Performance Evaluation of Regression Analysis Algorithms in Predicting the Enrollment of Basic Education

Elizalde L. Piol¹, Luisito Lolong Lacatan², Jaime P. Pulumbarit³

¹Department of Education & AMA University, Philippines

²College of Engineering, Laguna University

³Bulacan State University, Malolos Bulacan

Abstract-- The use of Linear Regression in predicting enrolment has been shown to be beneficial, although it varies with various datasets and attributes; varying weights of the correlation of the attributes can be discarded if they do not impact the prediction. Data collecting had grown since prior investigations, resulting in a more complicated dataset with many varieties. As a result of the data being created by multiple clerks, cleaning and combining proved tough; nonetheless, the fundamental parameters remain intact. Different algorithms were examined but Linear Regression obtained the highest accuracy with a 12.398 percentage for the absolute error and a root mean squared of 26.936 to create a tangible model to anticipate the enrolment of Region IVA CALABARZON in the Philippines. This demonstrates that it was 2.067 percentage points more than the prior research.

I. INTRODUCTION

During the Covid19 epidemic, public and private schools in the Philippines implemented Learning Modality (LM). The Department of Education (DepEd) created a television learning style to encourage assistance in the module type approach in order to retain learners' interest and willingness to continue their studies [1], [2]. However, some of the students do not have access to the program since they do not own televisions. As a result, the distribution and support of instructors in completing the work per topic has become challenging owing to the country's access to the internet, particularly in the country's metropolitan and isolated locations [3], [4].

The simplest way to deal with the learners is to offer them with learning materials that parents can help the learners answer. The printed modules'(PM) dilemma is dependent on student enrolment, which is subsidized by the government [5]. The enrollment expectation had not been forecast, which means that the materials have no accurate statistics and rely only on when the learners registered in the school.

One of the problems is that particular locations produce too much or too little PM, resulting in a shortage of bond sheets and ink for printers and photocopiers [6] [7]. There are also delays in PM production owing to gathering the number of registrants first before production, which results in late learning weeks of planned instruction delivery. Various techniques were used to test the new system, however the test resulted in more issues [8], [9].

To tackle this problem, the correct prediction technique must be found, which relates the prior grade to the future grade or averaging the data from the previous data to get the new forecast. However, population growth accelerates at a pace of six times the rate of inflation [10]. To fix this problem, we might take the most recent number of registrants and multiply it by the inflation rate of six. This may alleviate a problem, but there are a number of other difficulties, such as changing addresses due to causes such as job, returning to hometown, and others, that would be additional considerations in estimating the number of enrollees [11].

Forecasting methods include linear regression, deep learning, decision trees, gradient boosted trees, random forests, and support vector machines [12], [13]. The goal of this study is to anticipate the number of primary school enrollment in Batangas City and the rest of Batangas Province using several algorithms and to suggest the best performance analysis. The study's findings would serve as the foundation for LM production in the province. Though none of the methods achieve a complete degree of accuracy, the substantial value reduces the percentage error for LM printing.

II. DATA PREPARATION

The municipalities of Batangas City, and the province of Batangas has been the highest population in terms of students in the primary school.

The data was gathered through the DepEd division office of Batangas City, Philippines. The data was presented contains parameters of grade level, name of school, gender and year of the academic year [14], [15], [16].

Figure 1. Weight by correlation

To prepare the data, data cleansing was performed. Figure 1 shows that, using the weight by correlation technique, other parameters that would have no influence on the prediction, such as school ID, town, and district, are removed. The second step is to assign the quantity of data to certain rows based on the criteria you've selected. Third, a replacement or averaging procedure was used to check the data for null values. The following stage is deduplication, which removes any duplicate values[17]. In any field, there must be no duplicate values. Following that is verification, which checks the data to determine if the values from the source data are legitimate, and lastly importation, which prepares the data for all of the algorithms.

The combined data yielded 29,038 items, which were separated into two groups: the training dataset and the testing dataset. 70 percent for training and 30 percent for testing, which will be used to judge the model's performance. The linear regression model with the lowest absolute value was 14.465 and a dataset of 3,445 rows. As the dataset size grows, the linear regression will be examined to see if it achieves a lower or greater accuracy.

III. METHODS

The technique for evaluating the linear regression model will be carried out in stages [18]. The first stage is data collection, the dataset was collated and merged with different dataset within the region. Next is data cleaning, preparing the data and converting it to a binomial datatype compatible with linear regression. This step also covers deduplication, replacement and verification.

Next is splitting the dataset to two parts which includes having a training and testing dataset. Next is training the dataset, this process involved linear regression algorithm. The creation of model and testing the performance in the dataset will be the last stage. As a result, the dataset will be evaluated with multiple algorithms to see whether the model is the best match for the dataset [19]. The comparison will also display each process's distinct topologies, relative error, standard deviation, training time, and testing time [20].

The enrollment statistics from 2017-2020 were filtered and aggregated from the data acquired in different sections of Region IVA CALABARZON of the Philippines to build a larger dataset from the previous study.

The use of data cleaning improved the dataset's quality by picking the appropriate characteristics using correlation, deleting duplicate entries, and managing data. The end result will be a prepared dataset suitable for linear regression training and testing.

