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Regression Based Modelling to Predict the Undergraduate Students Performance After Pandemic in Educational Institutions

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Abstract: The linear regression model was utilized as our major tool for doing forecasting. A regression model is a technique that is used in statistical analysis and may be used to make inferences about the trend of data. This technique can be used to create predictions about the data. The LR model is applicable and useful in a wide variety of contexts and circumstances. This model has seen widespread use due to the ease with which it can be implemented and the benefits it provides in terms of creating accurate projections of academic accomplishment. In this paper, regression-based modelling to predict the performance of undergraduate students after pandemic in educational institutions is developed. The model is conducted by the combination of various machine learning algorithm with regression model. The simulation shows an improved rate of accuracy in predicting the students' performance in face-to-face mode than the existing online mode. The results further reveal an improved performance of students post pandemic era than during the pandemic.

***Keywords*:** *Linear regression, machine learning, student performance, educational institutions*.

1. Introduction

As a improving step against the spread of the one-of-a-kind 2019 coronavirus epidemic, the utilization of emergency remote learning has witnessed a recent boost in popularity. This rise in popularity has occurred relatively recently (COVID-19) [1]. The term emergency remote learning is used in the field of education to refer to a conceptual paradigm that entails a swift transition from traditional in-person course delivery to that of online instruction. This is done with the goal of providing ad hoc solutions to deal with unanticipated conditions, and it is done with that objective in mind. Both instructional design and policy consideration are required components of online education [2].

The design process may be skipped totally or only partially implemented during this emergency shift, depending on the gravity of the crisis. It is necessary to have support for emergency remote learning in a variety of situations, not just in the conventional classroom environment [3]. It is imperative that there be an adequate supply of materials if one wants students to be successful in an environment that promotes distance learning [4]. Because of the abrupt shift brought on by the unusual proliferation of COVID-19, it is probable that the typically rigorous design approach will not be practicable. This is because of the sudden shift brought on by the unprecedented proliferation of COVID-19 [5].

Distance education, also known as electronic learning or e-learning, is now available to students at all of the universities. This is made possible by recent developments in online education, which have enabled all of the universities to provide students with the option of participating in distance education [6].

The majority of educational institutions have established significant departments that are staffed by qualified specialists in order to make distance education more accessible and develop a unique program of instruction for both students and faculty. This is done in an effort to develop a unique program of instruction for both students and faculty [7].

Learning management systems have incorporated a variety of various technology tools, in an effort to improve the overall quality of the interactions that take place during online learning. However, it is unclear how much of an influence this dramatic transition has had on the levels of pleasure and confidence that students have in their abilities to learn remotely while attending colleges.

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It is unclear how much of an influence this dramatic transition has had on the levels of pleasure and confidence that students have in their abilities to learn remotely [8].

According to one understanding of the phrase, satisfaction among students refers to a short-term attitude that is the consequence of an appraisal of student educational experience, services, and facilities [9].

Online education has the potential to result in lower levels of student satisfaction when compared to learning in a traditional classroom setting. According to a number of studies, students who get their education online report lower levels of overall happiness and a sense of accomplishment in their lives [10]. In the past, researchers have found that when looking at how satisfied students were with their learning, the results were generally favorable. This was identified while looking at how satisfied students were with their learning. This was the case when it came to the level of contentment that students had with their educational experiences [11].

It has been established that a student level of contentment with the educational advantages that they obtain from their participation in e-learning is a moderating factor in the educational gains that they derive from their engagement in e-learning. Because this is such a potent indicator of the student overall academic success, it is absolutely necessary to conduct an evaluation of the extent to which students are pleased with the material that they are currently learning [12]. On the other side, a number of highly renowned educators have come to the conclusion that the outcomes of online classes are on par with, and in some cases even exceed, those attained in regular classrooms [13]. Because of the COVID-19 laws, which made it mandatory for students to take their classes online, there has been a resurgence in interest in conducting research into the factors that can make the experience of e-learning less enjoyable for students. This interest has been sparked as a direct result of the laws [14].

