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# APPLICATION OF DECISION TREE ALGORITHM FOR PREDICTING STUDENTS' PERFORMANCE VIA ONLINE LEARNING DURING CORONAVIRUS PANDEMIC

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**ABSTRACT**

The novel coronavirus (SARS-CoV-2) pandemic has resulted in the worldwide closure of educational institutions such as universities. Accordingly, teaching in most countries now takes place remotely via digital platforms. As education moves from conventional to online instruction, student performance is a key concern for management because numerous factors could affect learning. This study proposes to evaluate the attributes of distance learning that could affect student performance and then adopt a classification algorithm to recommend improvements to higher education organizations. The relevant educational data for the algorithm were gathered in the 2020–2021 academic year from student surveys in four classes at the College of Sciences and Arts at Qassim University (Unaizah, Kingdom of Saudi Arabia). The data were then subjected to decision tree analysis, which generated a model based on 66 classification rules. The results of the present study showed that the model developed using data-mining rule-based classifiers is efficient for predicting a student's final course grade. In order to evaluate the accurate of the correctly classified instances; three different classification methods were tested, i.e., Bayes Net-D, naive Bayes, and J48. As a percentage of the correctly identified cases using the three separate algorithms, the overall accuracies of the evaluation results were 90.2439%, 87.8049% and 95.0617 % respectively.

**Keywords:** *Artificial Intelligence, Machine Learning, Classification; Learning; Algorithm, Model; Education*

## 1. INTRODUCTION

Data-mining algorithms have a number of applications, such as in banking, economics, education and communications [1-3]. Currently, in higher education, a variety of data-mining methods and models are being used to evaluate learning [4-7] and strengthen the design of higher education. As a result, researchers [4] have suggested a system to demonstrate how these techniques can improve the quality of conventional methods and data-mining features can be used to improve the model at many stages. In addition, the model was established to serve as a more informative approach to enhance decision-making procedures. The study [5] used the rough set theory of classification to deal with data from the students in the study, and the Rosetta toolbox was used to assess their information to evaluate the quality of their different studying conditions. The examples are explained in plain English. Using a similar system, the research by [6] discussed the results obtained with data from a wide assortment of students who worked on a small selection of tasks. Researchers extracted measurements of academic behavior while writing the program and then found structures or criteria that could be used to maximize student behavior in computer languages, particularly in coding. The results showed that various factors, such as student behavior and the reliability of the code, had little impact on the performance of the student. The approach in [7] is an inspiration for the development of the research method developed in [4] and is used as a reference for the use of machine learning in education. To prove the accuracy of the prediction, one of the sub-measures implemented by [2], the student observation of the programming course, was developed and validated. The method made it easier for managers to predict the students' performance in that particular class.

The dataset related to students that was used in this study was collected in the 2020-2021 academic year. To evaluate and test the proposed model, this study used the Weka machine learning toolkit. The main objective of this study is to use rule-based

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classifiers to investigate students' performance and predict final course grades. The survey provided a plethora of data by which to estimate the performance of students. The classification approach is often used to analyze academic achievement since there are many methodologies used to classify objects. The decision tree strategy is also used in this study. The data collected are limited to students who responded to the survey and who took part in the Operating System (CS 222), Software Engineering (CS 315), Algorithm Analysis and Design (CS 383) and Artificial Intelligence (CS 432) courses at Qassim University, College of Sciences and Arts in Unaizah in 2020.

### 1.1. Purpose of the Study

According to data from the United Nations Educational, Scientific, and Cultural Organization (UNESCO), as of 3 May 2020, nearly 1.2 billion students and youth worldwide had been affected by school and university closures, which accounts for 70% of this social segment globally. This same body examined the impact of university closures and developed a set of arguments to show that it is a phenomenon of extreme urgency. Among the implications of confinement for students are psychological stress, social isolation, difficulty accessing nutrition, and a lack of physical activity.

Progress is important for students in higher education because one of the criteria for a high-quality university is an excellent record of academic achievement, but predicting student progress has become more complex due to the large amount of data in educational databases.

