of SVM (SRM). Input vectors from SVM are mapped to a higher-dimensional space, where a maximal separation hyperplane is built. On either side of the hyperplane that divides the data, two parallel hyperplanes are built. The hyperplane that maximizes the separation between the two parallel hyperplanes is known as the separating hyperplane [17].

3. Methodology

The methodology used in this research were mix method approach which is a qualitative and quantitative technique. In part of qualitative approach our research technique as depicted in Figure 2 below that involve four important phases which are user Requirement & specification, design of system architecture, coding & implementation and software or system testing.

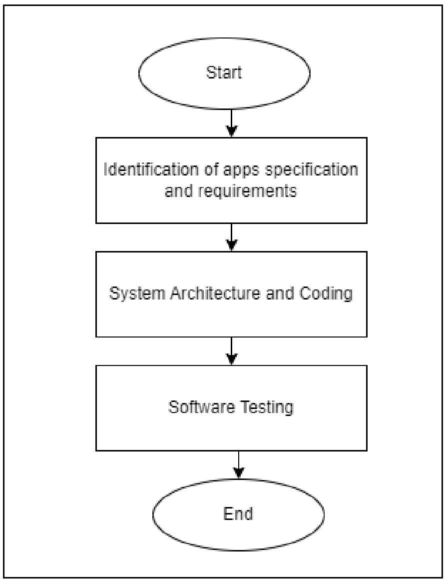

Fig. 2. Qualitative Technique

Based on the Figure 2, the first stage is identification of apps specification and requirement. This stage focuses on doing the Literature Review, understanding, and identifying both the system and mobile apps specification and requirements. This includes understanding the Data Analytics and AI techniques for student's performance analysis and prediction. Also understanding the hardware, tools, and programming requirements for coding the system and mobile application.

Second stage of the qualitative technique which is system architecture and coding focuses on designing for both the system and the mobile application. The flow of the process is quite straight forward. The system keeps the record of student academic progress in secure server. The system has an internal AI based data defining and evaluating module, and the Data Analytic engine which are always ready to produce report, prediction, and suggestion when requested by the stakeholders. The stakeholders may request the system to show student's performance from static or mobile devices anywhere and anytime. Then, the software testing phase will be conducted by using the model that already being identified and tested in real environment.

Meanwhile, the quantitative approach also conducted which is the technique of data preparation and processing were employed. This stage is part of system design but focus to be given on the preparation of the data to the system. The data set for this research will be collected from academic records sections at UPTM and other MARA poly-techs under KPTM. The training data set will cover for three semesters, and we anticipate for more than 150 instances. A such, the data will undergo three stages which is data description, data cleansing and data pre-processing.

Table 1 below shows the data description that consist of features, description, and value for each data set.

Table 1
Data Description of UPTM Students

Features	Description	Value
Gender	Student's gender either male (M) or female (F)	Nominal (M or F)
Sponsorship	Whether sponsored for study by MARA or others either yes (Y) or no (N)	Nominal (Y or N)
GPASem1	Grade Point Average of Student for semester 1	Numeric (0-4)
GPASem2	Grade Point Average of Student for semester 2	Numeric (0-4)
GPASem3	Grade Point Average of Student for semester 3	Numeric (0-4)
GPASem4	Grade Point Average of Student for semester 4	Numeric (0-4)
CGPA	Cumulative Grade Point Average of Student	Numeric (0-4)
Class	Prediction either low, medium or high risk	Nominal (LowRisk, MediumRisk, HighRisk)

Besides that, data Cleansing is the process of removing anomalies such as irrelevant features from the existing data to get an accurate and unique data collection. To deal with inaccurate, inconsistent, and incomplete data as shown in Table 2 below, the information of KUPTM students that consist of irrelevant features will be eradicated.