According to the findings of a meta-analysis that compared traditional classrooms with online learning, student satisfaction with their education was contributed to by both types of educational settings, traditional classrooms and online learning [15]. Learner satisfaction in online classrooms has been linked to a variety of factors, including student technology skills, their motivation to learn, their receptivity to feedback from instructors, and the inventiveness of the student course ideas. It has been found that the amount of support that is offered by teachers is closely proportional to the level of contentment that is felt by online students [16].

When students engage in meaningful conversation with one another, they report higher levels of satisfaction with their overall educational experience. Learner levels of contentment can be affected by a wide variety of personal characteristics, including their temperament, perspective on technology, familiarity with other tools of a comparable sort, and level of expertise, amongst other factors [17]. One of the most important factors that plays a role in determining how happy students are in school is the extent to which students believe they have control over their own education and the responsibilities that have been delegated to them. This is one of the most important factors that play a role [18].

E-learning has several sides, and one of them is the concept of self-efficacy in relation to online learning. On the topic of self-efficacy, a substantial amount of research has been carried out both in conventional classroom settings and in those that are conducted online [19]. When we speak of self-efficacy, we are referring to a person belief in his or her own ability to effectively achieve a desired objective on their own without the assistance of another person. When it comes to learning, it is more significant than any other mental function because it is directly connected to how well a student does in class. Additionally, it is more significant than any other mental function. It is significantly more important than any other mental function [20].

According to Bandura social cognitive theory, the degree to which an individual believes they are capable of performing well in academic settings plays a key influence in the process of learning. It is hypothesized that a student perception of their self-efficacy can act as a moderator between the positive and negative impacts of e-learning on their satisfaction level and their understanding. This is because a student satisfaction with conceptual understanding are both related to their level of satisfaction with e-learning. The student levels of learning pleasure may be negatively influenced, though, if they put their academic self-efficacy at risk by choosing not to participate in a particular activity.

The investigation was carried out by collecting information from 400 students and 7000 exam scores covering a total of 74 distinct subjects that were subsequently organized into 8 distinct areas of expertise.

2. Related works

The authors of [21] devised a method for determining how well a student will perform on future exams by utilizing a student grade from previous tests in addition to their grades from the most recent exam in the student course. This system makes its predictions based on a student historical performance. The purpose of this research is to identify, on a regional as well as a topical level, children who are regarded as being at risk. This will give teachers the ability to provide immediate feedback on how their students are progressing in their studies. These kinds of data might be utilized as a guide for the creation of effective remedial treatments for these children, which would lessen the likelihood of those students dropping out of school. After including all of the partial grades in the projection, the final result was a model accuracy performance of 95%, which was the best possible score that could be achieved.

Elbadrawy et al. [22] have developed a model that takes into account a wide variety of different factors, such as the student previous performance in the classroom, the unique characteristics of each individual course, and the student level of engagement with the learning management system (LMS) itself. Because of this, the algorithm is able to reliably predict the grades of the students (aka, student engagement). The created model was able to achieve a greater than 20% improvement in its performance regarding the accuracy of its predictions.

Liu and d'Aquin [23] have made an effort to estimate the level of success that a student will have by making use of two distinct types of characteristics, namely, demographics and the amount of contact that a student has with an online learning system. Their model, which explores the association between demographic variables and performance, was created using supervised learning-based methodologies, and they made use of data from the Learning Analytics dataset. According to the data, the students who had the highest levels of success were those who had previously earned at least some college credit and who came from households in which the financial circumstances were stable.

Hussain et al. [24] investigate whether or not it is possible to anticipate difficulties that students might have in digital electronics lab sessions by evaluating the behaviors of previous students. The researchers specifically examine how students behaved while enrolled in the course. As a direct result of their efforts, they were not only able to determine which prediction model was the most accurate but also the major factors that contributed to the model achievements. During the course of the research that was carried out, five separate elements were taken into consideration. These aspects are as follows: typical use, typical idle use, typical activities, typical activities connected with typical activities, and typical keystrokes. When paired with five-fold cross-validation and a random split of the data, the ANN and SVM-based models reached the greatest levels of accuracy performance possible, which was 75%. Once the Alpha Investing strategy was implemented into the SVM model, the performance of the model increased to 80% of its potential.

The alternative machine learning models were evaluated and compared in a comprehensive study by the authors of [25]. The authors of this study have retrieved and analyzed a wide range of statistics. The SVM model comes out as having the best accuracy when compared to the other models that were used in this inquiry. This was determined by comparing its accuracy to the accuracy of the other models.

