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RESEARCH PAPER

# Selecting Minimum Acceptable Student's Mark to Participate in Bologna Final Exam Using Machine Learning Approach.

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**A B S T R A C T:**

In the higher education sector, the minimum acceptable mark for participation in the final examination in the Bologna system can vary depending on the particular institution, program, and country. In general, most institutions require students to have a minimum overall score of "pass" to be eligible to take final exams. However, some institutions may have to change the minimum acceptable mark to be in line with the approved system and their examination policy. This research sheds light on the possibility of accepting extra students to participate in the final exam, if their scores are slightly lower than the general admission score, and predicting their success based on the student's grades in previous years. Linear and Polynomial regression (supervised machine learning analysis) were used to give promising results when applied to previous actual records of students in the College of Engineering and hundreds of random marks to increase the accuracy of estimating students' acceptance mark rate for entering the final exams and passing them by considering the new mark rate less than the standard and traditional one. This research will help weak grades students and allow them to participate in the final exam with the possibility of success.

**KEY WORDS**: Student Record, Machine Learning, Linear Regression, Polynomial Regression, Bologna exam.
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## 1. INTRODUCTION

Despite the occurrence of great changes at the level of higher education with the introduction of the Bologna system (Cappellari and Lucifora, 2009), there were many criteria that make the student participate in the final exam. In order to be able to participate in the final exam for this system or the previous system, a required point or marks must be obtained to participate in the exam, in general, the average are grade "C" or "2.0" in the GPA (Grade Point Average) system, or it was greater or equal to (50%) of the courses' cumulative grades.

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Prediction and giving the evaluation of a person's competency can be divided into Functional and Non-functional criteria. (Krishna and Chandran, 2021) present that predictive analytics are useful to sports clubs by helping them select the players they want to buy, according to many functional factors (e.g. age, height, speed, stamina, scoring rate, etc.), to determine the close price to fit on club's budget and prevent fraud about the player's performance. (Márquez-Vera et al., 2013) mentioned the non-functional criteria (e.g. age, gender, students' social behavior, parents' education) that can evaluate student competency according to previous years. Trying to predict his final marks, it was very hard to guess whether the student will or will not pass the exam.

(Bydžovská, 2016) mentioned how to obtain these type of data (functional and non-functional) using questionnaires process, based on data mining : classification and regression analysis. (Thangavel et al., 2017) used Logistic Regression to improve the placement performance of the students, depending on historical data that resides in educational organization. Where Logistic Regression gives good knowledge relationship with the dependent variables.

Many research predicted the student's future grade according to their performance, activities, and marks. They use different type of algorithms Linear Regression (Alshanqiti and Namoun, 2020), Neural Network (Tsiakmaki et al., 2020), Decision Tree (Vijayalakshmi and Venkatachalapathy, 2019), and Naive Bay's model (Meiriza et al., 2020), additionally, verifying and expecting the dropout students from taking the exam (Del Bonifro et al., 2020), depending on their performance. Most previous researches were based on fixed input data (i.e. statistics, saved, and historical), then applied different kinds of algorithms to get the output results. In this paper, the input data is varied (i.e. small rated reduced gradually) and processed using supervised machine learning with different types of regression analysis (e.g. Linear, n-orders Polynomial) on the real and random historical datasets and comparing among them to estimate and increase the accuracy of the results, trying to find the minimum acceptable mark that can be considered to the student so that he can participate in the exam. This paper is to investigate whether if the student is gotten marks less than (25/50)% of cumulative course marks and pass in the final exam methodologically, then why didn't he participate? this will make the policy of decision marks to entering the exam will be changed and give a chance to the students who are forbidden before to do the final exam.

## 2. MATERIALS AND METHODS

This section is divided into three parts according to the process sequence. The first will discuss how to obtain and arrange real and random data to be ready for processing. The second will calculate the results from the data in the first part using machine learning regression. The last part will select the acceptable marks for the students to be able to enter the final exam. The whole parts and process are illustrated in Figure 1.