Table 2
Examples of Noisy Instances in The Dataset

Gender	Sponsorship	GPASem1	GPASem2	GPASem3	GPASem4	CGPA	Class
M	Y	3.78	3.13	3.26	3.06	3.31	LowRisk
M	Y	2.78	1.89	?	2.13	2.57	MediumRisk
M	Y	3.72	3.82	3.15	?	3.46	LowRisk
M	Y	3.83	3.83	3.89	?	3.75	?

The last stage is data pre-processing. The process of data pre-processing will be conducted using Waikato Environment for Knowledge Analysis (WEKA) that have option of "filter". There are two types of filters in WEKA which are supervised and unsupervised. Both categories can filter for attributes and instances separately. WEKA is an open-source software consisting of a wide range of algorithms for data pre-processing, classification, clustering, regression, and association rules. In this research, we selected four widely used machine learning algorithms. From lazy algorithms, we chose k-Nearest Neighbours (k-NN) implemented as IBK in WEKA. RepTree is an implementation of decision tree in WEKA. Similarly, we chose Multilayer Perceptron (MLP) which is a class of Artificial Neural Networks (ANN) and the fourth algorithm which is Naïve Bayes. We employed tenfold cross-validation. In this technique the training dataset is split into 10 identical length intervals. In each cycle, the nine intervals are used for learning purpose and the tenth for testing the algorithm's performance. It is an iterative process, and, in each iteration, a new interval is chosen for testing part.

4. Results and Analysis

The data had been collected from KUPTM academic record that focusing on Faculty of Computing and Multimedia (FCOM) students of program Diploma in Computing Science (CC101). There are 89 data set had been used after the process of filtering and data cleaning. Figure 3 below shows the visualization of all eight (8) instances which are gender, sponsorship, GPASem1, GPASem2, GPASem3, GPASem4 and CGPA and the class of prediction either low, medium or high risk. Figure 3 shows the visualization of all attributes that already being run using WEKA to be analysed.

