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Analyzing Factors Influencing Mathematics Performance in BECE Using Logistic Regression

Abigail G. Obayori¹, Rashedat Olarenwaju²

^{1&2}*Department of Computer Science, Nasarawa State University. Keffi, Nasarawa State, Nigeria*

Abstract -The impulse of most developing countries to attain a generally acceptable extent in the quality of education becomes one of the many policy objectives. No developing country progresses without a proper attention to science and technology. Science, the fundamental discipline, should be encouraged. Mathematics must be taken into consideration being the foundation of all disciplines. The performance of students in mathematics at junior secondary school level is dwindling, which in turn progresses to senior secondary school and tertiary institutions. Many factors affect the attainment of high grades by students in mathematics, and one of such is students' emotions that lead to a lack of interest in solving mathematical problems. Some students find it difficult to study after school hours, and a lack of parental support also affects students' performances in mathematics, as studying is important for students' success. The level of academic failure of public secondary schools is of great concern to parents, stakeholders, and the government. Despite unending efforts by teachers to impart and instill knowledge, and efforts of the government to provide a conducive environment by the provision of learning materials, students are still not getting it right. This study investigates the declining performance of junior secondary school students in mathematics in Pasali, Kuje, FCT, Nigeria. Despite government and teacher efforts, student outcomes remain poor due to various factors such as emotional challenges, lack of parental support, and inadequate study habits. Using data from 235 students and 19 variables (e.g., sex, age, location, emotions, family support), the study applied machine learning algorithm, Logistic Regression (78% accuracy) and Random Forest (98% accuracy), to classify student performance as Pass or Fail. The research highlights the broader implications of math failure on national development, emphasizing the need for improved infrastructure, reduced overcrowding, and enhanced ICT access in public schools to foster better educational outcomes and future STEM expertise.

Keywords: Logistic regression, Machine learning, Random Forest, STEM Education, Students' emotions,

I. INTRODUCTION

For a better progress of Nigeria, government need to pay proper attention to science and technology. Science, the fundamental discipline, should be encouraged. Mathematics is a foundation of all disciplines and must be taken into consideration. Numerous applications of mathematics can be found in the physical and agricultural sciences, weather prediction, engineering, computer, textile, and aerospace sectors [1]. Practically all of man's daily actions involve mathematics, even educated and uneducated people must deal with manipulations and mathematical problems. Mathematics is one of the core subjects in the Nigerian educational system. Students at all levels must have a credit pass in order to be admitted to study any course in a higher institution [2]. The poor performance of students in mathematics at senior secondary school is rapidly increasing. It is challenging to envision a world without mathematics. The Basic Education Certificate Examination (BECE) is used to evaluate students at the conclusion of a nine-year education program with the use of internal and external assessments of students [3]. A significant concern is the junior secondary student's academic performance in mathematics. The sensation of fear, phobia, or anxiety that greet mathematics appears not to be so for other subjects, as students perceived mathematics as a monster that so many students are scared of. The level of academic failure of public secondary school students in Kuje Abuja are of great concern to parents, stakeholders and government. Despite unending efforts by teachers to impact and instills knowledge couple with the efforts of government to provide a conducive environment by the provision of learning gadgets. Hence, perturbed by this challenge, a study of this nature needs to be approved in order to predict the performance of students.



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Most studies adopted statistical techniques to predict the attainment of students in secondary school, which may not be able to compare variables in a timely manner [3-4]. Their focus is mainly on public secondary schools. The measure of academic performance utilized by these studies were expo factor and mean square error. It is crucial to forecast how well students will succeed academically in all subject areas [3], Predicted performance of Students' Mathematics in Junior Secondary School, (JSCE) utilizes the data of 4,698 students who are graduates from 2000 to 2003, who also graduated from senior secondary school Certificate (SSCE) between 2003 to 2007, discovered that result of JSCE significantly predicted the result of SSCE. The study utilized the previous knowledge but failed to identify other factors that could have affected student's performance. In the same way [5], utilizes the data of 850 students drawn using a multi-stage sampling process from those who took the SSCE. The Centralized Secondary School Examination 2017 result sheet, BECE 2016 result sheet, SSCE 2018 result sheet, and the Mathematics Test Anxiety Questionnaire (MTA) were used to gather data. Multiple regression analysis was used to assessed the data. He demonstrated that CSSE, BECE, and mathematics examination anxiety had both a composite and relative impact on students' mathematical achievement. This study resolves to relaxation and exercises as solution to overcome mathematics anxiety, but could have considered the use of expressive writing. Georgeakopoulos, 2021 [6] enrolled 152 private school pupils in a course using the provided curriculum and syllabus, the pupils' overall performance in terms of engagement in the class was additionally used to predict the students' mathematical ability. Nevertheless, social, psychological, or economic issues are not mentioned in the study. Several factors that critically affect academic performance of students have been discovered in numerous earlier research. [1] suggested that Prior knowledge of the students and performance variables are important in predicting students' performance, used five (5) science areas with O' Level marks. These were from the June 2015 West African Examination Council results, which were made public in November 2015.

