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Predicting Students' Learning Outcomes without Coding Stress: Analysis of Software Applications

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ABSTRACT

Do I need to become a programmer before forecasting student learning outcomes in classrooms? Teachers and academicians who wish to anticipate student learning achievement in their schools but cannot do so because they cannot write a line of code to do so face significant issues with this question and similar hood questions. This study examines how all instructors, regardless of field, can use software programs to forecast student learning achievement in their classrooms. A dataset with 1,200 attributes was split into training and testing sets. Prediction of students' learning outcomes in WAEC through Mock examinations in secondary schools involved scores in English Language, Mathematics, and Computer Studies in forming the dataset. The dataset were preprocessed to remove any errors that might have affected the study's final prediction model. The results demonstrated that it is possible to forecast students' learning outcomes using software programs. Software programs can transform students' learning outcomes from undesirable to desirable and better. It should be encouraged to use software programs to forecast student learning achievement so that adjustments can be made before the pupils are subjected to external exams.

Keywords: Prediction, Software Application, No-Coding, Learning Outcomes, Analysis

Introduction

Literature establishes a variety of perspectives to measure students learning success, which includes tests, practical assessments, internal examinations (Mock examinations), and external examinations (WAEC or NECO). Ideally, all these measures are put in place to reveal the current state of students' learning outcomes or to be used for future learning output of the student's performance. It is no longer a story that technology has revolutionized how things were handled or done some years back. The widespread of using java, python, or R, which takes learners months before correct coding could be achieved to implement prediction over datasets, has reduced drastically as a result of software applications available to do the same thing without wasting too much time as in writing a series of codes to achieve similar objectives. Nobody denies that education is changing, and technology has a big part in changing the current educational landscape (Ulfa & Fatawi,2021)

Students' outcome-based learning has become a new school of thought in education. This educational paradigm shifts teaching focus from traditional teacher goals to student outcomes. Therefore, student learning outcomes are seen as Bloom's Taxonomy (knowledge, skills, and values) that students must achieve at graduation or the end of the O level of education in secondary schools. Predicting student learning outcomes provides other valuable benefits and the ability to make corrective interventions during the learning process; however, several articles focus on the intelligent prediction of student performance. We aim to understand the prospects of predicting student learning outcomes using software applications instead of writing codes. We believe that students' performance should not be judged solely based on external examinations like WAEC and NECO but by using Mock examinations to correct and adjust various factors that can hinder the external tests mentioned. Measurable student outcomes are designed to improve the learning process and educational program quality. These results estimate what students can do with the knowledge they have learned. Direct assessment methods are designed to find specific evidence of student learning, while indirect assessment methods are based on allowing students to reflect on their learning experience. It is necessary to determine the goal and proficiency a priori and then match the student's performance with the corresponding ability. Therefore, educational institutions face a series of factors regarding students' learning outcomes. These factors can adversely affect students' performance or later affect their careers in education. Nowadays, predicting students' learning outcomes has remained a significant study concern. The following research questions guide the study:

- How to determine the student learning outcomes in academic performance using software applications?
- How do software applications can review and guide student academic learning outcomes for the better performance?

Related Literature

The prediction of student learning outcomes has been the focus of scholars in education. It has also brought and drawn the attention of academia toward how students' performance could be known before it happens. These and other reasons have made past authors research overwhelmingly on students' learning outcomes predictions:

Namoun & Alshanqiti (2021) used a decade of research work conducted between 2010 and November 2020 to explain a significant deal of the intelligent techniques used to predict student performance, where academic success was strictly measured using student learning outcomes. ACM, IEEE Xplore, Google Scholar, Science Direct, Scopus, Springer, and Web of Science were used as databases. PICO and PRISMA were applied to produce and narrate the key outcomes of the research. The student learning outcomes were measured via students' achievement and performance. The study employed a supervised learning approach using a regression algorithm as a classification model. Finally, student online learning activities, term assessment grades, and student academic emotions were the most evident predictors of learning outcomes. Yassine, Kadry & Sicilia (2016) viewed student learning outcomes as critical factors of student academic success. Likewise, Hellas et al. (2018) noted that academicians measure student success from different perspectives, including final grades, grade point average (GPA), and future job prospects. The timely prediction of student learning outcomes enables the detection of low-performing students, thus, empowering educators to intervene early during the learning process and implement the required interventions. Therefore, fruitful interventions include student advising, performance progress monitoring, intelligent tutoring systems development, and policymaking (Zhang & Li, 2018). Accreditation bodies, such as Accreditation Body for Engineering and Technology (ABET) and Accreditation Council for Business Schools and Programmes (ACBSP), use the students' learning outcomes, according to Namoun & Alshanqiti (2021) and Rajak (2018), as the building blocks for assessing the quality of educational programs. Such importance calls for more research efforts to predict the attainment of learning outcomes, both at the course and program levels.