The authors of the study [26] present a model that, via the utilization of data mining and video learning analytics, is able to determine whether or not students will be successful in higher education. Questions were asked of a total of 722 different people as part of the information gathering process. There were no additional classifications that were taken into consideration outside of previous performance, engagement, personality, and institutional considerations. RF algorithm turned in the best performance out of the eight that were used, with an accuracy of 88% being reported by it.

The authors of this paper [27] aim to anticipate how well students will succeed in one of two different classes by conducting research on a wide range of factors and basing their findings on those findings. In order to determine which students have successfully completed the course and which have not, the authors employ a feature-following support vector machine in conjunction with a random forest.

Artificial Neural Networks (ANN) were applied in a different study [28] to the challenge of predicting how well students will do in online education. The data set was finished, utilizing the information of a total of 3518 unique students. Only the previous performance and the amount of involvement with the learning platform were taken into consideration, out of a total of five categories. Because of this, the focus was cut down to just two of the categories. It was discovered that the ANN-based model had an accuracy of 80% when it came to forecasting the performance of the students based on the findings.

3. Proposed Method

In order to accomplish the goals we set for ourselves regarding classification in this specific research project, we employ a strategy that is predicated on regression.

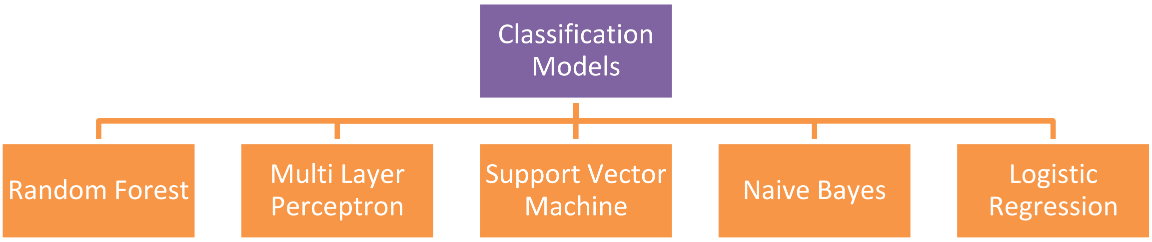

Fig 1: Prediction Model

With linear regression models, it is feasible to make predictions; however, this can only be done once the parameters of the models have been defined before it is able to make any predictions. Symbols are used to depict the connection that exists between the different variables in a mathematical equation.

The objective of regression analysis, as demonstrated by Equation (1), is to estimate the value of a continuous objective (y) as a function (F) that is dependent on the variables that serve as predictors ((x1, x2, x3,... xn)), a set of parameters (1, 2,..., n), and error. This can be accomplished by comparing the observed values of the predictor variables (β1, β2,... , βn) with the predicted values of the continuous objective *e*. A set of parameters with values ranging from one to n and another set of parameters with values ranging from one to one thousand are utilized in order to achieve this goal.

$$Y = F(x, \beta) + e \quad (1)$$

The variable denoted by y is the independent variable, which is also commonly referred to as the result. The variables denoted by *x* are the predictors. The residual is defined as the difference between the value that was actually obtained from the predictor and the value that was expected to be obtained from it. The regression coefficient is a type of statistical metric that is applied in the process of carrying out a regression analysis. Training a regression model was done to determine the most accurate values for the model parameters so that it could achieve the level of accuracy that was desired. This was done by figuring out the best possible values for the model parameters (as measured by an error metric such as the sum of squared errors).

We examined the efficacy of our classification system by comparing it to the many alternative models that are already on the market using five different categorization methods. The applicability of regression models that are created via machine learning is dependent on a large variety of characteristics, the particulars of which can vary from one problem to the next. The size of the dataset, the number of features, and the pattern in which the data are distributed are all examples of the kinds of variables that fall under this category, along with a variety of additional factors. Not all problems can be modeled, and even when they can, the results may not always meet the requirements of the user in some circumstances.

Two factors were taken into account throughout the selection process for the models that will be employed in this investigation. The previous work that has been done on these issues while utilizing the same dataset. The number of different classifiers that can be used to classify data is fairly extensive. During the process of choosing the best models, those that had a high error rate were disqualified from further evaluation.