Nonetheless, a major setback to the method is that it lacked comparison of variables using different approaches. Hence the approach does not give an efficient mechanism for the forecast of student academic performance. To conquer these setbacks in connection this study, the Logistic Regression algorithm is used to train and test datasets which in turn predict the outcome of students' performance in mathematics. This research is necessary because it investigates student's lack of interest, emotion, engagement

and study time which is a major setback to student's performance in mathematics. This study aims to developed a prediction model for student's performance in mathematics at BECE level using machine learning techniques. The component of artificial intelligence known as machine learning which allows a system to learn automatically, was used to train and test data sets. The parameters investigated includes: Age, sex, parent education, parents' job, emotion, study time, health, distance to school, interest .and previous results among other factors are used to predict the performance of students in mathematics. The difference between the previous studies and our study is the use of Logistic Regression algorithm to compare and classify the performance of students. Also, Differential Emotion Scale (DES) was used to measure the emotion of students.

The prediction results aids admission personnel in identifying applicants who would likely to succeed in senior school and making the distinction between suitable and unsuitable candidates for admission. The projection of students' academic success in junior school results can be used by admission officer to know which student perform well in mathematics. This can assist to identify students' areas of weakness and promote progress. It aids in establishing a distinction between quick and slow learners. The outcome of academic performance prediction can be used to create policies that ensure students who don't have a propensity for academic success to be identified early in their academic careers, preventing ongoing resource waste on such individuals.

The subject of this study is the academic achievement of students in mathematics at the public junior secondary school Pasali, located in the Kuje metropolitan area of the Federal Capital Territory, Abuja. Currently enrolled JSS III students make up the study's sample. Three years' worth of student results (2020–2022) were used as a trend. A random sample technique was employed to gather the student's file. The Differential Emotion Scale was utilized in the mathematics emotional experiment to gauge pupils' feelings. The student performance on the emotional test was assessed solely through expressive writing.

II. METHOD

2.1 Study Area

Kuje is one of the six Area councils within the Federal Capital Territory (FCT) of Nigeria, located in the southwestern part of Abuja. It is both a town and a local government area (LGA), serving as the administrative headquarters of the Kuje Area Council. It lies approximately 8.8833°N, 7.23333° E (NPC, 2006). Kuje is

accessible via the Umaru Mus Yar'Adua Expressway (Airport Road) and is connected to Gwagwalada, Garki, and Lugbe by well-trafficking roads.

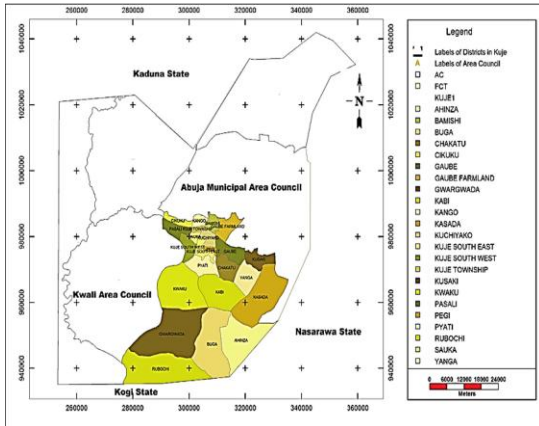


Figure 1: Geographical location of the study area [7]

2.1.1 Population, Sample, and Sampling Technique

The target audience for this study are junior secondary school students in Pasali Kuje Area Council, FCT, Abuja. The data from students' assessment results were utilized. The dataset for this research is students' cumulative results of JSS I, JSS II, and JSS III (First and second terms), and other factors were used to predict students' performance in BECE.