Ulfa & Fatawi (2021) predicted student activities that would improve the student's learning outcomes using a concept mapping approach. After using the linear regression method to analyze the collected data, it was found that working on exercises using concept mapping yielded significant results in improving students' learning outcomes. Ulfa & Fatawi (2021) added that every educator must provide quality learning experiences to promote student success in learning. Several important aspects need to be considered in organizing education, such as the use of application software which has many advantages, including the ease of administering, managing, documenting, monitoring, content delivery, and evaluating learning, utilization of software applications to improve the quality of education as well as the application of learner-centred learning strategies (Daniel, 2015; Zohair, 2019; Hellas et al., 2018).

Sindhu et al. (2021) viewed that student learning outcomes should not only be assessed using assessment grades. Instead, it is recommended that exploring the prospect of predicting the attainment of student outcomes to infer student performance can be a better way out

Arizmendi et al. (2022) conducted a study to predict customers' behaviours using smart-home devices via a learning management system (LMS). In the end, an empirical example demonstrating the ability of LMS data to predict student success, summarize essential features, and assess model performance across different model specifications was achieved. The study by Merug (2021) focused on analyzing the performance of some students over a semester, taking into account a lot of factors such as personal, psychological, and environmental factors, predicting the student academic performance using the Python programming language in machine learning. It was observed that the predictive algorithms could accurately forecast students' course scores based on their performance.

Methods

The study used two software applications (RapidMiner and GMDH-Shell-DS) to determine how student learning outcomes in academic performance will be improved using software applications. A dataset of 1,200 attributes was used and split into a 70/30 ratio. The Naïve Bayes classification algorithm was used in RapidMiner, while the standard classification algorithm was used in GMDH-Shell-DS. The results were interpreted using accuracy, precision, Kappa statistics, charts, and confusion matrix based on the results generated from each software application.

Results

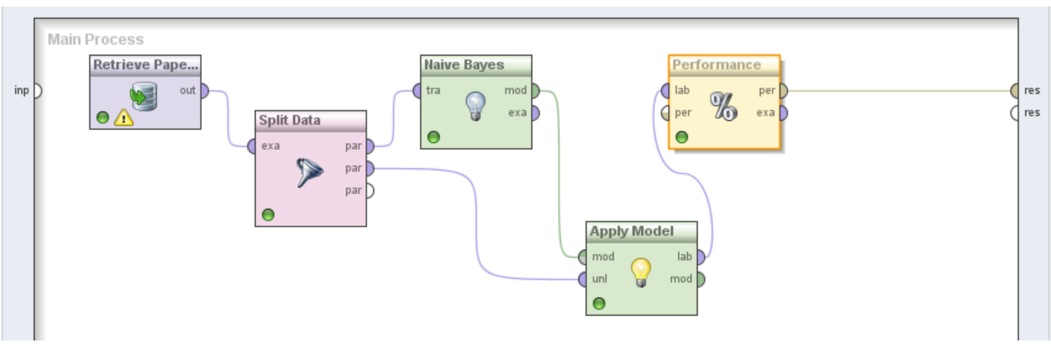

Fig. 1: Main Process Model in RapidMiner

In Fig.1, the boxes showed the required process needed to be put into predicting student learning outcomes. It involved the dataset, split data process, Naïve Bayes classification algorithm, the application of the model, and the performance process, respectively.