Random Forest (RF)

The bagging procedure is applied to a dataset that consists of N components so that these groups of trees can be trained using the methodology. A random sampling strategy that incorporates replacement is used across a scale of N samples and applied to the training set. After then, the data that was presented to the decision tree can be utilized to train it in order to make better decisions. Iterations of this approach must not fall below or above the threshold of T.

In the case of classification trees, the prediction of the unknown entity is arrived at all *T* trees. On the other hand, in the case of regression, the final prediction is arrived at via the average value, as given by Eq. 8. More information regarding both of these approaches can be found further down in this section.

$$y = T^{-1} \sum f_i(x') \quad (2)$$

where

x' - unseen sample,

y - predicted value,

fi - trained decision tree, and

T - iterations.

$$y = \text{mode}\{f1(x'), f2(x'), \ldots, fi(x'), \ldots fT(x')\} \quad (3)$$

where

$f_i(x')$ - prediction class

i.- data sample

It has been demonstrated that the RF method is useful in managing large datasets that contain a wealth of qualities while concurrently assessing the relative value of each component of the problem at hand. It possible for things like random variation, outliers, and overfitting to have an impact on it. The RF is distinct from other techniques for classification since it employs a consolidated vote that is obtained from the results of a number of other classification procedures.

Multilayer Perceptron (MLP)

A technique known as the multilayer perceptron (MLP), which employs supervised learning, serves as an excellent demonstration of this concept. The perceptron from neural networks produce a single output via the linear combination of those inputs and their associated weights, as shown below.

$$y=\alpha\sum w_i x_i+\beta \quad (4)$$

where

wi – weight

xi – input variable

β - bias and

α - non-linear activation function.

Multi-layer structure consists of an input/output layer, one or more hidden layers, and an output/transfer layer. Also included is a hidden layer or layers. In addition, the MLP has at least three unique node layers. During the training phase of the MLP, a back-and-forth method is used to update the model parameters (biases and weights) based on the prediction error. This is done in order to maximize the accuracy of the model (feedforward pass followed by a backward pass).

Support Vector Machine (SVM)

The support vector machine, sometimes known as an SVM, is a popular model for supervised machine learning that is used to solve classification and regression problems. It has been demonstrated that this paradigm is successful in solving linear as well as non-linear issues. The objective of the support vector machine, often known as an SVM, is to generate a hyperplane. SVM performs remarkably well in applications that incorporate enormous datasets that cover a variety of domains.

$$f(w) = 0.5\|w\|^2 \quad (5)$$

Naïve Bayes (NB)

The Nave Bayes method is a probabilistic algorithm that generates results by applying Baye theorem. This method is often referred to as the NB method. This strategy could be considered naive because it makes the assumption that each attribute contributes equally and independently to the likelihood of the target class. One of the many advantages that NP possesses is the ability to resist the influence of background noise. It has been demonstrated beyond a reasonable doubt that it performs admirably with datasets that are both high-dimensional and extensive in scope.

$$P(a|b) = [P(b|a)\ P(a)] / P(b) \quad (6)$$

Logistic Regression (LR)

The concept of probability serves as the conceptual basis for the method known as logistic regression (LR), which is applied by professionals in the field of machine learning (ML) with the aim of classifying events as either successful or unsuccessful. The LR model can be thought of as a linear regression model for the cost function rather than a linear one.

This simplification allows for the model to be viewed in a more straightforward light. LR performs exceedingly well on a wide variety of problems, is easy to implement, and calls for the computer to use very few resources. The fact that it presumes a linear relationship between the variables that are independent and those that are dependent is its most fundamental flaw.

4. Results and Discussions

In this section, the proposed model is evaluated using the parameters that is set in Table 1.

