Using Data Mining Techniques to Predict Students' Performance. a Review

N D Lynn* and A W R Emanuel

Magister Informatika, Universitas Atma Jaya Yogyakarta, Indonesia

Abstract. Predicting students' performance is an essential activity towards the success of the world's education sector. However, the action continues to present itself as a challenging task due to the existing large data amounts in educational databases. On the other hand, some institutions lack systems that are capable of analyzing and monitoring students' performance. This problem could be partially due to a lack of awareness about the importance of predicting students' performance. In addition to that, the existing studies on performance prediction methods are still inadequate in identifying and convincing educators with the most suitable method for predicting students' performance. This review explores the commonly used data mining techniques to predict students' performance in previous studies to find out the most suitable technology that can be trusted with predicting students' performance. The result of the study showed that the decision trees algorithm is the best classification technique that gives trusted and accurate results when it comes to student performance prediction. Predicting students' performance helps in monitoring the students' progress, both pass and fail, and therefore provides a gap for early interventions and decision making by educators. This opportunity dramatically helps in promoting the education sector by raising the academic standards of educational Institutions.

1. Introduction
Throughout the study life of students, performance is one of the most critical aspects of their success. This condition is because usually, performance is an essential part of learning from junior school to higher institutions of learning. Providing quality education to students requires continuous monitoring of learning and teaching activities in an education environment. However, this tends to be difficult because of large amounts of data in educational databases. Nevertheless, the new technology of big data and machine learning comes in to solve all these problems. Big data is a set of methods and techniques that necessitate a new form of combinations to find large hidden values from various complex datasets on a considerable scale. This technology is very advantageous in a way that it can determine the patterns obtained from data analysis to understand hidden information and ease decision making [1], [2].

Currently, many methods have been proposed by researchers to evaluate the performance of students in the education field. However, one of the most recently popular proposed and applied procedures to predict the performance of students is data mining. This method has several advantages; for example, data mining techniques can be used in e-learning since it is easy to access students' log data, and automatic data analysis can be done [3]. In big data and machine learning technology, the application of data mining in the education domain is known as 'education data mining' (EDM). This aims at converting education data into very useful information which brings a positive impact to the education sector and
promotes research practices such as predicting student performance [4]. Performance prediction can help strengthen the education sector and assist responsible leaders in providing practical teaching approaches, thus encouraging higher achievements since student performance is monitored right from the early stages of education. Therefore, students are also equipped with the understanding and improving their learning activities to avoid risks such as school dropouts, poor performance, and failure to graduate. To ease the process of students’ performance prediction, we propose a systematic review to help us achieve this study's objectives that are;
1. To identify the commonly used methods to predict student performance.
2. To find out the most suitable method for student performance prediction among the commonly used methods.

2. Literature review

2.1. General applications of data mining
Analyzing large amounts of data is a necessity. Presently, data mining continues to achieve significant success in many areas of human activities such as medicine, business, and robotics. It is, therefore, beneficial to all Institutions and enterprises of all kinds to collect and analyze their data. With proper analysis, administrators in health sectors can learn trends and identify issues that come up in the patients' records, find ways of managing the hospital's human resources better and enhance the performance of hospital staff [5], [6]. In addition to that, nowadays, the technology of big data gives a chance to professional health workers to screen and predict mental illness [7], derive essential health trends, and support timely preventive care [8]. With the significant increase of data in the agricultural domain, data mining is the only capable technology employed to transform agriculture into smart agriculture [9],[10],[11].

Data mining technology can also be employed to monitor energy consumption of household appliances thorough monitoring of electricity consumption patterns (ECPs) and their relationship with household features, thereby economizing the electricity consumption in residential areas [12], [13]. The technology of machine learning and data mining can be applied in cyber-manufacturing systems to detect and effectively manage cyber security and computer network intrusions by using big data tools [14], [15]. In addition to the above, the technique of data mining can be useful for financial firms to correct their material incase of an inaccuracy. Applying algorithms such as SVM, naive bayes, and ANN on financial data gives an easy way of revising past published financial statements [16], [17]. Big data applications can be also used to spot trends in blogs and understand the similarities and differences in social media messages to make an easy way of operation for online businesses to operate [18].

2.2. Data mining in education
Several researchers have been successful in doing their researches about data mining applications in education, and this can be witnessed by following previous reviews about educational data mining [4], [19], [20], [21], [22], [23]. In the studies, different data mining techniques are employed to support various activities in the education field. The aspects supported include predicting dropout of students [24], predicting cognitive skills of students in an education environment [25], predicting at-risk students [26], and slow learners [27], predicting student course selection [28], and career choices [29], student retention management [30], and predicting student performance [31], [32], [33].