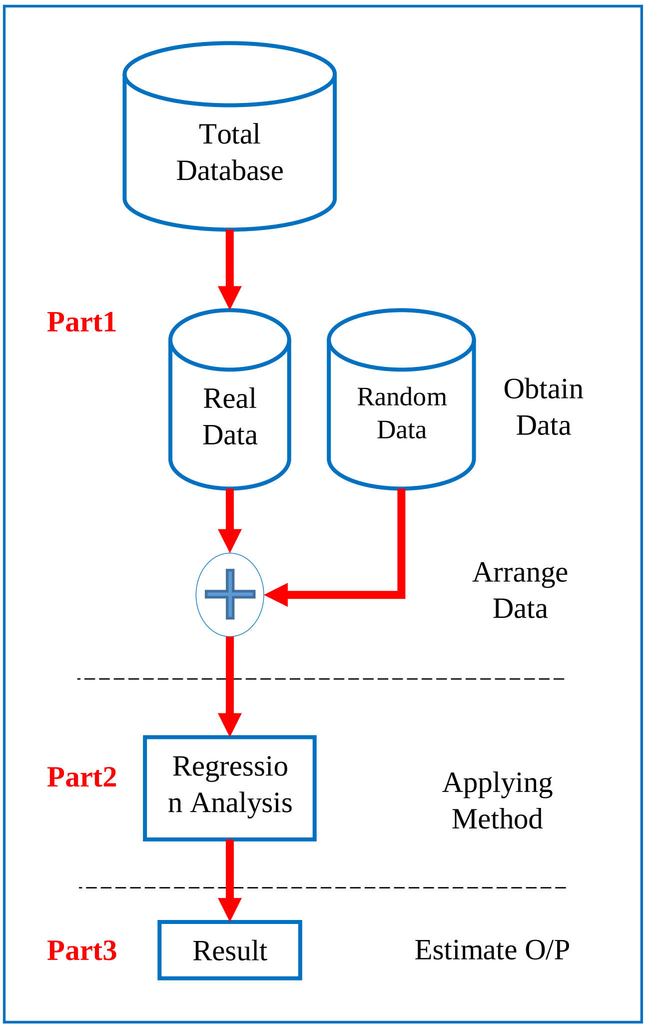


**Figure 1 Illustrate the process parts and sequence**

### 2.1 Obtaining and Arranging Data

This research deals with the data marks of students, and this kind of data is not arranged to be processed directly, obtaining and arranging these data must be done first, these data can be classified mainly into two types:

a) Real Data: obtained from historical marks records of each student in Salahaddin University College of Engineering for the last 3 years.
b) Random Data: generated randomly to give more accurate results to estimate the final decision for the student's situation to enter/withdraw the final exam.

Real data from previous years can provide a very good attitude about the student's performance in his department, this data will increase every academic year, it is less than 30 records per student due to the department policy plan, additionally, the research will neglect the students' whose their marks are over the pass rate because they will already enter to the exam. To solve this kind of data lacking, random data will be generated to cover the deficits in records. Figure 2 (a) illustrates the marks for normal and (b) weak students, assuming the course effort marks of the subject is 50%, the final is 50% and the Total will be from 100% the Sum of both of them. This research is focused on weak students because normal students who pass the exams do not need any help to enter the final exam, they are already in.