Table 1: Parameters for Simulation

Variables	*N*
Male	213
Female	1009
Medical	287
Non-medical	935
18–25	1021
26–35	162

> 35	37
Diploma	43
Bachelor’s	1017
Postgraduate	160
90–100	655
80–89	377
70–79	164
< 70	25

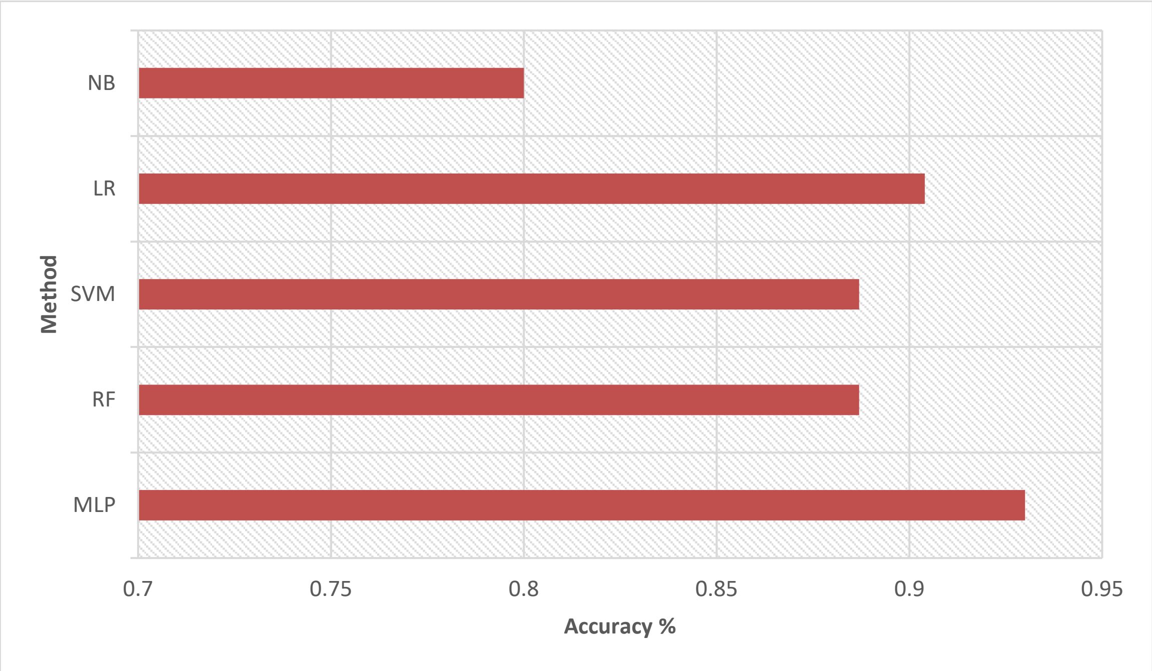

Fig 2: Accuracy of predicting student performance

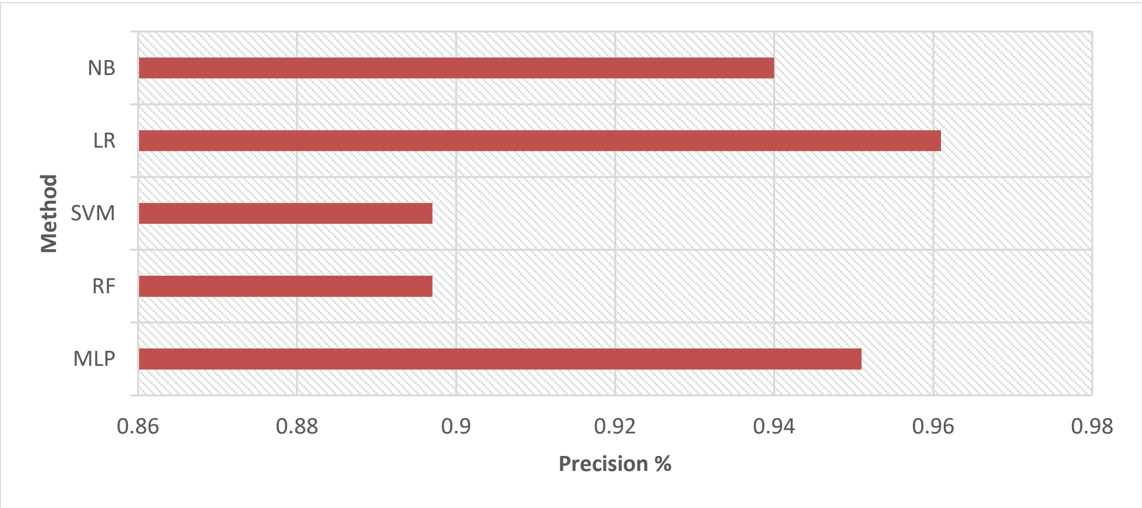

Fig 3: Precision of predicting student performance

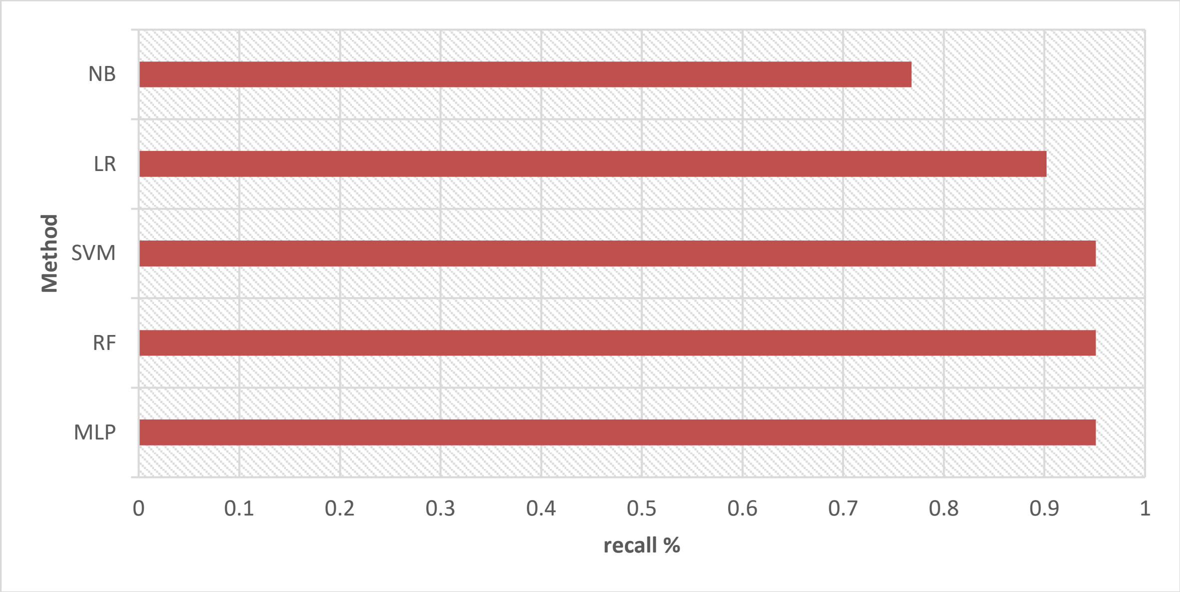

Fig 4: Recall of predicting student performance

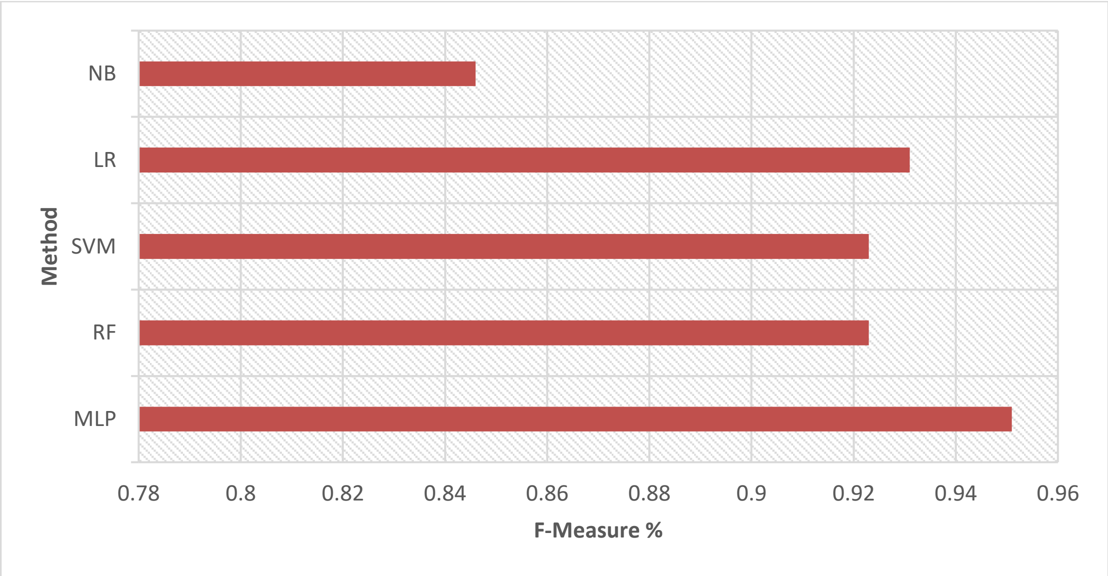

Fig 5: F-Measure of predicting student performance

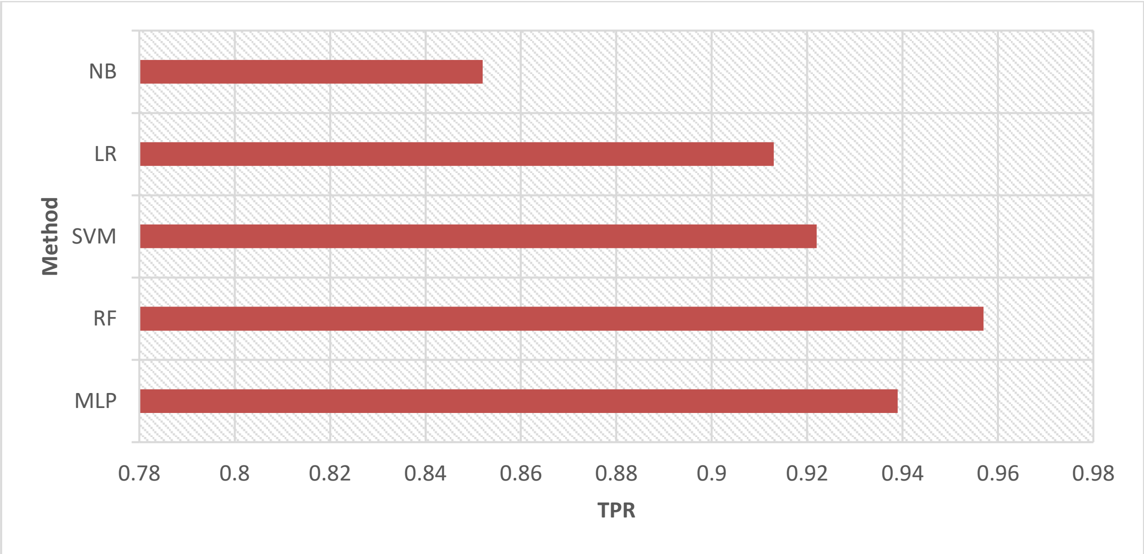

Fig 6: TPR of predicting student performance

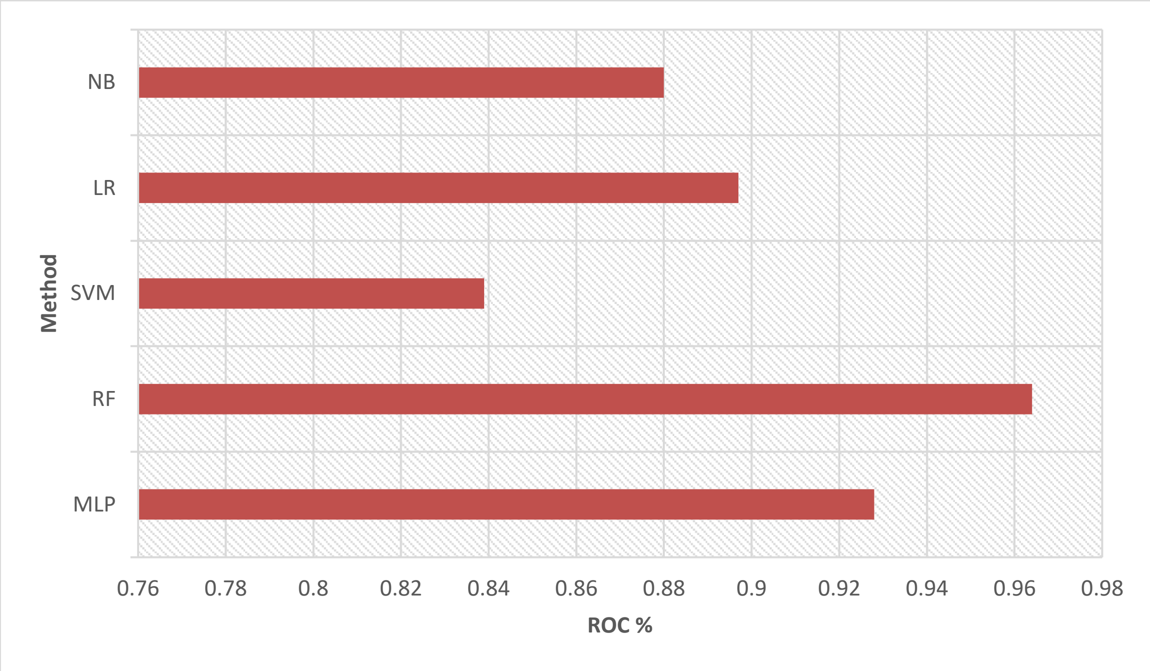

Fig 7: ROC of predicting student performance

According to the findings, the participation of students in various direct mode teaching and learning activities leads to considerable improvements in those student grade point averages. Given these data, it would appear that a model of linear regression would be an adequate choice for forecasting the academic achievement of the students. The collected data made it possible to construct the model using linear regression by selecting which variables were included within the equation. The overall academic performance of students is expected to improve throughout the course of the upcoming semester, according to a linear regression model that incorporated the variable age into its predictions. The figure 2 to fig 7 shows the results achieved in this method.