1	Evidence to pass with poor grade	1.000	0.000	0	Evidence to pass with poor grade
2	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
3	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
4	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
5	Evidence to pass with average grade	0.003	0.997	0	Evidence to pass with average grade
6	Evidence to pass with average grade	0.000	0.973	0.027	Evidence to pass with average grade
7	Evidence to pass with average grade	0.000	0.959	0.041	Evidence to pass with average grade
8	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
9	Evidence to pass with poor grade	0.145	0.855	0	Evidence to pass with average grade
10	Evidence to pass with poor grade	0.999	0.001	0	Evidence to pass with poor grade
11	Evidence to pass with poor grade	0.752	0.248	0	Evidence to pass with poor grade
12	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
13	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
14	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
15	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
16	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
17	Evidence to pass with average grade	0.011	0.989	0	Evidence to pass with average grade
18	Evidence to pass with average grade	0.004	0.996	0	Evidence to pass with average grade
19	Evidence to pass with average grade	0.000	0.955	0.045	Evidence to pass with average grade

Fig. 2: Sample Screenshot that compares predicted and prediction matching.

Fig.2 to 4 collectively showed the actual predicted variables and model prediction variables. By comparing, most indicated and model prediction variables are the same except in some cases, such as serial numbers 121, 200, and 204, respectively, in Fig. 2, 3, and 4 (Double-pointed blue-coloured arrows indicate them).

114	Evidence to pass with good grade	0	0	1	Evidence to pass with good grade
115	Evidence to pass with good grade	0	0	1	Evidence to pass with good grade
116	Evidence to pass with good grade	0	0	1	Evidence to pass with good grade
117	Evidence to pass with good grade	0	0	1	Evidence to pass with good grade
118	Evidence to pass with good grade	0	0.000	1.000	Evidence to pass with good grade
119	Evidence to pass with good grade	0.000	0.000	1.000	Evidence to pass with good grade
120	Evidence to pass with average grade	0.000	0.908	0.092	Evidence to pass with average grade
121	Evidence to pass with average grade	0.000	0.005	0.995	Evidence to pass with good grade
122	Evidence to pass with average grade	0.000	0.999	0.001	Evidence to pass with average grade
123	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
124	Evidence to pass with good grade	0	0	1	Evidence to pass with good grade
125	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
126	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
127	Evidence to pass with average grade	0.003	0.997	0	Evidence to pass with average grade
128	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
129	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
130	Evidence to pass with poor grade	1.000	0.000	0	Evidence to pass with poor grade
131	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
132	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade

Fig. 3: Sample Screenshot that compares predicted and prediction matching.

190	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
191	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
192	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
193	Evidence to pass with poor grade	1.000	0.000	0	Evidence to pass with poor grade
194	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
195	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
196	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
197	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
198	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
199	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
200	Evidence to pass with poor grade	0.199	0.801	0	Evidence to pass with average grade
201	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
202	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
203	Evidence to pass with average grade	0.000	1.000	0	Evidence to pass with average grade
204	Evidence to pass with poor grade	0.466	0.534	0	Evidence to pass with average grade
205	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
206	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
207	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade
208	Evidence to pass with poor grade	1	0	0	Evidence to pass with poor grade

Fig. 4: Sample Screenshot that compares predicted and prediction matching.

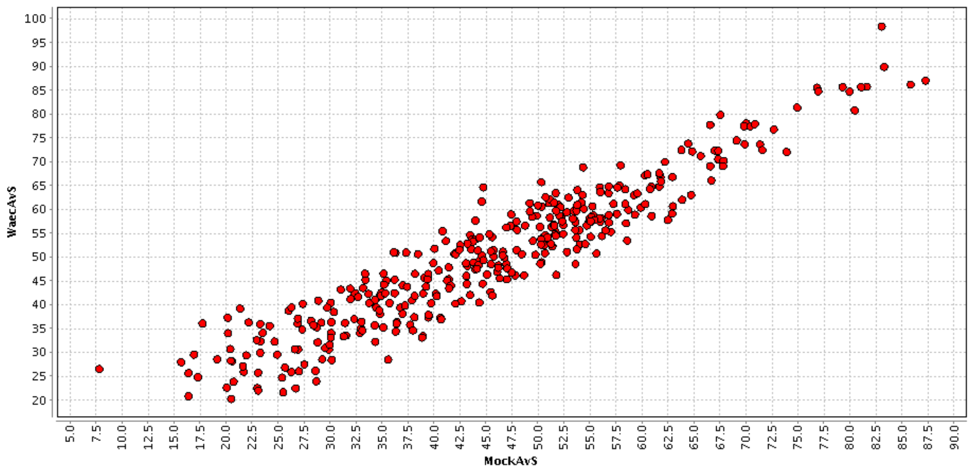

Fig. 5: Scatter plot showing the relationship between WAEC Average scores and Mock Average