The first objective in this study is to propose a set of attributes to improve the quality of higher education institutions. The second objective is to adopt a classification algorithm to evaluate student data to promote the quality of higher education organizations.

The structure of this paper is as follows: The background and literature review are provided in Section 2; the proposed model is described in Section 3; the experiments and evaluation of this study are discussed in Section 4; and the conclusions are presented in the last section.

## 2. LITERATURE REVIEW

Recently, artificial intelligence procedures have been increasingly applied at various universities [8–12]. According to [11], these use educational data-mining strategies to build viable models to enable managers to enhance student performance. The approach is an integration of clustering and predictive modeling of more than 13 school sessions involving 1,062 graduates. Accuracy, review and score estimation are used to test the approach with the most significant results approaching 96%. [12] These procedures adopted a cluster analysis to divide students based on learning. Test design and training was restricted to Saudi Arabia, but the indications are that the data-mining approach is increasingly being applied to other universities. These studies are founded on empirical testing, such as the clustering algorithm [20], and then applied to a method of analysis, such a decision tree or pattern tracking [11, 13-15].

In [13], three methods (teacher, course and infrastructure) were used to measure features related to a course [16]: institutional support, technology infrastructure, course design, learning process, teacher support, content evaluation and assessment, and learning efficiency. [17, 18] In [19], the statistical method was used to evaluate course, teacher, student and infrastructure factors. The authors [21] discussed how to support teaching and learning by using electronic technology. [22] The researchers proposed a massive open distance-learning course to overcome capacity limitations at universities, [23] and the study provided research tools on educational data mining and learning analysis. [24] This research introduced a comparison framework (BotDetectorFW) based on the classification method to improve detection. [25] Data-mining methods were used to construct a tool to find and filter relevant articles on COVID-19 based on student names. [26] To detect denial-of-service attacks, they suggested using a data-mining technique for various forms of classification algorithms. [27] The study proposed a neural network to enable learning, retrieve information from texts and respond to questions. [28] The study presented the idea of linking SVM notions to Pawlak's rough sets in a single classification system. [29] Deep-learning models are proposed to significantly improve systems based on artificial intelligence. [30] The article suggests a summary of attribution-based post hoc explanations for the analysis and tracking of bias in information. [31] The research has been successfully applied to various sequences of decision-making assignments, machine learning applications and time series predictions.

One popular prediction technique is the decision tree. Due to its simplicity and ability to uncover small or large data structures and predict their value, it has been used by a large number of researchers

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[32-37]. According to [38-45], decision tree models are easy to understand because of their reasoning process, and they can be directly converted into a set of IF–THEN rules. Rule induction is an efficient, accurate prediction strategy. [46-48].

The assessed outcomes about online learning systems are meant to enable management and students to build the framework themselves. The techniques depend on the attributes of the framework, which are applied to explore their feasibility. The characteristics and attributes are generally used to measure online education and collaborative learning factors such as students, teachers, courses and infrastructure. Therefore, this study introduces a set of attributes that evaluate an online learning system from a student performance perspective to predict the final mark of a course in the study. The attributes are divided into four factors: students, courses, teachers and infrastructure.

## 3. THE PROPOSED MODEL

Cross-industry standard process for data mining strategy [49] was being introduced to create a recognized classification model. Fundamentally the technique consists of the following five phases: (1) collecting the relevant characteristics of the problem under investigation; (2) preparing the data; (3) constructing the classification model; (4) evaluating the model using one of the methods of evaluation; (5) and finally, using the student achievement potential prediction model. In the next subsections, these phases are presented.

### 3.1. Description of Influence Factors and Attributes

The features and factors are separated into four groups: Student, Course, Lecturer and Infrastructure. The attributes for the four groups it is shown in Figure 1.