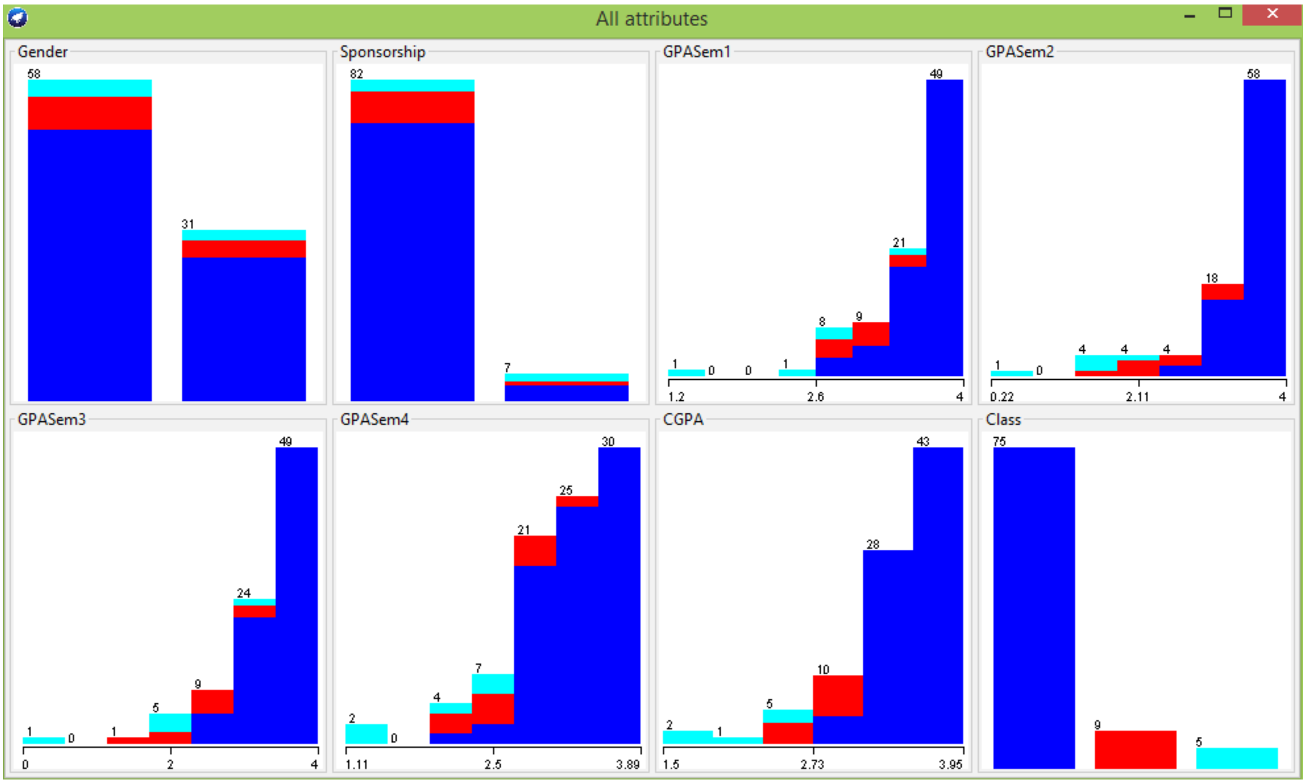

Fig. 3. Visualization of all attributes

The process of filtering and data cleaning had been done successfully by defining the correct data type either numeric or nominal. The unsupervised attribute filter had been applied and the attribute indices set to 3 before filtering. The three (3) different type of classification process used in this research are RepTree, k-NN and Naïve Bayes. The summarization of the accuracy of the instance using Rep Tree was described in Figure 4 below.

```
=== Summary ===

Correctly Classified Instances          85               95.5056 %
Incorrectly Classified Instances         4                4.4944 %
Kappa statistic                          0.8419
Mean absolute error                      0.0308
Root mean squared error                  0.1712
Relative absolute error                 15.8525 %
Root relative squared error             56.1444 %
Total Number of Instances               89

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.987    0.000    1.000      0.987    0.993      0.960    0.992     0.998     LowRisk
                 0.889    0.038    0.727      0.889    0.800      0.780    0.929     0.697     MediumRisk
                 0.600    0.012    0.750      0.600    0.667      0.654    0.794     0.472     HighRisk
Weighted Avg.    0.955    0.004    0.958      0.955    0.955      0.924    0.975     0.938

=== Confusion Matrix ===

  a  b  c   <-- classified as
 74  1  0 |  a = LowRisk
  0  8  1 |  b = MediumRisk
  0  2  3 |  c = HighRisk
```

Fig. 4. Summarization of RepTree Classification Result

The decision tree in Figure 5 uses RepTree algorithm with 10-fold cross validation approach and has shown the prediction accuracy 95.50%. It indicates that the data set are classified as positive value. There is strong significant relation between the CGPA and GPASem3. The result also shows that the Gender, Sponsorship, GPASem1 and GPASem2 has no correlation with dependent variable. The reason why variables such as Gender and Sponsorship shows insignificant because it is not part of the CGPA while GPASem1 and GPASem2 doesn't have strong effect on the CGPA of student. But GPASem3 has a highly significant with CGPA because it is a part of the CGPA.