The distribution of student grades shows that the vast majority of them will have grade point averages that are greater than the mean. We are able to draw the conclusion that the overall performance of the students will improve during the subsequent semester, in spite of the fact that they will be forced to complete their assigned assignments via electronic methods.

Even though students will be obliged to go through an online teaching and learning approach when they are participating in time, this will not prevent them from seeing an improvement in their GPA result. Students will not be prevented from seeing an improvement in their GPA result. This is due to a number of different factors. Students who have more time to get settled in before the start of class attribute a major portion of their increased sense of comfort and security to the fact that they have more time to do so in those situations. Because they won't be as self-conscious about their intelligence in front of other people, they'll have a greater desire to continue their education and seek out higher levels of knowledge.

In addition, students have the opportunity to increase their understanding of how to use technology to their advantage, both within and outside of the classroom setting. This presents an invaluable learning opportunity. The vast majority of educators did, in fact, delegate homework with the purpose of facilitating student acquisition of new knowledge and enhancing their ability to recall previously learned material. Nevertheless, in order for students to do the task that has been delegated to them, they need to have alternative options open to them. This is due to the fact that during the MCO session, they are unable to roam around or meet with the other members of their group. A better grade was awarded to them as a result of their increased expertise and the punctuality with which they completed the assignment.

The fact that some students are unable to keep up with the rapid speed of the activities associated with online teaching and learning might have a detrimental effect on their marks. It likely that they have absolutely no interest in participating in the online teaching and learning activities. Students might struggle to pass an online course for a variety of reasons, one of which is that they might not always have access to the internet, which makes it difficult for them to participate in class and complete assignments. This is just one of the reasons why students might have trouble passing an online course. This suggests that it is the job of the instructors to continually examine the feedback that is supplied by the students and make adjustments to their teaching tactics as well as the course materials in accordance with this feedback. The capacity to concentrate and get oneself ready for class are both skills that students who take their classes online need to work on improving in order to prevent themselves from falling behind in their studies.

5. Conclusions

The statistical technique has the potential to improve the academic performance of students. This is because it enables teachers to more precisely estimate the needs of their students and adjust the amount of support, they provide to match those needs. Because the learning environment is complicated and there are different learning aids that can limit the study, using the classic approach of prediction will just take additional time.

In this experiment, a linear regression model was used to estimate student future GPAs based on the GPAs they have achieved up to this point in the semester. This was done so that the researchers could better understand the relationship between past and future GPAs. A comparison was made between the student current grade point average (direct mode) and their grade point average from their online education during the prior semester. One can draw the conclusion that the student academic performance will not suffer as a direct result of their involvement in online education because the vast majority of students show growth as a direct result of their engagement in online education. The linear regression model can be used as a stand-in when attempting to forecast how well a student will perform academically in school.

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