The scatter plot (Fig. 5) established the relationship between the Mock and WAEC Average scores. The result implies that Mock examinations can be used to predict the WAEC performance of students because the linear relationship proves that there are high positive correlations between them. In Fig. 6, the scatter plot explained the division of actually predicted variables and model prediction variables in a clear and concise form

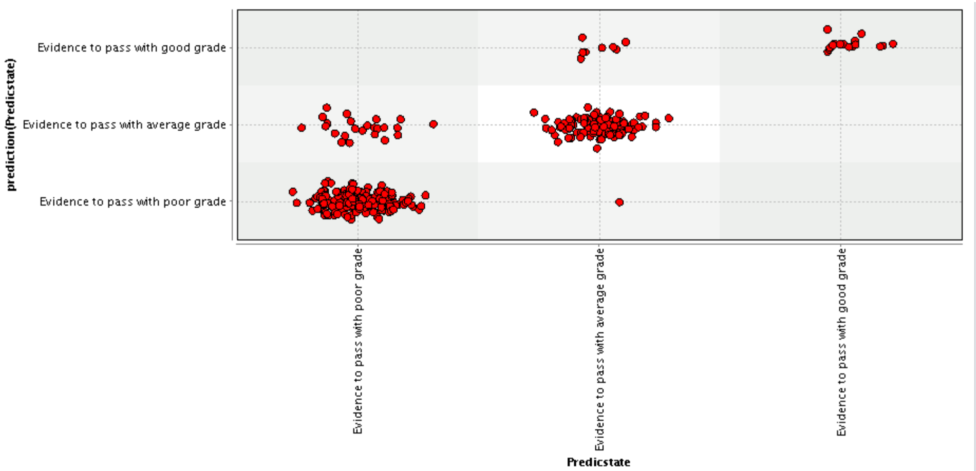

Fig. 6: Showing the Scatter plot of the relationship between predicted variables and actual prediction variables

Fig. 7 and 8 showed the values of model accuracy as well as Kappa statistics of the model. As displayed in the tables, the accuracy and kappa statistics are 90.83 and 83.00% showing an excellent model. The details of the metrics are explained in the summary table (Table 1 and 2)

accuracy: 90.83%

	true Evidence to pass with poor gr	true Evidence to pass with average	true Evidence to pass with good gr	class precision
pred. Evidence to pass with poor g	188	1	0	99.47%
pred. Evidence to pass with averag	24	122	0	83.56%
pred. Evidence to pass with good	0	8	17	68.00%
class recall	88.68%	93.13%	100.00%	

Fig. 7: Table of Accuracy performance of the model.

kappa: 0.830

	true Evidence to pass with poor gr	true Evidence to pass with average	true Evidence to pass with good gr	class precision
pred. Evidence to pass with poor g	188	1	0	99.47%
pred. Evidence to pass with averag	24	122	0	83.56%
pred. Evidence to pass with good	0	8	17	68.00%
class recall	88.68%	93.13%	100.00%	

Fig. 8: Table of Kappa Statistics performance of the model.

Summary table

Table 1: Metric Summary for RapidMiner

Metrics	Evidence to pass with poor grades	Evidence to pass with average grades	Evidence to pass with good grades
Accuracy	90.83%		
Kappa Statistics	83.00%		
Precision	99.47%	83.56%	68.00%
Recall	88.68%	93.13%	100%

The table 1 revealed that accuracy of the model (91%), Kappa Statistics (83%), Precision (>60%), and Recall (>80%). All these metrics showed and proved that the model from the software application performed accurately to be used to predict student learning outcomes. In addition to this, Table 2 (Confusion matrix) revealed that improper loading of variables was minimal because only 24 were erroneously loaded under evidence to pass with poor grades, whereas they were supposed to load under evidence to pass with average rates; also nine were erroneously loaded under evidence to pass with average grades whereas they were supposed to load under evidence to pass with poor grades and good grades while no misloading was found under evidence to pass with good grades matrices.