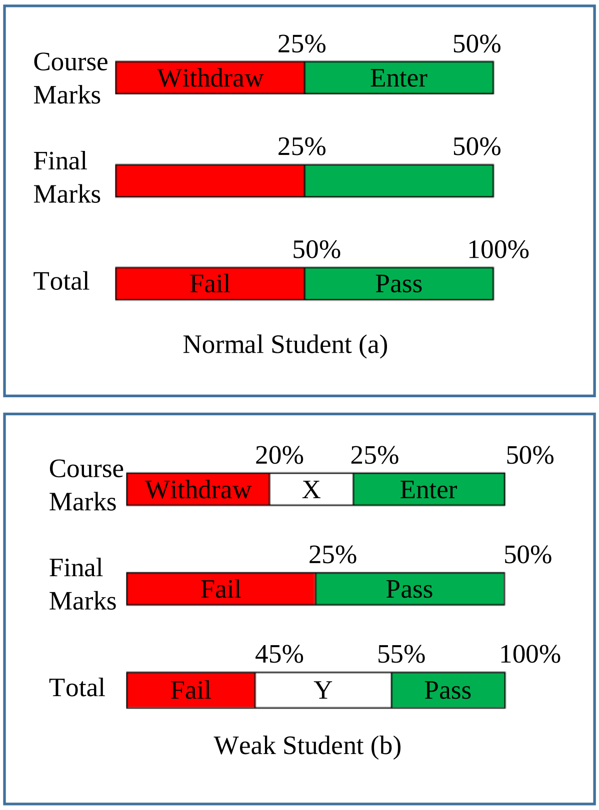


**Figure 2. (a) Normal Student Marks, (b) Weak Student Marks**

The database contains two types of weak student data, independent data (X) will represent the course marks of the weak student, which is confined between (20-25)%, and dependent data (Y) will represent the final exam, which is confined between (45-55)%, as shown in Figure 2 (b).

It is noted that the student in the first stages of college does not have any history in his grade record while data increases when crossing to the advanced stages, reaching the highest value of the real data in the last grades. Therefore, random and close data is added to the grades of the weak students grades, to improve the work of regression analysis for real and random data, and to increase the accuracy of the results.

## 2.2 Machine Learning: Regression Analysis

Regression Analysis (RA) is a predictive modelling technique that analyzes the relation between the target or dependent variable and independent variable in a dataset (Rong and Bao-Wen, 2018). The different types of RA techniques get used when the target and independent variables show a linear or non-linear relationship between each other, and the target variable contains continuous values. The regression technique gets used mainly to determine the predictor strength, forecast trend, time series, and in case of cause & effect relation.

RA is the primary technique to solve the regression problems in machine learning using data modelling. It involves determining the best fit line, which is a line that passes through all the data points in such a way that distance of the line from each data point is minimized. (Vadapalli, 2022)

RA is the process of fitting a function from a selected family of functions to the sampled data under some error function. Using regression you fit a function on the available data and try to predict the outcome for the future or hold-out data points. This fitting of function serves two purposes. (Anwar, 2021)

- You can estimate missing data within your data range (Interpolation)
- You can estimate future data outside your data range (Extrapolation)

Some real-world examples for RA include predicting the price of a house given house features, predicting the impact of SAT/GRE scores on college admissions, predicting the sales based on input parameters, predicting the weather, etc.

There are many types of RA techniques (Seber and Lee, 2003), and the use of each method depends upon the number of factors. These factors include the type of target variable, shape of the regression line, and the number of independent variables. Based on the family-of-functions (Montgomery et al., 2021), regression can categorized into:

1) Linear Regression (LR): It is one of the most basic types of regression in machine learning.

LR model consists of a predictor variable and a dependent variable related linearly to each other.

$$Y_i = f(x_i) = \beta_0 + \beta_1 X_i + e_i \qquad (1)$$

Where, $Y_i$ is the dependent variable, $X_i$ is the independent variable, $\beta_0$ is the intercept (i.e. $Y_i = \beta_0$ when $X_i = 0$), $\beta_1$ is the regression coefficient, and $e_i$ is the estimated error in the regression.

$$MSE = e_i = \sum (Y_i - f(x_i))^2 \qquad (2)$$

In case the data involves more than one independent variable, then LR is called multiple linear regression models.

$$Y_i = f(X_{i1}, X_{i2}, \dots, X_{im}) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_m X_{im} + e_i \qquad (3)$$

Where m is the number of independent variables (i.e. multiple inputs)

