

Analysis of ai algorithms for foreseeing university student's academic and co-curricular performance

Soheli Farhana ¹, Adidah Lajis ², Zalizah Awang Long ^{3*}, Haidawati Nasir ²

¹ UniKL MIIT

² Computer Engineering Section, UniKL MIIT

³ Information System Section, UniKL MIIT

*Corresponding author E-mail: 1. farhanas@unikl.edu.my¹

2. zalizah@unikl.edu.my³

Abstract

Evaluation of student's activity turns out to be more difficult because of the huge volume of information in the instructive databases. As of now in the universities, the absence of an existing framework to investigate and screen the understudy advancement and execution isn't being tended to. There are three main reasons why this is going on. To begin with, the examination on existing forecast strategies is as yet lacking to distinguish the most reasonable techniques for foreseeing the intelligent methods in the system. Second is because of the absence of examinations on the elements influencing understudies' accomplishments specifically courses inside university system. Third is to unavailability of the correlation between the academic and co-curricular activities. Subsequently, a systematical writing audit on foreseeing understudy execution by utilizing different artificial intelligence (AI) algorithms strategies is proposed to enhance performance accomplishments. This paper is briefly discussed and analyzed of the different AI algorithms to predict the performance analysis of universities student by correlating academic and co-curricular values. Finally, an ideal algorithm is proposed to develop the performance analysis system by comparing the above analysis results. The accuracy of the proposed algorithm is achieved to 95.38% through analysis. It could convey the advantages and effects to understudies, instructors and scholastic foundations.

Keywords: Performance; Student Academic; AI Algorithms.

1. Introduction

The traits that have been every now and again utilized is total review point normal (CGPA) and interior appraisal. Ten of thirty papers have utilized CGPA as their fundamental ascribes to anticipate understudies' execution [1]. The primary thought of why the vast majority of the specialists are utilizing CGPA is on the grounds that it has a substantial incentive for future instructive and vocation versatility for evaluating the student performance weight. It can likewise be considered as a sign of acknowledged scholarly potential [2]. Through the coefficient connection examination, the outcome demonstrates that CGPA is the hugest information variable by 0.87 compared to different factors [3]. In addition, in Christian and Ayub consider [4], CGPA is the most impact traits in deciding the survival of understudies in their examination, regardless of whether they can finish their investigation or not. In this investigation, inside evaluation was delegated task check, tests, lab work, class test and participation. All traits will be assembled in one characteristic called inside evaluation. The properties are for the most part utilized among the specialists to foresee understudies' execution [5].

While outside evaluation is distinguished as a check got in end of the year test for a specific subject [6]. The reason of why the greater part of the analysts utilized understudies statistic, for example, sex is on the grounds that they have distinctive styles of female and male understudies in their learning procedure [7]. Study done by Meit et al. (2007) found that the vast majority of female understudies have different positive learning styles and practices contrasted with male understudies [8].

Academic performance evaluation is more loyal in their teaching, self-coordinated, constantly safeguarded and centered. In opposite side, academicians have a powerful teaching system in their assessment [9]. They have self-inspiration, association and practice that were viably utilized by them. Along these lines, it is demonstrated that sex is one of imperative traits affecting understudies' execution.

There are additionally a few specialists in another investigation who have utilized psychometric factor to anticipate understudies' execution [10]. A psychometric factor is distinguished as understudy intrigue, contemplate conduct, connect with time, and academic achievements.

2. Materials and methods

2.1. The prediction methods used for student performance

In instructive information mining technique, prescient displaying is normally utilized in anticipating understudy execution. So as to assemble the prescient demonstrating, there are a few errands utilized, which are characterization, relapse and order. The most well-known assignment to anticipate understudies' execution is grouping. There are a few calculations under arrangement undertaking that have been connected to anticipate understudies' execution. Among the calculations utilized are Decision tree, Artificial Neural Networks, Naive Bayes, K-Nearest Neighbor and Support Vector Machine. Next, the explicit use of information mining methods gathered by calculations in foreseeing understudy execution will be portrayed in the following area.

2.2. Decision tree

Choice Tree is one of a famous strategy for forecast. The greater part of specialists has utilized this method due to its effortlessness and fathomability to reveal little or vast information structure and foresee the esteem [11]. Romero et al. (2008) said that the choice tree models are effortlessly comprehended on account of their thinking procedure and can be straightforwardly changed over into a set of IF-THEN standards [12]. Instances of past investigations utilizing Decision Tree strategy are foreseeing drop out highlights of understudy's information for scholarly execution, anticipating third-semester execution of MCA understudies and furthermore foreseeing the reasonable profession for an understudy through their standards of conduct. The understudy's execution assessment depends on highlights removed from logged information in an instruction electronic framework. The instances of a dataset are understudies last grades, last total review point normal (CGPA) and marks got specifically courses. These datasets were considered and dissected to discover the primary traits or elements that may influence the understudy's execution. At that point, the appropriate information mining calculation will be researched to foresee understudy's execution.

2.3. Neural network

The neural system is another prevalent method utilized in instructive information mining. The benefit of the neural system is that it can distinguish every single conceivable collaboration between indicators factors [13]. The neural system could likewise complete a total location without having any uncertainty even in complex nonlinear connection among reliant and autonomous factors [29]. In this way, the neural system strategy is chosen as extraordinary compared to other forecast technique. The characteristics examined by Neural Network are affirmation information [14], understudies' demeanor towards self-directed learning and scholarly execution. The rest are same papers what's more with Decision Tree strategy where specialists have utilized the two methods.