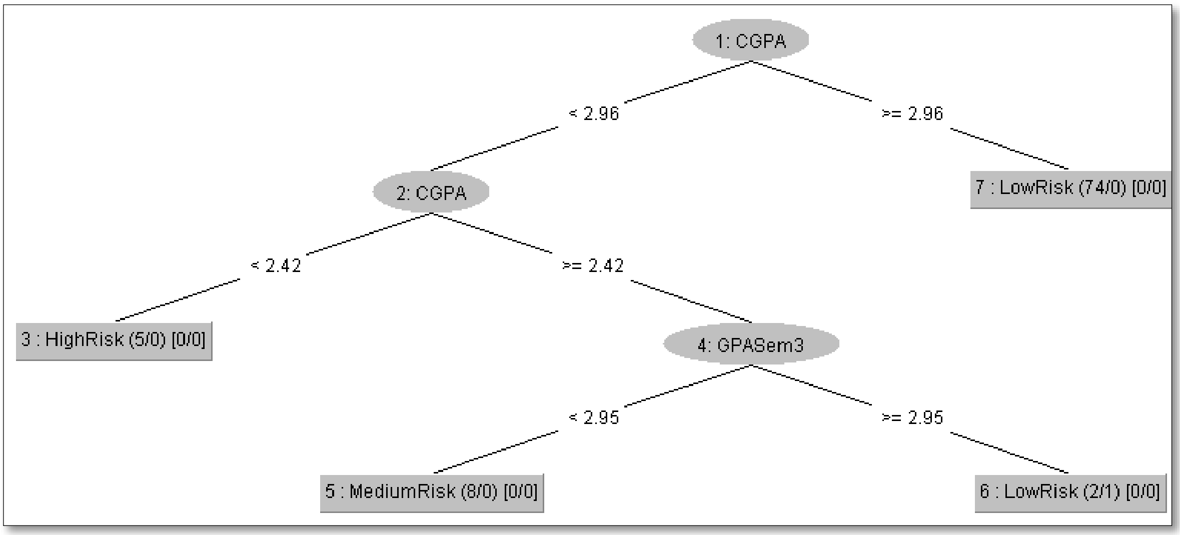

Fig. 5. Visualization of RepTree Algorithm Result

The purpose of prediction accuracy is to make sure that the technique and approach achieved the right measurement. Table 3 shows the prediction between RepTree, k-NN and Naive Bayes. The prediction accuracy of k-NN is 88.76% while Naïve Bayes shows 94.38%. The result shows RepTree had the highest accuracy compared to k-NN and Naïve Bayes.

Table 3
Prediction Accuracy

RepTree Decision Tree	k-NN Lazy Algorithm	Naïve Bayes
95.50%	88.76%	94.38%

Based on the data analysis, the UPTM Student Academic Performance Prediction System will be design and develop. As a result, the design of the system architecture for the system is illustrated as at Figure 6.