2) Polynomial Regression (PR): It is another types of RA techniques in machine learning, which is the same as Multiple Linear Regression with a little modification. In PR, the relationship between independent and dependent variables, that is $X_i$ and $Y_i$, is denoted by the (n) degree. It is a linear model as an estimator. Least Mean Squared Method is used in Polynomial Regression also. The best fit line in Polynomial Regression that passes through all the data points is not a straight line, but a curved line, which depends upon the power of $X_i$ or value of n.

$$Y_i = f(X_i) = \beta_0 + \beta_1 X_i^1 + \beta_2 X_i^2 + \cdots + \beta_n X_i^n + e_i \qquad (4)$$

3) Logistic Regression: It is one of the types of RA technique, it is a generalized form of LR, which gets used when the dependent variable is discrete. Example: 0 or 1, true or false, etc.. This means the target variable can have only two values, and a sigmoid curve denotes the relation between the target variable and the independent variable. Logic function is used in Logistic Regression to measure the relationship between the target variable and independent variables.

$$l = \frac{1}{1+e^{-(Y_i)}} \qquad (5)$$

4) Ridge Regression: This types of regression in machine learning which is usually used when there is a high correlation between the independent variables. This is because, in the case of multi collinear data, the least square estimates give unbiased values. But, in case the collinear is very high, there can be some bias value. Therefore, a bias matrix is introduced in the equation of Ridge Regression. This is a powerful regression method where the model is less susceptible to over fitting.

5) Lasso Regression: It is one of the types of regression in machine learning that performs regularization along with feature selection. It prohibits the absolute size of the regression coefficient. As a result, the coefficient value gets nearer to zero, which does not happen in the case of Ridge Regression. In the case of Lasso Regression, only the required features are used, and the other ones are made zero. This helps in avoiding the over fitting in the model. In case the independent variables are highly collinear, then Lasso regression picks only one variable and makes other variables to shrink to zero.

In both regression types (4, and 5), a penalty term of the regression coefficients ($\beta$) is added to the loss function ($e_i$) of Eq.2 (Nagpal, 2022), where:

$$\beta = (X^T X)^{-1} X^T Y \qquad (6)$$

$$Ridge\ Regularization \rightarrow min_{\beta_0,\beta}\left(e_i + \lambda \sum_{j=1}^{m} (\beta_j)^2\right) \qquad (7)$$

$$Lasso\ Regularization \rightarrow min_{\beta_0,\beta}\left(e_i + \lambda \sum_{j=1}^{m} |\beta_j|\right) \qquad (8)$$

Where λ is a nonnegative regularization parameter corresponding to one value of Lambda, β0 is a scalar, and β is a vector of length m.

6) Bayesian Linear Regression: This type uses the Bayes theorem to find out the value of regression coefficients. In this method of regression, the posterior distribution of the features is determined instead of finding the least squares. Bayesian Linear Regression is like both Linear Regression and Ridge Regression but is more stable than the simple Linear Regression. (Nasteski, 2017)

## 2.3 Selecting Acceptable Marks

After collecting, arranging, and applying RA for adequate data, it is time to estimate the lowest mark that can be considered as a course mark to the student to be able to enter the final exam. There are three types of course mark data (Xi) that can be obtained in this research:

i) Xi between (25-50)% of this belongs to Normal students, it is out of the process.

ii) Xi between (20-25)% of this belongs to weak students, it will be processed.
iii) Xi less than (20)% will be estimated and selected as the acceptable mark.

For example, if the average course mark is 25% for a student in any subject, and his final exam average mark is 55%, then this is an indication that this student is a pass in this subject even if his course mark is 20%, not 25%. This led to a query, can the withdraw point mark be reduced in cases similar to that student? This research aims to check more than hundreds of records for each student to reach the lowest mark that can be considered to enter the final exam with the possibility Pass in the Total mark evaluation.

## 3. RESULTS

This research will estimate the lowest acceptable mark that could be considered for a student to verify his entry to the final exam based on his previous marks. Linear and polynomial regression in Matlab will be used in this data. Three steps are applied to reach final results, which will explain the methods used in sections 2.1, 2.2, and 2.3, respectively:

Step (I) Organize Data: The data is taken from previous history saved in real records of the university for the students, and from random records to complete the lack of real records for weak students. The data will contain the total number of students (S) and their marks (i).