2.1.2 Data Collection

The dataset was obtained from the school's archive. Questionnaire and bio data from page 52 of the Appendix were given to students in order to gather vital information. The acquired dataset of students contains 19 parameters with 235 records of students' results



Figure 2: Students Filling the Questionnaire and Bio Data Form

Questionnaire and bio data was filled by each of the students as seen in Figure 2. Ten students were sampled for expression display using Differential Emotion Scale (DES).

Tables of detailed parameters of students and differential class output are in the Appendix.

2.1.3 Techniques for Data Analysis

To obtain understanding of a particular issue or event, data analysis involves inspecting, purifying, manipulating, and modelling data. Data collecting, data cleaning and pre-processing, exploratory data analysis, data visualization, statistical inference, and/or machine learning are some common data analysis approaches, though they might vary based on the type of data and the problem or phenomenon being examined. Researchers can better comprehend their data and find answers to crucial issues by employing data analysis tools.

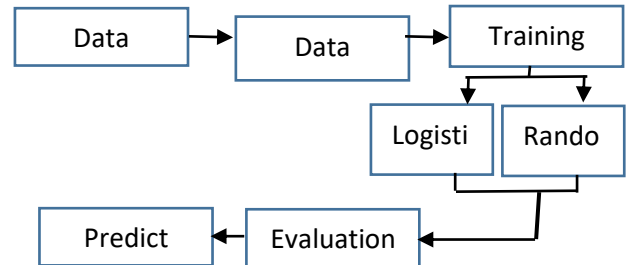


Figure 3: Block Representation of the Suggested System

2.1.4 Data Gathering

The research used a variety of methods to collect and manage the records or data, both quantitative and qualitative, including the use of questionnaires and bio data. As a result, the main tool for gathering information from students was a (closed-structured). More so, the school has a well-organized database for keeping track of student performance. Online scores entered by teachers for their students are uploaded and printed out for collection. It is this result that the students bring for teachers to compile, which will be sent to Education Resource Centre (ERC) that handles the external examination and thereby release the final result.

2.1.5 Data Preprocessing

Applying data pre-processing processes is crucial for creating a predictive model that works since machine learning classifier performance suffers when data is presented in its raw form. Skewed data are present in the obtained dataset, which is in a raw format. The pre-processing procedures that were carried out as follows: Data conversion from text to numbers: Transforming categorical variables into a numeric form is a pre-processing procedure that involves converting categorical variables that have many values for a single variable. In order to properly conduct experiments on the machine/deep

learning-based supervised learning classifier, such attributes must be translated into a numerical representation. By designating a different number to each category variable, we used the Pandas library's "Categorical" function to translate them into numerical representation. Preparing the data and putting it in the library are the initial steps in data pre-processing. Here, records with empty values are eliminated and the data is converted in preparation for processing. There were 62 records overall that had one or more columns with empty values. A total of 235 records were obtained after these records were eliminated. The record values were then translated for use with Python programming (Anaconda 3). Before being employed in a machine learning model, the datasets are assessed, prepped, and cleaned. Data preparation is the term for this process. This entails filling in data types such as integer and float for objects. Columns, non-null count, and Data type are entered.

2.1.6 Data Cleaning

The datasets have been cleaned up and prepared to display the non-null count and data type as object, integer, or float. 250 data sets were provided for the study, but after data cleaning, only 235 datasets were used. The first stage of data pretreatment is preparing data by deleting rows with empty values and converting data for evaluation as well as processing. The study's record values are then converted for use in Sci Kit Learns built-in classifiers for data processing

2.1.7 Dataset Training

To train and find patterns that produce predictions, the dataset was employed in a machine learning model. A few datasets are trained specifically for this investigation. The process usually involves a number of steps. Logistic Regression is used in model training, and at this step, the model is trained using the prepared data. About 75% of the datasets are used for training.

2.1.8 Testing of Dataset

The dataset testing process is a vital step in the data analysis procedure. After training, the datasets must be tested to ensure they are complete, correct, and suitable for the analysis being performed. Approximately 25% of the datasets used in this study are tested.