Table 2: Confusion Matrix Summary for RapidMiner

Metrics	Evidence to pass with poor grades	Evidence to pass with average grades	Evidence to pass with good grades
Evidence to pass with poor grade:	188	1	0
Evidence to pass with average grade:	24	122	0
Evidence to pass with good grade:	0	8	17

ID	Actual	Predictions	Hit/miss
1	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
2	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
3	Evidence to pass with average grade	Evidence to pass with average grade	Hit
4	Evidence to pass with average grade	Evidence to pass with average grade	Hit
5	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
6	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
7	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
8	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
9	Evidence to pass with average grade	Evidence to pass with average grade	Hit
10	Evidence to pass with average grade	Evidence to pass with average grade	Hit
11	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
12	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
13	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
14	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
15	Evidence to pass with average grade	Evidence to pass with average grade	Hit
16	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
17	Evidence to pass with average grade	Evidence to pass with average grade	Hit
18	Evidence to pass with average grade	Evidence to pass with average grade	Hit
19	Evidence to pass with average grade	Evidence to pass with average grade	Hit
20	Evidence to pass with average grade	Evidence to pass with average grade	Hit
21	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
22	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
23	Evidence to pass with poor grade	Evidence to pass with average grade	Miss
24	Evidence to pass with average grade	Evidence to pass with average grade	Hit
25	Evidence to pass with average grade	Evidence to pass with average grade	Hit
26	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit

Fig. 9: Sample Screenshot that compares actual predicted and prediction matching.

In using another software application (GMDH-Shell-DS), similar results were obtained with slight differences. Fig. 9 to 11 showed the predicted variables against model prediction variables; as can be seen, a few comparisons showed 'miss', which implies wrong matching (See serial numbers 23, 55, 75, and 460, respectively) indicated by double-pointed orange-coloured arrows.

ID	Actual	Predictions	Hit/miss
53	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
54	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
55	Evidence to pass with poor grade	Evidence to pass with average grade	Miss
56	Evidence to pass with average grade	Evidence to pass with average grade	Hit
57	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
58	Evidence to pass with average grade	Evidence to pass with average grade	Hit
59	Evidence to pass with average grade	Evidence to pass with average grade	Hit
60	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
61	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
62	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
63	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
64	Evidence to pass with average grade	Evidence to pass with average grade	Hit
65	Evidence to pass with average grade	Evidence to pass with average grade	Hit
66	Evidence to pass with average grade	Evidence to pass with average grade	Hit
67	Evidence to pass with average grade	Evidence to pass with average grade	Hit
68	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
69	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
70	Evidence to pass with average grade	Evidence to pass with average grade	Hit
71	Evidence to pass with average grade	Evidence to pass with average grade	Hit
72	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
73	Evidence to pass with average grade	Evidence to pass with average grade	Hit
74	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
75	Evidence to pass with poor grade	Evidence to pass with average grade	Miss
76	Evidence to pass with average grade	Evidence to pass with average grade	Hit
77	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
78	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit

Fig. 10: Sample Screenshot that compares actual predicted and prediction matching.

ID	Actual	Predictions	Hit/miss
445	Evidence to pass with good grade	Evidence to pass with good grade	Hit
446	Evidence to pass with good grade	Evidence to pass with good grade	Hit
447	Evidence to pass with average grade	Evidence to pass with average grade	Hit
448	Evidence to pass with average grade	Evidence to pass with average grade	Hit
449	Evidence to pass with average grade	Evidence to pass with average grade	Hit
450	Evidence to pass with average grade	Evidence to pass with average grade	Hit
451	Evidence to pass with average grade	Evidence to pass with average grade	Hit
452	Evidence to pass with average grade	Evidence to pass with average grade	Hit
453	Evidence to pass with average grade	Evidence to pass with average grade	Hit
454	Evidence to pass with average grade	Evidence to pass with average grade	Hit
455	Evidence to pass with average grade	Evidence to pass with average grade	Hit
456	Evidence to pass with good grade	Evidence to pass with good grade	Hit
457	Evidence to pass with average grade	Evidence to pass with average grade	Hit
458	Evidence to pass with good grade	Evidence to pass with good grade	Hit
459	Evidence to pass with average grade	Evidence to pass with average grade	Hit
460	Evidence to pass with good grade	Evidence to pass with average grade	Miss
461	Evidence to pass with good grade	Evidence to pass with good grade	Hit
462	Evidence to pass with average grade	Evidence to pass with average grade	Hit
463	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
464	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit
465	Evidence to pass with poor grade	Evidence to pass with poor grade	Hit

Fig. 11: Sample Screenshot that compares actual predicted and prediction matching.