*Step (I)*

- ***S*** *is the number of total students*
- ***k*** *is the current student of* ***S***
- $X_{ik}$ *is the current vector of student and marks (independent) out of 50%*
- $Y_{ik}$ *is the current vector of student and marks (dependent) out of 100%*
- *Both* ***X*** *&* ***Y*** *are organized from real and random dataset*

*End Step (I)*

Step (II) Create Regression Data: the independent Xi and dependent Yi will be the input data to the LR and PR (with n order, from 2 to 5), and this will extract the formula output of each regression method used in this research. Table 1 shows only ten out of hundreds of the input and output marks data to describe the derivation of created regression data of k student, the output data LR, PRn2, PRn3, PRn4, and PRn5 (i.e. using multifunction of regression method will increase the accuracy of output results) will drive from Xi and Yi using equation 1 and 4 respectably.

**Table1. Input (Independent X, Dependent Y), Output (LR, PR) data for student k**

| *no* | $X_{ik}$ | $Y_{ik}$ | $LR_{ik}$ | $PRn2_{ik}$ | $PRn3_{ik}$ | $PRn4_{ik}$ | $PRn5_{ik}$ |
|---|---|---|---|---|---|---|---|
| *1* | 22 | 50 | 50.07 | 50.50 | 50.46 | 50.13 | 50.59 |
| *2* | 23 | 47 | 50.23 | 50.66 | 50.69 | 50.30 | 49.89 |
| *3* | 23 | 50 | 50.23 | 50.66 | 50.69 | 50.30 | 49.89 |
| *4* | 23 | 47 | 50.23 | 50.66 | 50.69 | 50.30 | 49.89 |
| *5* | 24 | 48 | 50.38 | 50.52 | 50.58 | 51.30 | 51.57 |
| *6* | 22 | 50 | 50.07 | 50.50 | 50.46 | 50.13 | 50.59 |
| *7* | 20 | 50 | 49.77 | 49.27 | 49.30 | 49.12 | 49.17 |
| *8* | 22 | 50 | 50.07 | 50.50 | 50.46 | 50.13 | 50.59 |
| *9* | 24 | 55 | 50.38 | 50.52 | 50.58 | 51.30 | 51.57 |
| *10* | 25 | 53 | 50.53 | 50.08 | 50.05 | 49.89 | 49.86 |

Figure 3 shows the five types of regression results, these results belong to a student. Since the research focuses on weak students, the domain of Xi is [20,25] and the range of Yi is

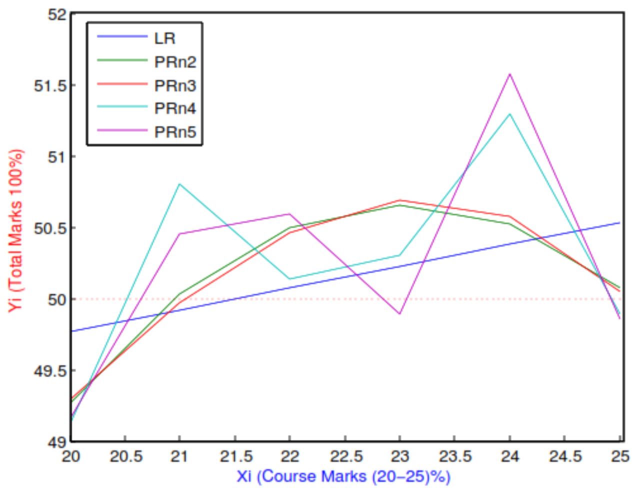


**Figure 3. Shows different type of Regression Output**

[45,55].

Table 2 shows all coefficient (β) values for all regression methods that are applied for Xi and Yi.