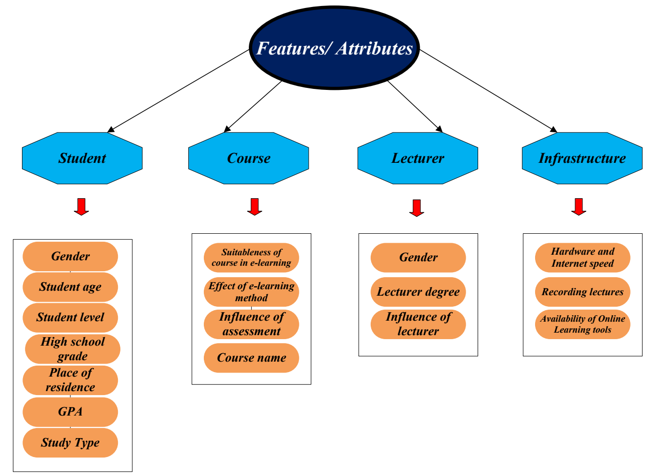


*Figure 1: Influence features and attributes*

### 3.2. Collecting the Relevant Features

In this phase, targeted respondents collected the relevant features among computer science students at the College of Sciences and Arts at Qassim University (Unaizah, Kingdom of Saudi Arabia) who were studying the following courses: Operating System (CS 222), Algorithm Analysis and Design (CS 315), Software Engineering (CS 383) and Artificial Intelligence (CS 432). Initially, 17 features were obtained but some were eliminated since they did not apply to the research. Also removed were irrelevant attributes such as the sex of the student and lecturer and the lecturer's degree. In all, 13 conditional attributes and one class attribute were considered. Table 1 presents a description of the attributes and possible representation values of their attributes. In these four courses, the class attribute was the student grade. The relevant attributes and data views are shown in Figures 2 and 3, respectively.

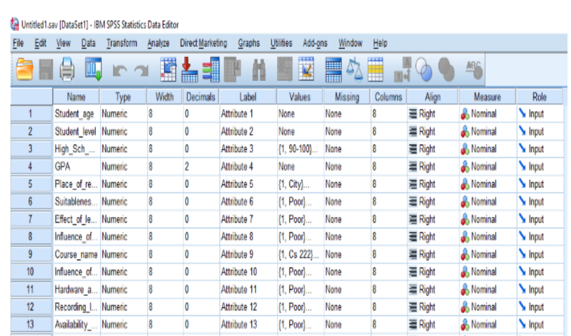

*Figure 2: Relevant attributes*

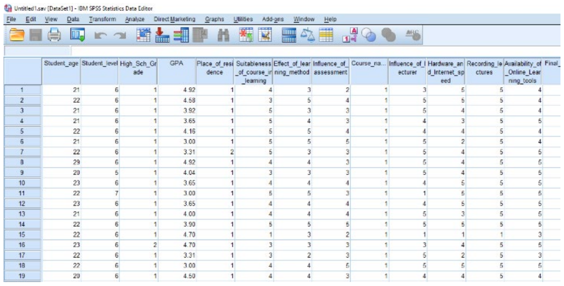

Figure 3: Data view

### 3.3. Preparing the Data and Selecting the Relevant Attributes

For this step, the collected data were organized in tables in a format appropriate for the data-mining algorithms used. In fact, because irrelevant attributes could degrade the proposed classification model, the best set of features was used in this study. In addition, the same standard value was used for all data, and the data were cleaned. Preparing inputs for data-mining research is a major part of the time and energy involved. The Weka system takes inputs in an attribute-relation file format (ARFF). Figure 4 shows an ARFF, and Table 1 shows the symbolic attribute description. Finally, the list of the most relevant attributes comprised the following: GPA, recorded lectures, high-school grade, lecturer influence, e-learning method effect, assessment influence, hardware and internet speed, online learning tool availability, e-learning course suitability, place of residence, course name, student age and student level.