2.1.9 Data Analysis:

In order to draw conclusions, identify trends, and create well-informed judgments, data must be analyzed and understood. It necessitates the use of statistical and computational tools to gather, compile, and analyze data in order to gain useful insights. Dataset analysis is done using a machine learning model.

2.2 Model Prediction:

The model is fed the necessary attributes, and after being trained and tested on a number of datasets, it is used to predict outcomes for new data. In order to forecast students' performance as Distinction (A), Very Good (B), and Credit (C) as pass, this study compares the attributes from which the outcome is formed.

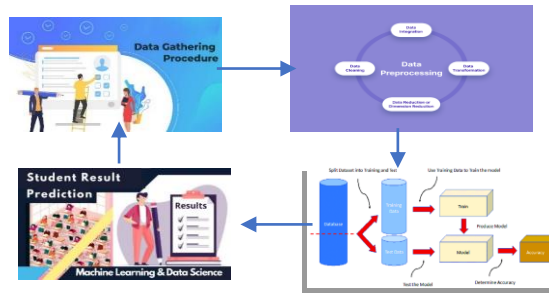


Figure 4: Framework of the Model

From Figure 4 the Framework of the Model is displayed. This involves data gathering, data preprocessing, Training and testing of the model and finally the prediction and classification of Grades.

2.2.1 Mathematical Model for students' academic performance prediction

A total of 19 parameters was used, expressed as (X1. X2 ...X19). Logistic regression has an output which is always 0 and 1, making it suitable for the classification case in this study.

$$h_{\theta}(X) = g(\theta^T X) = \frac{1}{1 + e^{-\theta^T X}} \tag{1}$$

where $h_{\theta}(x)$ is the probability that the output is 1 on input x , θ are the parameters that need to be fitted to the data, and $g(z)$ is a sigmoid function that asymptotes at 1 and at 0, it is expressed as in Equation 3.2

$$g(z) = \frac{1}{1 + e^{-\theta^T X}} \tag{2}$$

The logistic regression hypothesis using all the 19 features used in this study is expressed as in Equation 3.3

$$h_{\theta}(X) = g(\theta_0 + \theta_1 X_1 + \theta_2 X_2 + \dots + \theta_{19} X_{19}) \tag{3}$$

Where g is the sigmoid function, θ are the parameters chosen from the training set, and (x_1, \dots, x_{19}) are the 19 parameters used in the present study. The Equation 3.3 is called the decision boundary that categorized students as pass or fail. The values of the parameters θ are determined using the cost function for logistic regression which is expressed in Equation 3.4:



$$J(\theta) = \frac{1}{m} \sum_{i=1}^m y^{(i)} \log(h_{\theta} x^{(i)}) + (1 + y^{(i)}) \log(1 - h_{\theta}(x^{(i)})) + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2 \quad [4]$$

Where $J(\Theta)$ is the cost and Θ is the vector of the parameters θ . The training set is expressed as $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}) \dots (x^{(m)}, y^{(m)})\}$ where m is the number of records. The term on the right, known as a regularization term, guards against over fitting. The term λ is the regularizations parameter that acts as a control on the fitting parameters. As the sizes of the fitting parameters increase, the penalty on the cost function increases, the penalty depends on both the square of the parameters Θ and the size of λ (Lee et al., 2006) To find the parameters θ , we determine those parameters that minimize $J(\Theta)$ in Equation 3.4. This is achieved by using gradient descent, which tunes the parameters in order to achieve a reasonable logistic regression model from the given input - output data (Mgala, 2016).

2.2.2 Performance Matrices Used

The performance evaluation metrics used for the purpose of this research are highlighted and discussed below:

Confusion Matrix: A matrix called the confusion matrix is employed to evaluate how well a certain set of test data performs the categorization models. Until the test data actual values are known, it cannot be determined. It's also known as an error matrix since it displays model performance faults as a matrix.