**Table 2. The $\beta$ values of all Regression types**

| $\beta$ | LR | PRn2 | PRn3 | PRn4 | PRn5 |
|---|---|---|---|---|---|
| $\beta_0$ | 46.69 | 29.29 | 114.60 | 33803.90 | 527471.22 |
| $\beta_1$ | 0.15 | 6.94 | -12.36 | 6052.91 | 119387.55 |
| $\beta_2$ | x | -0.15 | 0.71 | -405.10 | 10791.07 |
| $\beta_3$ | x | x | -0.01 | 12.03 | -486.84 |
| $\beta_4$ | x | x | x | -0.13 | 10.96 |
| $\beta_5$ | x | x | x | x | -0.10 |

*Step (II)*

- *From Eq1,*

  $LR_{is} = Y_{is} = \beta_{0s} + \beta_{1s} X_{is}$

  $Y_{is} = X_{is}\ \beta_{is} \ \rightarrow \quad \beta_{is} = X_{is}^{-1}\ Y_{is}$

  $$Y_{is} = \begin{bmatrix} y_{1k} \\ y_{2k} \\ \vdots \\ y_{jk} \end{bmatrix}, \quad X_{is} = \begin{bmatrix} 1 & x_{1k} \\ 1 & x_{2k} \\ \vdots & \vdots \\ 1 & x_{jk} \end{bmatrix}, \ \beta_{is} = \begin{bmatrix} \beta_{0s} \\ \beta_{1s} \end{bmatrix}$$

  $k = current\ student,$

  $i = current\ marks = \{1,2,\dots,j\},$

  $\beta_0 = intercept,\ \beta_1 = \ slope$

- *From Eq4,*

  $PR_{is} = Y_{is} = \beta_{0s} + \beta_{1s}X_{is}^1 + \beta_{2s}X_{is}^2 + \cdots + \beta_{ns}X_{is}^n,$

  $n = order\ of\ polynomial\ function$

  $Y_{is} = X_{is}\ \beta_{is} \quad \rightarrow \quad \beta_{is} = X_{is}^{-1}Y_{is}$

  $$Y_{is} = \begin{bmatrix} y_{1k} \\ y_{2k} \\ \vdots \\ y_{jk} \end{bmatrix}, \quad X_{is} = \begin{bmatrix} 1 & x_{1k}^1 & x_{1k}^2 & \dots & x_{1k}^n \\ 1 & x_{2k}^1 & x_{2k}^2 & \dots & x_{2k}^n \\ & & \vdots & & \\ 1 & x_{jk}^1 & x_{jk}^2 & \dots & x_{jk}^n \end{bmatrix},$$

  $$\beta_{is} = \begin{bmatrix} \beta_{0k} \\ \beta_{1k} \\ \vdots \\ \beta_{jk} \end{bmatrix}$$

*End Step (II)*

Step (III) Estimate the Output: after extracting the formulas in step (II) and their coefficients from Table 2 of each type of regression, it is time to estimate the values of Y by applying descending values of X=[24;23;22;21;20;19;18;17;16;15] and the coefficient values (β).

*Step (III)*

By following the method in step II to find [X] for all types of regressions to calculate

*Y= [X][β]*

$$LR = [X]\begin{bmatrix} 46.69 \\ 0.15 \end{bmatrix}, PRn2 = [X]\begin{bmatrix} -29.29 \\ 6.94 \\ -0.15 \end{bmatrix},$$

$$PRn3 = [X]\begin{bmatrix} 114.60 \\ -12.36 \\ 0.71 \\ -0.1 \end{bmatrix}, PRn4 = [X]\begin{bmatrix} -33803.90 \\ 6052.91 \\ -405.10 \\ 12.03 \\ -0.13 \end{bmatrix},$$

$$PRn5 = [X]\begin{bmatrix} 527471.22 \\ -119387.55 \\ 10791.07 \\ -486.84 \\ 10.96 \\ -0.10 \end{bmatrix}$$

*End Step (III)*

Figure 4 shows the estimated output for all regression types that used for student k, and the results show the minimum accepted values that can be considered to predict his success is between (20 and 21)%, and Table 3 shows the output data for all descending values.