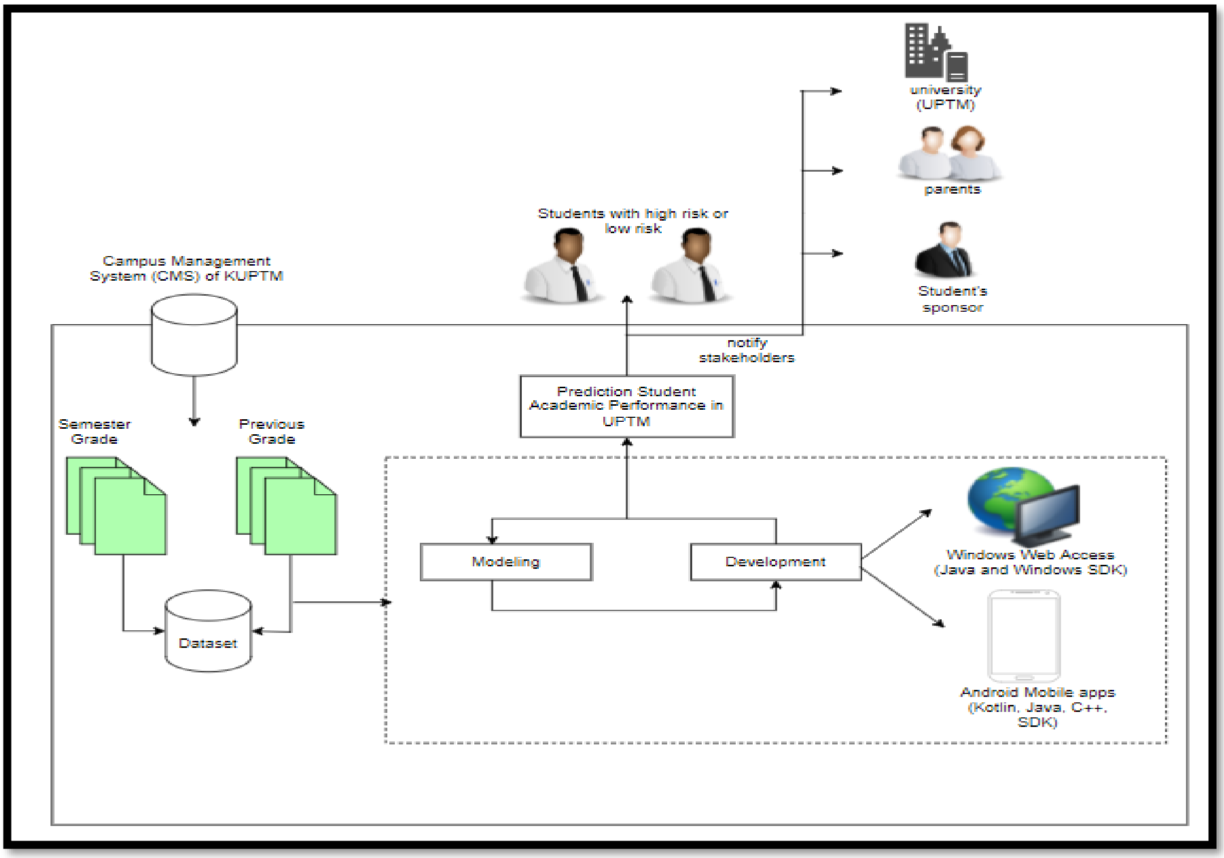

Fig. 6. System Architecture

As for implementation part, the development both for Window web-access and Android mobile apps to access the system model will be conducted. The Window web-access will be written using Java and Window SDK. Meanwhile, for Android apps will be written using Kotlin, Java, and C++ languages.

The model will be tested in real environment for one semester over a class with 25 students. Once exam-1 ended, the model will be executed to identify students in danger of ending the semester with unsatisfactory results.

5. Discussion

The dataset is tested and analysed in WEKA using various kind of classification algorithm such as RepTree Decision Tree, k-NN Lazy Algorithm (IBK) and Naïve Bayes. Those algorithms are verified by 10-fold cross validation check. The results show that RepTree are performing better than Naïve Bayes in term of accuracy, performance, and error. Accuracy of each classifier is shown in Table 4 and Figure 7.

Table 4
Accuracy of Correctly Classification Result

Classification Algorithm	Correctly Classified Instance
RepTree Decision Tree	95.50%
K-NN Lazy Algorithm	88.76%
Naïve Bayes	94.38%

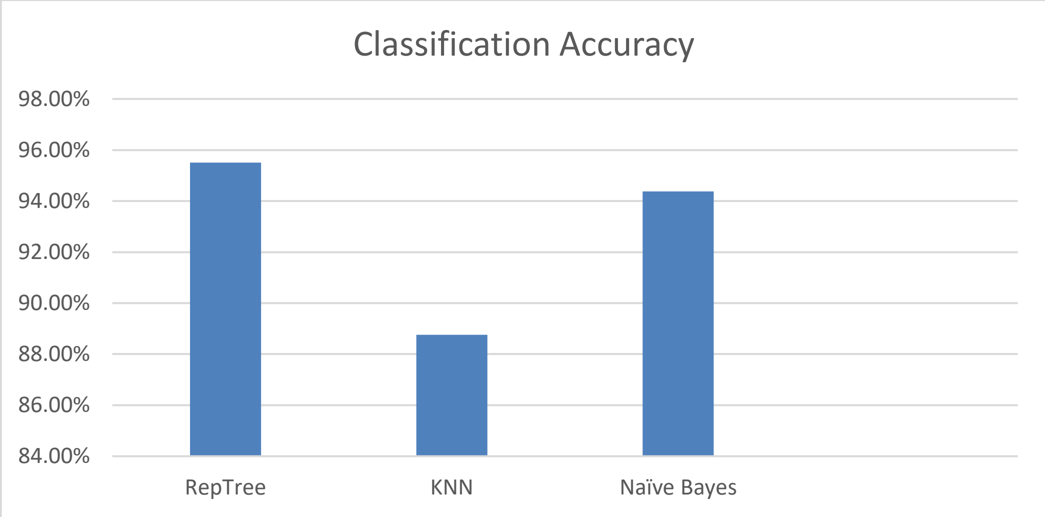

Fig. 7. Graphical of Accuracy

Performance and error are shown in Table 5 and Figure 8 as the result of mean absolute error and root mean squared error.