20,326 population would run under training for formulation of the model, while the remaining 8,712 will be evaluating the model for the performance [21]. While the relative error will define the difference of the accuracy, other attributes will be considered. The time performance of the training and testing the linear regression that was used in the study[22].

Figure 2. Methodology

A comparative study on the different algorithms using the same dataset will be used in Decision Tree, Deep Learning[23], Random Forest, Gradient Boosted Tree and Support Vector Machine.

Most algorithms do not fit a specific dataset, which is why selecting the right method for each dataset is critical[24]. Some of the predictive algorithms only results into a binomial result which are 1 or 0, true or false and yes or no, but some have multiple output which are called multivariate results which are person, cat, dog. In this state, the usage of different algorithms would consider the prediction output. Thus, calculating method is based on the variable setting and coefficient state[25]. where the dependent variables are considered and see how much this column may affect the prediction result, moreover, the independent variables may be disregarded during the prediction since it has indirect relevance to the prediction. The computation of the regression analysis is reliant on the dependent and independent variables, as stated in the formula below.

Formula

$$Y_i = f(X_i, \beta) + e_i \quad (1)$$

Y_i = dependent variable

f = function

X_i = independent variable

β = unknown parameters

e_i = error terms

By suiting a linear equation to experimental data, linear regression seeks to model the joining between two variables[26][27]. a variable is regarded as an explanatory variable, while the other is regarded as a dependent variable. A modeler, for example, could wish to use a linear regression model to match people's weights to their heights.

IV. RESULT AND DISCUSSION

The major property of linear regression is to calculate all parameters with the given weight corresponding to the coefficient and the standard coefficient based on the enrollment data for the [28] forecasting of the enrollees for the Region 4A for the school year 2022-2023. The preparation would lead to a close number of learning material to printed allocated for both elementary and high school students within the area. [2]

Table 1 displays the coefficient for each of the attribute items. Detailing the criteria will show that various levels have an impact on the region's enrolment population.

Table 1.
Linear Regression Coefficient

Attributes	Coefficient
Level.grade1	-0.148
Level.grade2	4.5
Level.grade3	0.145
Level.grade4	-0.522
Level.grade5	1.192
Level.grade6	2.068
Level.grade7	1.289
Level.grade8	3.005
Level.grade9	-0.117
Level.grade10	2.358
Gender.Male	-1.814
Gender.Female	0.456
Year	-0.308

When two qualities are combined, it is notable that there are few examples of the coefficient heading towards the positive note. This is seen in the diagram below.

Attribut...	Gender ...	Level = ...	Level = ...	Level = ...	Level = ...	Level = ...	Level = ...	Level = ...	Total	Year
Gender ...	1	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.041	0.000
Level = ...	-0.000	1	-0.133	-0.167	-0.167	-0.167	-0.167	-0.167	-0.016	-0.000
Level = ...	-0.000	-0.133	1	-0.133	-0.133	-0.133	-0.133	-0.133	0.040	0.216
Level = ...	-0.000	-0.167	-0.133	1	-0.167	-0.167	-0.166	-0.167	-0.008	0.000
Level = ...	-0.000	-0.167	-0.133	-0.167	1	-0.167	-0.167	-0.167	-0.019	0.000
Level = ...	-0.000	-0.167	-0.133	-0.167	-0.167	1	-0.166	-0.167	0.009	0.000
Level = ...	-0.000	-0.167	-0.133	-0.166	-0.167	-0.166	1	-0.167	0.031	0.001
Level = K...	0.000	-0.167	-0.133	-0.167	-0.167	-0.167	-0.167	1	-0.021	-0.001
Total	-0.041	-0.016	0.040	-0.008	-0.019	0.009	0.031	-0.021	1	-0.005
Year	0.000	-0.000	0.216	0.000	0.000	0.000	0.001	-0.001	-0.005	1

Figure 3. Correlation of the attributes

The integration of the variables shows that the gearing is pointing in the other direction, as seen in figure 3. In other cases, the traits contradict each other in such a way that when one grows, the other diminishes.

Table 2.
Comparative Results

Model	Root Mean Squared Error	Absolute Error (%)	Training Time (milliseconds)	Scoring Time (milliseconds)
Decision Tree	27.119	17.289	~0	1
Random Forest	27.12	17.267	1	1
Gradient Boosted Tree	27.048	17.078	34	10
Support Vector Machine	28.116	15.701	12000	716
Deep Learning	27.031	17.129	445	40
Linear Regression	26.963	12.398	5	3

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Using different algorithms with the same dataset, the following results had been shown in the table 2. With an evident result of 26.963 for the root mean square of the linear regression and a 12.398 percentage for the absolute error. The difference of each algorithm is close but the linear regression is still the best model for the dataset used for enrollment prediction. While the decision tree offers the best performance in training and testing time, the performance of accuracy is still the factor to consider.

V. CONCLUSION

Based on the results, the real implementation may have a linear regression accuracy of 87.602 percent. The timing may be delayed or varied by milliseconds, but the performance must be considered. A 3.303 percent difference in support vector system with the same dataset and a 2.067 percent difference from the prior research. As a result, the model becomes more efficient as the dataset's richness increases.

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