Correctly classified instances 1187 98.9% RMSE 0.195 x-measure 0.980
Incorrectly classified instances 13 1.1% Weighted F-measure 0.989

		Predicted class				
		Evidence to pass with average grade	**Evidence to pass with good grade**	**Evidence to pass with poor grade**	**Total**	**Recall**
	Evidence to pass with average grade	454	0	0	454	1.000
Actual class	**Evidence to pass with good grade**	2	67	0	69	0.971
	Evidence to pass with poor grade	11	0	666	677	0.984
	Total	467	67	666	1200	
	Precision	0.972	1.000	1.000		
	F-measure	0.986	0.985	0.992		
	Baseline	0.622	0.943	0.564	0.564	
	Accuracy	0.989	0.998	0.991	0.989	

Fig. 12: Table of metrics for measuring the performance of the model.

Summary Table

Table 3: Metric Summary for GMDH-Shell-DS

Metrics	Evidence to pass with poor grades	Evidence to pass with average grades	Evidence to pass with good grades
Accuracy	98.90%		
F-Measure	99.2%	98.60%	98.50%
Precision	100.00%	97.20%	100.00%
Recall	98.40%	100.00%	97.10%

Table 4: Confusion Matrix Summary for GMDH-Shell-DS

Metrics	Evidence to pass with poor grades	Evidence to pass with average grades	Evidence to pass with good grades
Evidence to pass with poor grades:	0	11	0
Evidence to pass with average grades:	0	454	0
Evidence to pass with good grades:	666	2	67

The table 3 revealed that accuracy of the model (99%), F-measure (>90%), Precision (>90%), and Recall (>90%). All these metrics showed and proved that the model from the software application performed accurately to be used to predict student learning outcomes. In addition to this, Table 4 (Confusion matrix) revealed that improper loading of variables was minimal because only 13 were erroneously loaded under evidence to pass with average grades, whereas 11 were supposed to load under evidence to pass with average grades and 2 to load under evidence to pass with average grades but loaded under evidence to pass with poor grades and evidence to pass with good grades. At the same time, no misloading was found under evidence to pass with poor and good grades matrices.

Discussion

The analysis presented under the results clearly shows significant benefits in successfully using software applications to predict students' learning outcomes. In this study, RapidMiner and GMDH-Shell-DS software applications were used to achieve and test the formulated research question, ' How to determine the student learning outcomes in academic performance using software applications?' The software applications do not require writing a series of codes before achieving similar objectives of predictions, and it also saves time programmers use in coding and testing. It is encouraged to be used by everyone without a scientific background. All these and more prove that software applications can be used to determine the student's learning outcomes.

Similarly, using software applications in prediction will change students' academic learning outcomes to a better stage by using the applications for tests, assignments, classes works, and mock examinations to examine the students' strengths and weaknesses before the actual external examination is conducted. By doing this, students with some deficiencies would be easily noticed and apply a pedagogical approach to improve his/her learning capabilities and begin to do well. The results answer the research question, ' How do software applications change student academic learning outcomes for the better?' In support of this findings, Namoun & Alshanqiti, (2021) asserted that the timely prediction of student learning outcomes enables the detection of low performing students, thus, empowering educators to intervene early during the learning process and implement the required interventions. Yassine, Kadry & Sicilia (2016) also viewed student learning outcomes as critical factors of student academic success. Likewise, Hellas et al., (2018) noted that academicians do measure student success from different perspectives, ranging from students' final grades, grade point average (GPA), to future job prospects

Conclusion

In the modern educational system, predicting student's academic achievement is critical. In this paper, indicating students' learning outcomes without coding Stress was discussed—prediction of student learning success that allowed an insight into intervention. We achieved model accuracy superior to the use of a manual approach, as it is revealed in the literature. An empirical study used the most prevalent software applications on a student dataset. Using RapidMiner and GMDH-Shell-DS gives a higher accuracy rate in which results indicate the students were classified with a high correctly classified rate. Predicting students' learning outcomes helps to give students any necessary assistance from academics and school administration.

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