Table 5
Mean Absolute Error and Root Mean Squared Error of Classification Result

Classification Algorithm	Mean Absolute Error	Root Mean Squared Error
RepTree Decision Tree	0.0308	0.1712
K-NN Lazy Algorithm	0.0882	0.2692
Naïve Bayes	0.0432	0.1872

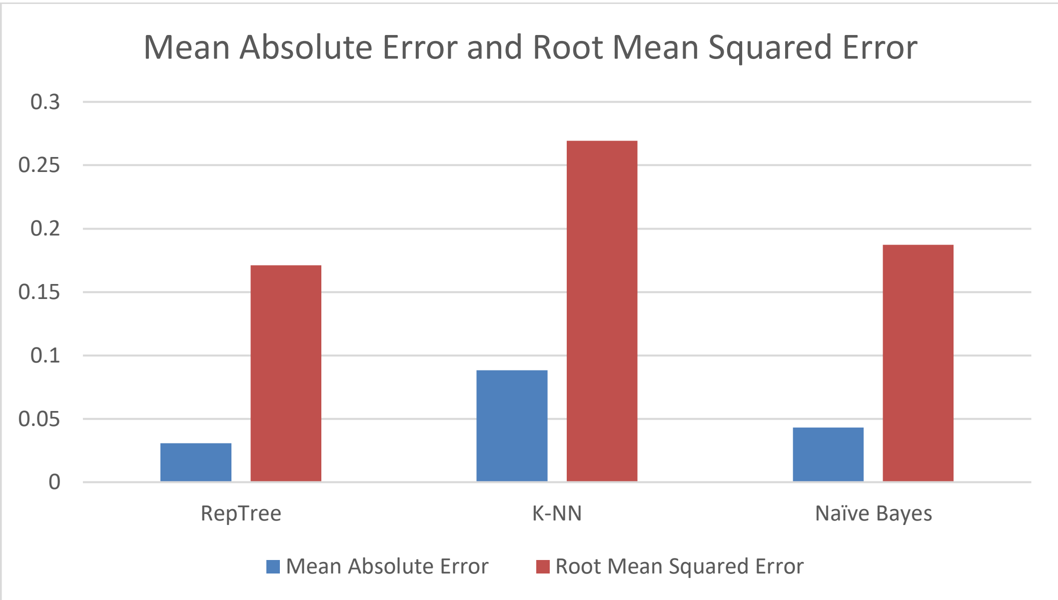

Fig. 8. Graphical of Mean Absolute Error and Root Mean Squared Error

Table 6 shows the confusion matrices for three (3) different type of algorithm which are RepTree, K-NN and Naïve Bayes that describe the performance of the classification models.

Table 6
Confusion Matrices

RepTree Decision Tree			
Actual Values	**Predicted Values**		
	LowRisk	**MediumRisk**	**HighRisk**
LowRisk	74	1	0
MediumRisk	0	8	1
HighRisk	0	2	3
K-NN Lazy Algorithm (IBK)			
Actual Values	**Predicted Values**		
	LowRisk	**MediumRisk**	**HighRisk**
LowRisk	73	2	0
MediumRisk	3	4	2
HighRisk	0	3	2
Naïve Bayes			
Actual Values	**Predicted Values**		
	LowRisk	**MediumRisk**	**HighRisk**
LowRisk	72	3	0
MediumRisk	0	8	1
HighRisk	0	1	4

Based on the result and analysis, the Decision Tree using Rep-Tree algorithm shows the highest accuracy compared with K-Nearest Neighbours and Naive Bayes. Besides, the attributes that influence the student performance also already being identified.