A. 2.2.3 Accuracy

It is the nearness of the measurements to a specific value. In other words, if something measured repeatedly, the measurement is accurate if it is near to the true value of the quantity being measured (Dervenis, 2022). Accuracy can be defined mathematically as follows:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} = \frac{F19 + F00}{F19 + F18 + F01 + F00} \quad [5]$$

Recall is a performance metric used in information retrieval and machine learning to evaluate how effectively a model can extract relevant data from a dataset. The ratio of true positives to the sum of true positives and false negatives is used to calculate it.

$$\text{Recall} = \frac{\text{true Positives}}{\text{True Positives} + \text{False Negatives}}$$

Where: True Positives: the quantity of accurately predicted good outcomes

False Negatives: The number of instances in which the model misinterpreted positive data as negative.

2.2.4 F-Measure

Recall and precision are combined into a single measure using this technique, which accounts for both features. Precision and recall don't provide a complete picture on their own. Either we have low precision with excellent memory, or we have bad precision with excellent memory. A single score utilizing the F-measure can be used to express both issues. Precision and recall can be merged after computing the two scores to get the F Measure for binary or multi-class classification problems. This is how the standard F measure is determined:

$$\text{F-Measure} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad [6]$$

2.2.5 Mean Square Error (MSE):

The average squared difference between a dataset's expected values and actual values is known as the mean square error (M S E). It is frequently used in regression analysis to gauge a predictive model's degree of accuracy. The difference between each predicted value and its corresponding actual value is squared, and the average of all squared differences is used to calculate the MSE:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad [7]$$

where n = number of data points, y_i = observed values and \hat{y}_i = predicted values. The model does a better job of forecasting the data values when the MSE is smaller.

2.2.6 Model Justification

The use of two crucial prediction approaches which includes Logistic Regression that predict and classify the outcome of students' performance as Pass or Fail. And Random Forest which predict and classify the outcome of student's performance as Distinction, Credit, and Pass, justifies the research methodology. While different methods are utilized for predicting grades and students' academic achievement. The best predicted features and performing models are also determined using these machine learning techniques. Additionally, by using these methods, complicated interactions between the parameters can be captured, leading to predictions that are more accurate.

III. RESULTS AND DISCUSSION

3.1 Data Description

A thorough understanding of the dataset is essential to ensure the reliability of results. This includes inspecting variable distributions, detecting missing values, handling them appropriately, and analyzing relationships between variables.

The dataset comprises information from 235 students, each described by 19 attributes. The academic data spans Junior Secondary School levels JS1, JS2, and JS3, specifically their 1st and 2nd term results. These data were used to predict students' likely performance in Mathematics at the Basic Education Certificate Examination (BECE).

Table 1: Shows a sample of the cumulative results of students

| JS1 1st Ter m | JS1 2nd Ter m | JS1 3rd Ter m | JS2 1st Ter m | JS2 2nd Ter m | JS2 3rd Ter m | JS3 1st Ter m | JS3 2nd Ter m | Score | Average |
|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|-------|---------|
| 68 | 69 | 70 | 71 | 72 | 69 | 72 | 70 | 561 | 70.125 |
| 59 | 50 | 52 | 60 | 61 | 54 | 56 | 60 | 452 | 56.5 |
| 60 | 61 | 66 | 65 | 67 | 61 | 69 | 70 | 519 | 64.875 |
| 70 | 65 | 60 | 63 | 65 | 62 | 61 | 68 | 514 | 64.25 |
| 92 | 95 | 92 | 95 | 96 | 90 | 83 | 87 | 730 | 91.25 |
| 73 | 68 | 68 | 71 | 70 | 69 | 68 | 70 | 557 | 69.625 |
| 75 | 81 | 90 | 70 | 69 | 95 | 68 | 73 | 621 | 77.625 |

Table 1 shows the cumulative results of students in JS 1 and 2 (1st, 2nd, and 3rd terms) and JS 3 (first and second terms), including total scores and averages. The total score is calculated by adding the scores for each term. The average score is determined by dividing the total score by 3. The JS 3 third term result is from the external examination, BECE, which will be used to determine the students' final JS 3 results. This study uses the available termly results to predict students' performance in mathematics at BECE.