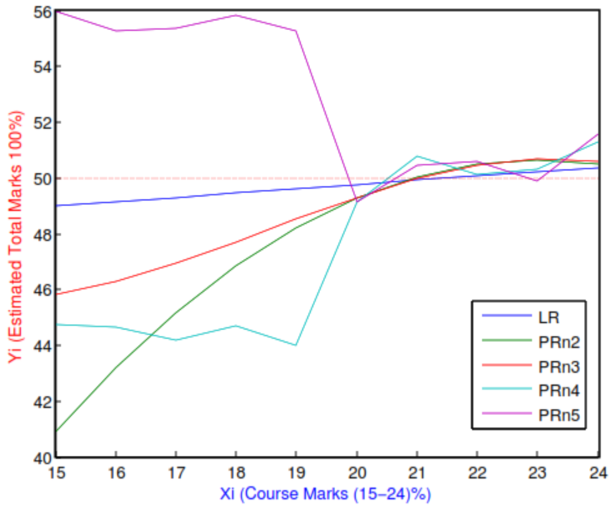


**Figure 4. Shows Estimated Values of Regression Types**

**Table 3. Estimated Yi according to new Xi**

| no | X | LR | PRn2 | PRn3 | PRn4 | PRn5 |
|---|---|---|---|---|---|---|
| *1* | 24 | 50.38 | 50.52 | 50.58 | 51.30 | 51.57 |
| *2* | 23 | 50.23 | 50.66 | 50.69 | 50.30 | 49.89 |
| *3* | 22 | 50.07 | 50.50 | 50.46 | 50.13 | 50.59 |
| *4* | 21 | 49.92 | 50.03 | 49.97 | 50.81 | 50.45 |
| *5* | 20 | 49.77 | 49.27 | 49.30 | 49.12 | 49.17 |
| *6* | 19 | 49.61 | 48.20 | 48.52 | 44.02 | 55.25 |
| *7* | 18 | 49.46 | 46.83 | 47.70 | 44.72 | 55.84 |
| *8* | 17 | 49.30 | 45.17 | 46.93 | 44.20 | 55.37 |
| *9* | 16 | 49.15 | 43.20 | 46.28 | 44.64 | 55.27 |
| *10* | 15 | 49.00 | 40.92 | 45.83 | 44.74 | 55.99 |

## 4. DISCUSSION

The results above show how to calculate different types of regression and estimate the outputs of missing or under-range values of inputs. Also, not all the regression types have the same trends, as shown in Figures 3, and 4. These methods are applied to S students to find the minimum acceptable mark of less than 25% for a K student to be able to enter the final exam with a high possibility to Pass it, additional to that, the results can show the minimum mark of a K student and the average minimum mark of S students. Applying these methods will not select the minimum acceptable mark for a student only, but the average acceptable mark for all students.

## 5. CONCLUSIONS

The course mark is considered the limit for the student to enter the final exam, the exam mark is divided into 50% of the course mark and 50% of the final exam mark, and according to the instructions of the department or the examination policy, where the student had to obtain more than 25% of the course mark to be allowed to take the final exam. The course marks are divided according to the quality of the student into three types, Pass (≥25%), far away from Pass (<<25%), and close to Pass (25-20)%. This research serves the third type, whose mark is close to 25%, depending on the student's grades and performance in previous years. By using the analytical regression of the student's data, it is possible to expect the lowest mark to be considered, which is less than 25%.The data was created and organized for more than 100 students with 100 data real and random records for each student for more than 100 running attempts, to increase the accuracy of the results 5 analytical regression methods were used on these data, taking the average of these methods to calculate the minimum acceptable mark, which ranges from (18-20)% for the current student, as well as, for all students, which ranges from (20-21)%. Finally, the minimum acceptable mark is changed to help these weak students to join with the others. This research will give a second chance to these students, who have good history marks to participate with the possibility of passing the final exam.

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