This study's major goals are to monitor student's academic performance, pinpoint those who exhibit poor academic aptitude, and suggest preventative measures. Decision tree model leads in practically all evaluation metrics, according to the models' evaluation. High accuracy demonstrates the system's ability to have the lowest mean absolute error and mean squared error compared to the other two (2) different algorithm. A decision tree's ability to accurately categorise the instances within the classes is demonstrated by a higher correctly classified instance. Figure 9 shows the run information of RepTree Classification using 10 -fold cross-validation and unpruned tree.

```
REPTree
============

CGPA < 2.96
|   CGPA < 2.42 : HighRisk (5/0) [0/0]
|   CGPA >= 2.42
|   |   GPASem3 < 2.95 : MediumRisk (8/0) [0/0]
|   |   GPASem3 >= 2.95 : LowRisk (2/1) [0/0]
CGPA >= 2.96 : LowRisk (74/0) [0/0]

Size of the tree : 7

Time taken to build model: 0 seconds
```

Fig. 9. Run Information of RepTree Classification

A decision tree's ability to accurately categorise the instances within the classes is demonstrated by a higher correctly classified instance. The higher the accuracy the superiority of the decision tree even though the evaluation only reveals a slight difference in the metrics. Additionally, decision tree classifiers offer simple explanations that even average users may understand [18]. As a result, it is recommended to use a decision tree-based model for future analysis.

Decision trees' main benefit is that it is simple to learn and interpret. Based on Figure 9, the decision tree splits the CGPA and GPASem3. The decision tree's rules help the model become further clearer. It demonstrates that CGPA is the most important aspect of students' success, followed by the GPASem3. It demonstrates that students with CGPAs of 2.42 and lower have probability of high risk to graduate on time. Besides, the students having CGPA higher than and equal with 2.42 with GPASem3 less than 2.95 have probability of medium risk. But the result of low risk is based on students having CGPA higher than and equal with 2.42 with GPASem3 more than an equal with 2.95.

The web-based system to monitor and predict the student performance of KUPTM will be developed by implementing the IF-THEN rules that already being identified successfully. The model will execute by transforming it in an easy way to understand procedure and the preventive approach for the students with a poor performance will be designed. As the supportive measures, the output model reveals the GPASem3 as one of the key factors and thus the lecturer especially coordinator program, mentor and subject lecturer should constantly emphasis over its significance. This measure can reduce the number of inefficient students.

In terms of prevention measure, students who are at risk of failing the class will be sent for advising meetings. The instructor is free to schedule interviews with each student and make safety plans that consider their different perspectives. The instructor may also schedule extra classes to help the at-risk students get back on track. The main goals of extra lessons are to motivate the students and review the course material.

6. Conclusions

The research conducted had apply the concepts of Data Mining which is under Classification. Classification Algorithms like Decision Tree, Naïve Bayes and Support Vector Machine can help us for predicting student's performance. The prediction model used in this research are RepTree, k-NN and Naïve Bayes. The result of prediction accuracy of k-NN is 88.76% while Naïve Bayes shows 94.38%. The finding state which is RepTree had the highest accuracy compared to k-NN and Naïve Bayes techniques. It shows that the RepTree algorithm would be the best prediction model which is will focus the research in term of developing the system of monitoring students' academic performance at UPTM. The finding also shows that the RepTree would be the best algorithm compared to other classification method use for prediction model.

Meanwhile, the implementation of the system would apply an artificial intelligent approach which can provide a good model of system for users especially educational institution [19]. This prediction model can help parents and teachers or lecturers to keep track of student's performance and provide required counselling and guidance. The study also can provide analysis which is help in providing scholarship and other required training to the student. As such the educational institution would benefit from the system implementation as it would provide the organization success through the students' performance monitoring and predictions models.

Acknowledgement
This research was funded by URG grant from UPTM-KUPTM.DVCRI.RMC.15 (04).

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