Table 2: Investigating study time and sex to students' performance

| Study time | Sex | JS1 Total | JS2 Total | JS3 Total |
|------------|-----|-----------|-----------|-----------|
| 0 | F | 69.000 | 68.670 | 69.50 |
| | M | 76.330 | 77.330 | 74.50 |
| 2 | F | 73.835 | 75.000 | 71.50 |
| | M | 70.335 | 69.335 | 74.25 |
| 3 | F | 68.000 | 68.000 | 69.00 |
| | M | 70.330 | 69.670 | 70.50 |

From the Table 2, time and gender were used to compare the students' scores in JS1, JS2, and JS3. Female students do worse than male students when their study time is shorter than an hour (zero). Male: 76.330, 77.330, and 74.50; Female: 69, 68.670, and 69.50. When you have one or two hours to study. Female tends to score better marks than Male. Female: 72, 72, and 71.50. Male: 70, 69.330 and 69.50. And when the study time is three hours and beyond, male students tend to obtained high score. Female: 68, 68 and 68, Male: 70.330, 69.670 and 70.50

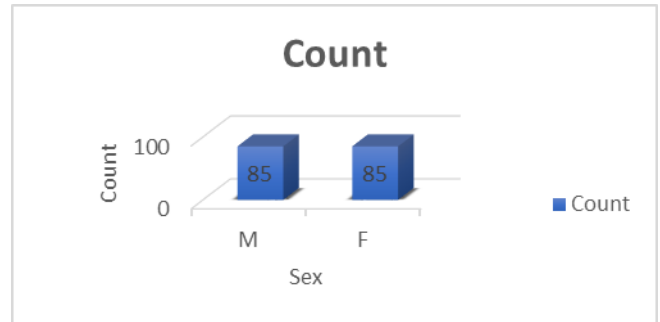


Figure 5: Investigates sex to students' performance

According to Figure 9, student achievement for male and female is nearly equal. However, female earned 92%, but male only received 88%. Analysis of the 2023 results from the West Africa Examination Council (W A E C), according to a report in the Sun newspaper on August 4, 2023, 823,043 female students registered compared to 798,810 male students, showing a gender disparity of 50.75 percent. The gender accuracy comparison for this study has been supported.

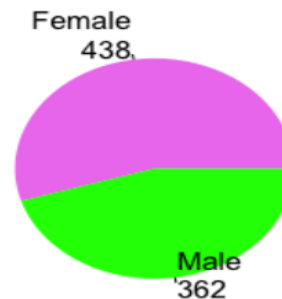


Figure 6: Gender comparison adapted from Feng, (2019)

As illustrated in the pie chart the female percentage is slightly greater than the male proportion. The comparative ratio between the numbers of female and male students is about 11:9 respectively in the synthetic dataset.(Feng, 2019)

Table 3: Investigates gender and the emotions of students to their performance

| Emotions | Sex | JS1 Total | JS2 Total | JS3 Total |
|----------|-----|-----------|-----------|-----------|
| 1 | F | 71.67 | 73.000 | 70.5 |
| | M | 69.00 | 67.670 | 68.0 |
| 2 | F | 70.00 | 68.835 | 69.5 |
| | M | 71.67 | 73.000 | 73.5 |

Table 3 relates gender and the emotion of the students to their overall scores in JS1, JS2, and JS3. One (1) depicts student's stable emotions, whereas two (2) depicts student's unstable emotions. The chart shows that female students perform better when their emotions are in check. Female 71.67, 73.0, 70.5 Male 69.0, 67.670, 61.0 However, male learners scored higher than female students when their mental states are unstable. Female: 70, 68.835, 69.5, male: 71.67, 73, 73.5.

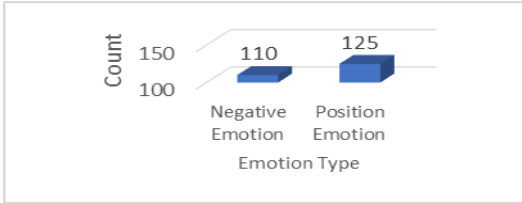


Figure 7: Shows the emotions of students

From Figure 7 the comparison of Emotions is measured with the differential emotion scale. It was found that emotionally stable students denote 1. And unstable students denote 2. The unstable students measured (124) outnumbered those with stable emotions (112). The feelings of men and women also differ slightly

Table 4: Differential Emotion Scale

| Emotion | Number of students | Types of Emotion |
|---------------|--------------------|------------------|
| Interest | 1 | Stable 1 |
| Joy | 2 | Stable 1 |
| Surprise | 3 | Stable 1 |
| Contempt | 4 | Stable 1 |
| Sadness | 5 | Unstable 2 |
| Anger | 6 | Unstable 2 |
| Disgust | 7 | Unstable 2 |
| Fear | 8 | Unstable 2 |
| Shame/Shyness | 9 | Unstable 2 |
| Guilt | 10 | Unstable 2 |

This is the display of students expressions, category 1-4 are grouped as stable emotion and from 5 – 10 are grouped as unstable emotions.