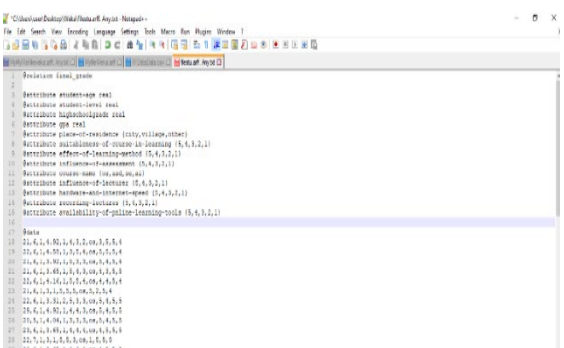

Figure 4: The Attribute-Relation File Format

For the attributes (Influence of lecturer, Suitableness of course in e-learning, Effect of e-learning method, Influence of assessment, Hardware and Internet speed, Recording lectures and Availability of Online Learning tools) the possible values are ( 1=Poor, 2=Below average, 3= Average, 4= Good, 5= Excellent).

*Table 1: The symploic attribute description*

| No | Attribute | Description | Possible Values |
|---|---|---|---|
| 1 | SF1 | Student age | Integer |
| 2 | SF2 | Student level | Integer |
| 3 | SF3 | High school Grade | 1 (90-100), 2 (80-89) 3 (70-79), 4 (other) |
| 4 | SF4 | Place of residence | City =1, Village =2, Other =3 |
| 5 | SF5 | GPA | 1=4-5, 2=3-3.99, 3=other |
| 6 | LF6 | Influence of lecturer | 1 to 5 (5 highest) |
| 7 | CF7 | Suitableness of course in e-learning | 1 to 5 (5 highest) |
| 8 | CF8 | Effect of e-learning method | 1 to 5 (5 highest) |
| 9 | CF9 | Influence of assessment | 1 to 5 (5 highest) |
| 10 | CF10 | Course Name and No | CS 222 =1, CS 315 =2, CS 383=3 CS 432=4 |
| 11 | IF11 | Hardware and Internet speed | 1 to 5 (5 highest) |
| 12 | IF12 | Recording lectures | 1 to 5 (5 highest) |
| 13 | IF13 | Availability of Online Learning tools | 1 to 5 (5 highest) |

Notes: * Course Grade: 1= 90-100, 2= 80-89, 3= 70-79, 4= other

For some cases, attribute datatypes must be changed to numeric attributes, although some AI algorithms are proficient in handling small datasets [50]. A multilayer perceptron artificial neural network requires numerical attributes for calculations [51-55]. Furthermore, the support vector machine algorithm, which was also utilized, was intended to use numerical attributes. In addition, as best practice for managing the multilayer perceptron neural network algorithm, attributes should also be in a standardized numerical form for the best classification results.

### 3.4. Building the Classification Model

The next goal was to use the decision tree technique to develop the classification model. It is an excellent and practical method as it is moderately quick and can easily be transformed into simple classification algorithms. The decision tree strategy relies primarily upon the use of the information gain index, which determines if the attribute is usually more valuable. The information gain relies upon the entropy measure. To build it, the decision tree was based on the gain ratio, which ranks and locates each attribute. The GPA was the attribute with the highest gain ratio and was considered to be the root node. This method was repeated for the remaining attributes, and a set of rules was generated by pursuing all the paths, meaning that the decision tree generated 66 classification rules. A few of the results are given in context in Table 2. The first column is the rule number; the second column is the generated rules; the third gives the number of students who successfully complied with the rules; and the last column shows the number of attributes included in a given rule. The table presents the rules in descending order depending on the number of the attributes in the rule. For the generated rules, the longest rule consisted of 10 attributes, while the shortest contained only 3. To achieve the goals set by this study, a system that facilitated using the generated rules was built to allow students to predict the final grade in the target courses (operating system, algorithm analysis and design, software engineering or artificial intelligence). Figures 5, 6 and 7 show the preprocess for some of the attributes.