However, among these aspects, predicting students' performance tends to be one of the most important and useful concepts in educational data mining. Student performance prediction involves estimating an unknown value, which is the student's score or mark [34]. This review, therefore, bases itself on student performance prediction as a crucial activity involved in educational data mining. The next section shows the research methodology, research questionnaire criteria, and research strategy, and then continues the survey to determine the results that will reach the objectives of the study as well as answer the research questions to make the research study valid.
3. Research methodology
This paper uses a 'systematic review' protocol to summarize existing information about predicting student performance clearly and systematically. Systematic reviews involve three phases, i.e., planning, conducting, and reporting the analysis [35].

This systematic review aims to support research questions, fulfill the gaps in previous related studies, and find out the most suitable and trusted method for predicting student performance while placing a new research work in the appropriate setting. Next, research questions were identified to lead to the intended results of the study.

3.1. The research questions
For any researcher to carry out a systematic review, it is essential to include research questions as they are always helpful in identifying the scope of the study. To formulate research questions for this study, the researchers followed the steps suggested by Kitchenham to structure the right research questions [35]. Kitchenham recommends considering questions from three viewpoints; that is, population, intervention, and outcomes. In this study; (1) population used was university students (2) intervention ie; data mining methods for student performance prediction (3) Outcomes measures and results ie; trusted prediction method, accuracy of performance prediction, and reduced student failure to graduate.

The research questions formulated for this study were:
Q1: What are the most commonly used methods in students' performance prediction?
Q3: Which one is the most suitable method for students' performance prediction among the commonly used methods?

3.2. The search strategy
In this study, the search strategy was used to search for related studies, using search terms and resources to be searched. This systematic review used search terms suggested and developed by Kitchenham in generating a search strategy [35]. The search strings obtained for this study were as follows: (students' performance) AND (techniques OR methods OR applications OR systems OR processes OR methodologies OR procedures) AND (educational data mining) AND (prediction OR estimation).

The search strategy of this study contains resources like searched databases of Science Direct, Springer and IEEE Xplore, Google Scholar, and ResearchGate. Other sources include backtracking of relevant References from the selected review articles and primary studies, conference proceedings, and the internet. Search items were mainly Journal articles and conference papers. The authors also applied a full search on the full text to avoid excluding related studies that did not have the main search strings in their titles. The papers and articles considered in this review were of publication period between 2010-2020.

3.3. Student performance prediction
Student performance prediction consists of identifying an unknown mark of a student [36]. However, some factors can affect students' performance, making this task challenging to accomplish. The elements may include the economic status of a student, demographic characteristics, students' psychological profiles, past scholar experiences, different cultural backgrounds, and interactions between fellow students [37]. Despite the above, for any institution to carry out a right performance prediction, majorly, they must first identify the risk factors that may affect prediction results. All educational institutions should always answer this critical question before taking prediction steps; "What are the important risk factors or variables for predicting student performance?"

These risk factors may include employed student performance prediction methods, and the data sets considered to obtain prediction results. The data sets may include attributes of the previous semester grade, gender, attendance, GPA, parents' education, parents' income, scholarship, first child, etc. Different Institutions consider different data sets to predict student performance. However, diverse data sets work well with varying methods of prediction.
Therefore, the predicted results may vary depending on the techniques used. Although these factors that affect prediction results are apparent, some variables may be delicate and difficult to understand and identify without applying a more sophisticated analysis. Therefore, using modern data mining techniques such as decision trees, naive bayes, and neural networks may accurately predict student performance (pass/fail) compared to other current models. The results from accurate predictions can help Institutions to attain quality education. Below, the conventional methods used for predicting student performance.

3.4. Conventional methods used for predicting student performance
The process of predictive modeling or predictive analytics are employed in educational data mining to predict outcomes, i.e., it is used in predicting the performance of students. In this domain, predictive analytics acts as an effective process that decision-makers and institution heads may use to optimize the limited resources and plan their Institution strategy and policy effectively [38], [30].

However, building predictive modeling requires the use of different tasks, such as categorization, regression, and classification. Among all these tasks involved in predictive modeling, classification is the most commonly used task for student performance prediction. Classification uses several algorithms to perform this task of student performance prediction. The algorithms include naive bayes, decision trees, support vector machine, and artificial neural networks. The most frequently used data mining methods for student performance grouped by their algorithms are explained in detail below.

3.4.1. Neural networks. Neural network is a biologically inspired analytical method capable of modeling extremely complex nonlinear functions. Neural networks are part of the popularly employed algorithms in the education domain for student performance prediction. ANN is mostly desired because it can classify patterns without requiring any training. Being inherently parallel and thus able to speed up the computational process makes ANN suitable for prediction activities in the educational data mining domain.

3.4.2. Decision trees. Decision trees are a classification approach that works by constructing decision trees following a top-down recursive divide-and-conquer way. These algorithms are increasingly becoming a well-known prediction approach in data science due to their working characteristics and usefulness in discovering useful models [30]. Some researchers have opted for this method due to its ease and ability to use all size data structures to estimate values [39]. Decision trees are easy to interpret because their tree-like structure brings the classification rules to real-life human reasoning [40].