2.4. Naive bayes

Innocent Bayes calculation is likewise a possibility for scientists to make a forecast. The goal of all these researches is to locate the best forecast procedure in anticipating understudies execution by making correlations [15,16]. Their examination demonstrated that Naive Bayes has utilized all of the traits contained in the information. At that point, it broke down every single one of them to demonstrate the significance and independence of every characteristic.

2.5. Support vector machine

Support Vector Machine is a directed learning strategy utilized for arrangement. There are three papers that have utilized Support Vector Machine as their technique to foresee understudies execution. Hamalainen et al. (2006) had picked Support Vector Machine as their forecast method since it suited well in little datasets [17]. Sembiring et al. (2011) expressed that Support Vector Machine has a decent speculation capacity and quicker than different strategies. [18]. In the meantime, the examination done by Gray et al (2014) showed that Support Vector Machine technique has obtained the most astounding forecast precision in recognizing understudies in danger of coming up short [19-22].

3. Optimal proposed algorithm

In this research, an optimal algorithm is called Naïve method is used to get student performance by fusing academic results and cocurricular activities of each students. There are four steps have been taken into account to complete this performance analysis. At first all the academic and cocurricular data will be collected among 500 students. Then, fuse the data into a fixed format. After that, the naïve method will be applied to analysis the data and finally classify them.

3.1. Data collection

In this step, CGPA of each of students of 500 to be collected and store in the proper table as their academic performance. Some of the cocurricular activities will be considered to and each of their activities on that particular activities are summed together and assigned them by marking based on their gross performance in each activity. Table 1 shows the GCPA of some of 500 students and Table 2 shows points of three different activities. These points will be gross calculated and finally fuse with CGPA to make one value for each student performance.

Table 1: Some of 500 Students' CGPA

Student ID	CGPA
201801	2.84
201802	4.00
201803	3.78
201804	3.66
201805	2.90
201806	3.36
201807	3.98
201808	2.20
201809	1.96
201810	3.50

Table 2: Some of 500 Students' Several Activity Point

Student ID	Activity-1	Activity-2	Activity-3
201801	2	4	3
201802	3	3	3
201803	5	4	4
201804	4	5	5
201805	5	3	2
201806	5	2	2
201807	3	5	3
201808	2	5	4
201809	5	4	5
201810	5	3	4
201811	4	4	4

3.2. Naïve method

Naïve method is a basic method to solve any predict the optimal results. Using this method, we proposed to find the best performance of the students by combining academic and cocurricular performances.

Naïve method delivers a path of solving the next possibility, $Q(c|x)$, from $Q(c)$, $Q(x)$, and $Q(x|c)$. naïve method then adopts the consequence of the value of a interpreter (x) on a specified class (c) is autonomous of the values of other interpreters. The relation in this prediction equation can be stated in the (1),

$$Q(c|x) = Q(x|c).Q(c)/Q(x) \tag{1}$$

Following table 3 shows the Naïve algorithm which we consider as an optimal algorithm to serve the performance measurement.

Table 3: Naïve Algorithm

```

Algorithm Naive (C, D)
V ← ExtractVocabulary
N ← CountDocs(D)
For each c ∈ C
Do Nc ← CountDocsInClass (D, c)
prior[c] ← Nc/N
textc ← ConcatenateTextOfAllDocsInClass (D, c)
for each t ∈ V
do condprob[t][c] ← (Tct+1)/(Σr(Tcr+1))
return V
    
```

4. Results & discussion

This section will discuss the results analysis of the recent works in predicting students' performance. This meta-analysis is based on the highest accuracy of prediction methods and also the main important factors that may influence the students' performance.

Fig. 1 shows the prediction accuracy that uses (classification method grouped by) algorithms for predicting students' performance. The analysis shows that the proposed algorithm accuracy is 95.38%. Therefore, Naïve algorithm is considered optimal algorithm by comparing others.

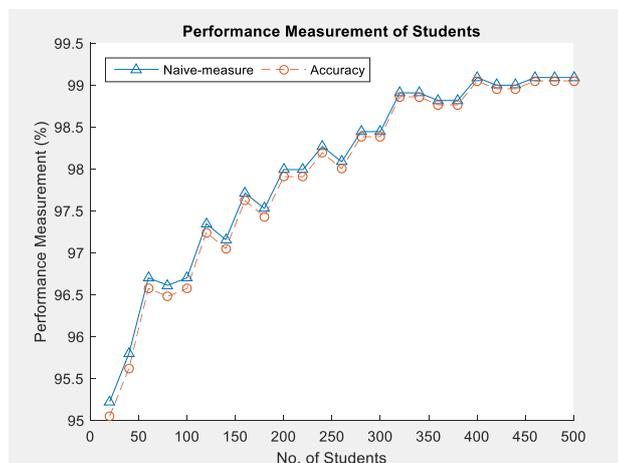


Fig. 1: Example of an Image with Acceptable Resolution.

5. Conclusions

This research discussed on the effectiveness of different AI algorithm for evaluating academic and student performances. This paper shows the complete analysis of the implementation of optimal AI algorithm for performance analysis. The analysis shows a set of students co-curricular activities and examination's mark that fuse all together and finally come out with a perfect outcome-based result that finally indicate the real performance of each student. This proposed optimal algorithm can be an idle in the field of any kind performance measurement area.

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