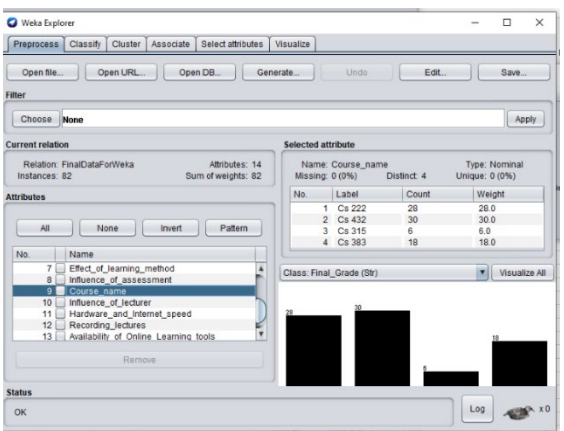


Figure 5: Preprocess Weka explorer for course name attribute

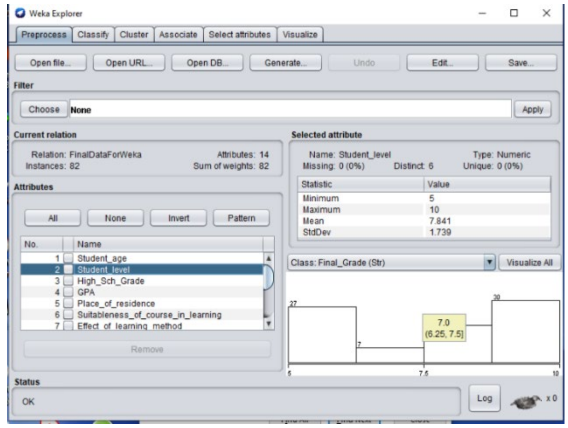


Figure 6: Preprocess Weka explorer for the student level attribute

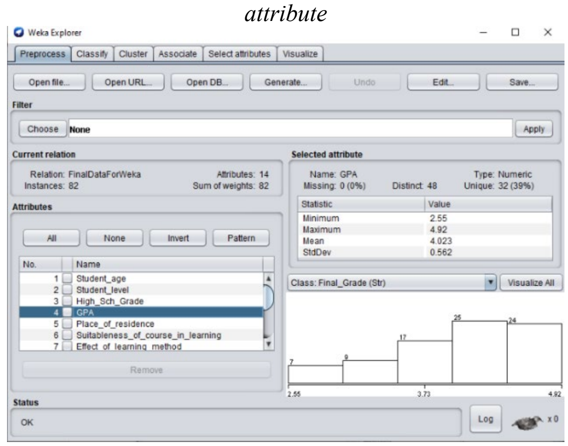


Figure 7: Preprocess Weka explorer for GPA attribute

Some of the discovered interesting rules are:

- IF GPA was A and hardware and internet speed is 3 and Place of residence is 1 or 2 then the predicted grade in the CS 315 course is C.
- IF Student level is 7 and GPA was A, and Influence of assessment is 2 or 3 and Recording lectures is 3 then the predicted grade in the CS 383 course is B.
- The influence of lecturer is 4, and the hardware and internet speed is 5 and High school grade is B and course assessment is 3, then the predicted grade in CS 383 is A.
- IF the GPA is A and Suitableness of course in e-learning is 4 and Influence of assessment is 2 and Recording lectures is 4 and Availability of Online Learning tools 3 and Influence of lecturer is 3 or 4 and course name is CS 432 then the predicted grade is A.
- IF the Suitableness of course in e-learning is > 3.5 and Influence of assessment is > 3 and Recording lectures is 3 and Availability of Online Learning tools 2 and Influence of lecturer is > 3 then the predicted grade in course name is CS 432 is A.

- IF the High school grade is B and Suitableness of course in e-learning is 4 and Influence of lecturer is 5 and Influence of assessment is 3 or 4 and Recording lectures is 3 and student level 9 is Availability of Online Learning tools 3 and GPA is B and Effect of e-learning method is 3 and the Place of residence is (1) city the course name is Cs 432 then the predicted grade is B.
- IF the Availability of Online Learning tools 4 and Suitableness of course in e-learning is 2 and Influence of lecturer is 2 and Influence of assessment is 4 and recording lectures is 4 and is and Influence of and course name is CS 315 then the predicted grade is C.