Some researchers used a decision tree algorithm to show the impact of data mining technology in education by predicting the dropout students [39], segmenting students according to their performances [41], student retention management [30], and predicting drop out of students [42]. In a particular prediction study, bagged trees, adaptive boosting trees, and random forests attained an accuracy of 88.7%, 95.7%, and 96.1%, respectively [41].

3.4.3. Naive bayes. The naive bayes method is a supervised classifier that bases on applying the bayes' theorem with strong naive independence assumptions between the explanatory variables and uses two simplifications where one uses the conditional independence assumption and the other ignores the denominator [43]. This algorithm is also one of the commonly preferred methods by researchers to carry out prediction activities since it learns fast, predicts equally, and does not need ample storage.

3.4.4. K-nearest neighbor. K-nearest-neighbor classifiers are an analogy-based algorithm that learns by comparing themselves with similarly given test training tuples. The algorithms can be employed in numeric predictions to return a real-valued forecast for an unidentified tuple. The algorithm, therefore, restores the reasonable value associated with the k-nearest neighbors of the unidentified tuple. When used for student performance prediction, KNN gave good results [20], [44].
3.4.5. **Support vector machine (SVM).** This algorithm is a classification technique for linear and nonlinear data. In the SVM supervised learning method, the original training data is transformed into a higher dimension using nonlinear mapping. SVM algorithm takes long training time but has a high accuracy and ability to perform excellently with small data sets as well as predict at-risk and marginal students [26]. Table 1 summarizes the prediction accuracy of artificial neural networks, decision trees, naive bayes, k-nearest neighbor, and support vector machine.

**Table 1.** Prediction accuracy results with the commonly used methods.

| Artificial neural networks | Decision trees | Naive bayes | K-nearest neighbor | Support vector machine |
|---------------------------|---------------|-------------|-------------------|------------------------|
| Accuracy                  | Citation      | Accuracy    | Citation          | Accuracy               | Citation      | Accuracy    | Citation      |
| 79.85%                    | [30]          | 91.5%       | [41]              | 75.9%                 | [41]          | 83%         | [25]          | 94%         | [41]          |
| 85%                       | [31]          | 80.65%      | [30]              | 95%                    | [43]          | 70.4%       | [45]          | 89.14%      | [31]          |
| 93%                       | [44]          | 91%         | [46]              | 97%                    | [20]          | 93%         | [20]          | 81.18%      | [30]          |
| 75%                       | [46]          | 66%         | [25]              | 63.8%                  | [33]          | 94%         | [44]          | 93.8%       | [26]          |
| 85%                       | [47]          | 98%         | [42]              | 75%                    | [46]          | 73.3%       | [45]          | 80%         | [25]          |
| 69%                       | [45]          | 98%         | [33]              | 73%                    | [25]          | 65%         | [45]          | 83%         | [48]          |
| 65%                       | [45]          |             |                   |                        |               |             |               |             |               |
| 48.3%                     | [44]          | 65.13%      | [27]              |                        |               |             |               |             |               |
| 96.1%                     | [41]          | 96.86%      | [42]              |                        |               |             |               |             |               |

4. **Result and Discussion**

The results of the commonly used student performance prediction methods above from 2010 to 2020 were analyzed and used to plot a graph of how they differ in their overall prediction accuracy. The diagram is shown in figure 1.

![Prediction accuracy for each classification technique](chart.png)

**Figure 1.** Performance prediction accuracy (2010-2020)

Figure 1 was obtained by studying the commonly used methods for student performance prediction in previous studies and their performances were compared with an aim of finding out the method with the highest accuracy, and the results were plotted on the graph in figure 1. The figure overall shows the prediction accuracy of the conventional prediction methods used to predict student performance that the authors examined in this study, all grouped by their algorithms from 2012 to 2020. As shown in figure 1, the decision trees method gave a high prediction accuracy of (98%), compared to all other methods. Naive bayes was the second-highest accurate with (97%). Then followed by the k-nearest neighbor.
method and support vector machine method, which gave a similar accuracy of (94%). Artificial neural network gave the least student performance prediction accuracy of (93%).

5. Conclusion and future work
Student Performance is a crucial factor that requires proper monitoring if the goal of education in higher educational institutions and at all levels of education is to be achieved. This condition is because student performance prediction helps institutional leaders in improving their educational systems. This study aimed at reviewing the commonly used classification techniques for predicting student performance. Among the widely used methods to predict student performance, the decision trees method proved to be the best method for predicting student performance compared to Naive bayes, k-nearest neighbor, support vector machines and artificial networks, due to its simplicity of use and ability to uncover small or large data structures and predict values which gives high accuracy.

In conclusion, the results from this review will help educators to monitor students' performance systematically by using the easiest and most accurate method to predict student performance. The authors believe that using the best prediction method helps educators to infer students' performance, which allows early interventions that may bring an increase in excellent academic performance rates, thus promoting education with high-quality achievers. In the future work, authors can use the data in this review as a basis for other related studies in the educational data mining field. Focusing on how to improve the accuracy of other methods would also be Important.

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