*Table 2: Sample of the generated rules*

| Rule No | Rules | Instance | No of attributes |
|---|---|---|---|
| 1 | IF the high school grade is B and Suitableness of course in e-learning is 4 and Influence of lecturer is 5 and Influence of assessment is 3 or 4 and Recording lectures is 3 and student level 9 is Availability of Online Learning tools 3 and GPA is B and Effect of e-learning method is 3 and the Place of residence is (1) city and Student age 22 or 23 then the predicted grade in Cs 432 course is B. | 17 | 10 |
| 2 | IF the high school grade is A and Suitableness of course in e-learning is 3 and Influence of lecturer is 2 and Influence of assessment is 1 or 2 and Recording lectures is 2 and student level 5 or 6 and is Availability of Online Learning tools 2 and GPA is A and Effect of e-learning method is 2 then the predicted grade in Cs 222 is C. | 11 | 9 |
| 3 | IF the availability of online learning tools 4 and suitableness of course in e-learning is 2 and Influence of lecturer is 2 and Influence of assessment is 4 and recording lectures is 4 and is Influence of and GPA is B then the predicted grade in Cs 315 course is C. | 14 | 6 |
| 4 | IF the GPA is A or B and Influence of lecturer is 4 and Influence of assessment is 3 or 4 and Recording lectures is 4 and is Availability of Online Learning tools 4 then the predicted grade in Cs 383 is B. | 6 | 5 |
| 5 | The influence of lecturer is 4, and the hardware and internet speed is 5 and High school grade is B and course assessment is 3, then the predicted grade in CS 383 is A. | 7 | 4 |
| 6 | IF GPA was A and hardware and internet speed is 3 and Place of residence is 1 or 2 then the predicted grade in the CS 315 course is C. | 4 | 3 |

## 4. EXPERIMENT AND EVALUATION

Predicting performance is essential for helping students and assuring their retention as well as improving the university's rank and the management of learning resources. Obviously, predicting student performance in each course is essential for helping students because it generates solutions for the difficulties they encounter and helps students overcome them.

This study also examined the potential of recognizing the important characteristics of a small dataset that was used to create a prediction model using a decision tree and a classification algorithm. For a more accurate model, we used several machine learning algorithms to evaluate the key indicators. Among the algorithms selected, the classification algorithm was able to identify key indicators in small datasets. The main results of this study demonstrated the effectiveness of using data-mining algorithms and machine learning to analyze data, train small dataset sizes, reach an acceptable accuracy rate and ensure a highly reliable analysis rate. Importantly, we also demonstrated the efficacy of using them to analyze and train a small dataset and to produce an acceptable classification with accurate and reliable test rates. To study the performance of the classification algorithm on the test dataset, the accuracy or error rate of the classification was usually used. The accuracy of the classifiers was

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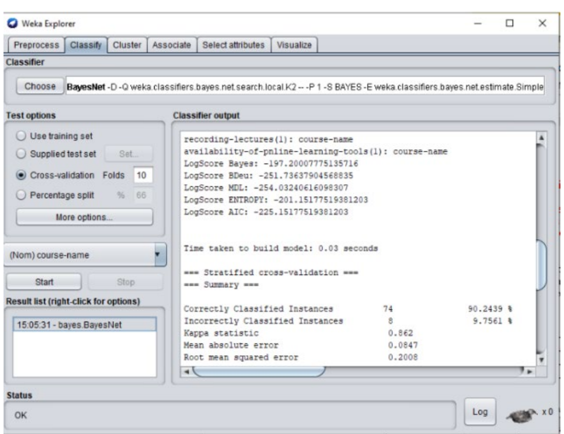
processed from the testing dataset, where it could be used to evaluate the overall display of different classifiers in the same domain. However, the class labels of the test records also needed to be identified, and the assessment methodology was expected to assess the order of the classification and process its accuracy.

This study aimed to answer the following questions: What is the best machine learning classification model for predicting a student's grade with a fair and meaningful accuracy rate using a limited dataset size? What are the most important attributes that could assist in the design of a classification model for predicting students' grades?

The Weka software was used to obtain the reliability of the study model. Three different classification methods were tested: BayesNet-D, NativeBayes and J48. The evaluation results of the proposed model are shown in Table 3, which illustrates the percentage of correct classifications. Figures 8, 9 and 10 show samples of the classification results, particularly the methods, classifier output and test option.

*Table 3: Classification accuracy of the 3 different algorithms*

| Algorithm | Cross-validation folds 10 | Percentage split 66% |
|---|---|---|
| BayesNet-D | 90.2439% | 89.2857% |
| NativeBayes | 87.8049% | 78.5714% |
| J48 | 95.0617 % | 92.8571% |



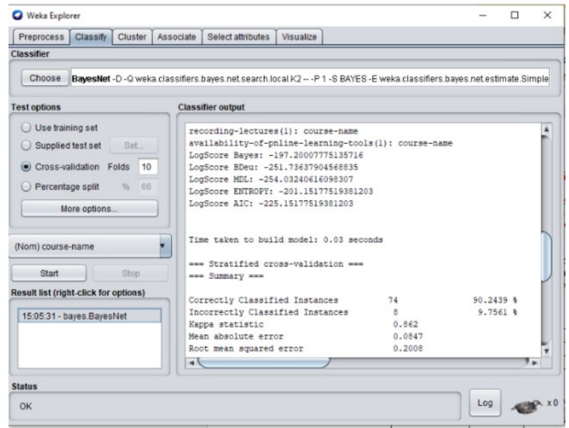
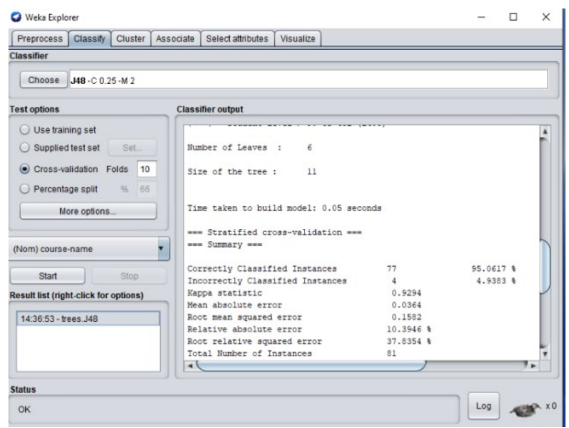


*Figure 9: NativeBayes cross-validation folds*



## 5. LIMITATION AND CONSTRAINTS

There are inherent limitations when fitting machine learning models to smaller datasets. As training datasets become smaller, the models have fewer examples to learn from, which increases the risk of overfitting.

## 6. CONCLUSIONS

Due to the SARS-CoV-2 pandemic and the respiratory disease COVID-19, most higher education institutes have become more concerned about student course performance. Therefore, predicting student performance is extremely valuable in helping institutions to retain students, improving their university ranking and managing learning resources. Obviously, predicting academic achievement could also help students identify and manage their educational difficulties. The aim of this study was to use a data-mining application to observe academic achievement data and to improve educational performance. Managers of higher education should use the classification model to improve course outcomes and draw up plans to enhance student performance. The information extracted by the data-mining algorithm in this study (the classification model) provided a better understanding of the student enrolment structure in the course and of the judgment of the higher education institution regarding the action needed to provide expertise, training and advice.

On the other hand, the rules generated from the proposed model and patterns allows the institutions' managers and management systems to update and improve their decisions, policies and methods, thereby enhancing the effectiveness of the control system. In addition, the managers of the educational system can improve their arrangements, upgrade their methodologies, and improve the nature of the board framework by using this knowledge. One of the most interesting proposals is collecting data about student learning from the university student database, which contains academic data for students, including personal information and data on enrolment, courses, grades and degrees. Furthermore, several classification methods can be used to validate the most appropriate method to suit students' data and to improve the accuracy of the classification. In conclusion, this study proposed a set of features and attributes to support the improvement of the quality of higher education organizations by evaluating student data to investigate the most affected attributes of student course performances. In this study, data from students were assessed for the attributes most affected by this situation and a set of features and attributes was identified which can be used for improving the quality of distance learning. Advancements in technology have a rapid impact on every field of life, whether it be educational or some other field. By analyzing the data, artificial intelligence has demonstrated promising outcomes in decision-making.

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