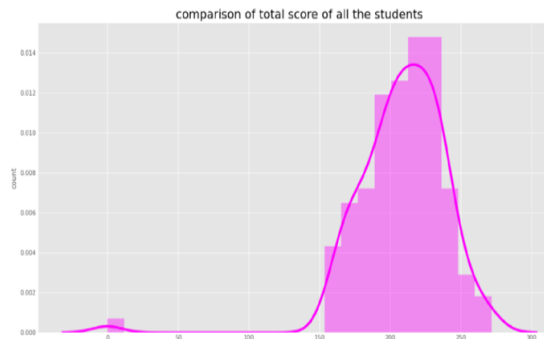


Figure 8: Comparison of total score of students from JS 1-3

Figure 13 shows the comparison of the total score of students from JS 1 – 3. The cumulative results of students from JS 1 – 3 are compiled together in this graph. The graph is a slope. Indicating that at JS 1 some students performance will drop and raise at the peak and will still decline towards the end of their JS 3.

Table 5: Comparison of the total score of students

| Class | Lowest Score | Highest Score |
|-------|--------------|---------------|
| JSS1 | 49.0 | 93.0 |
| JSS2 | 46.33 | 93.67 |
| JSS 3 | 50.5 | 905 |

3.3 Model Development

At this point, an algorithm is created by fitting and dividing the training datasets.

Numpy and the Pandas library were utilized in the study to manipulate data frames. For graph and scatter plot visualization, the following tools were used: Mat plot library, Sea Born, Plotly, and Dabl.

The effectiveness of our model was assessed using metrics and the Sci Kit Learn machine learning methodology. On the sci kit learn platform, a model selection process that entails data set partitioning, testing, and training is carried out. Label encoder is used during preprocessing. Regression with a linear model is imported. Importing Random Forest Regression was done in order to use Sci Kit Learn. Ensemble, mean squared error, and mean absolute error, Sqrt (mean squared error) and dabl are measures employed

3.4 Model Training and Testing

The datasets are split into two groups, the datasets are utilized for testing and training the model, respectively, with certain datasets accounting for 75% of the total. (X, Y, Test Size = 0.25) denotes a 25% sample size for the model test, which is implied by the expression. Panda's library and Numpy were employed in this study's data analysis.

3.5 Model Evaluation

Following training and testing of the model, the results of the qualities and the students' scores were utilized to forecast performance

Table 6: Summary of Model Metrics

| Evaluation | Result |
|---------------------------|--------|
| Mean absolute error | 1.7 |
| Mean squared error | 4.7 |
| Sqrt (mean squared error) | 2.2 |

After the training and testing step, the results of the student datasets were used to forecast how well students would perform, the total score and average were used. Age did not often affect the performance of the first five pupils in the above figure. The highest score is 730 and 561, respectively, for students who are 13 years old. Age 12 came in second with a combined score of 514 and 452. However, based on a study of the previous five students, age 10 pupils received the highest overall score (672), followed by age 11, who received a total of 576, and then ages 12 and 15. Age thus does not strongly indicate academic success or performance.

Table 7: Shows Model Performance

| Grade | Precision | Recall | F1-Score | Support |
|--------------|-----------|--------|----------|---------|
| A | 0.85 | 0.85 | 0.85 | 26 |
| B | 0.67 | 0.82 | 0.73 | 22 |
| C | 1.00 | 0.55 | 0.71 | 11 |
| Accuracy | - | - | 0.76 | 59 |
| Macro avg | 0.64 | 0.71 | 0.76 | 59 |
| Weighted avg | 0.81 | 0.78 | 0.76 | 59 |

From the table, the datasets of the students from continues assessment can only predict A, B and C. The evaluation of the outcome as Distinction (A), Very Good (B), and Credit (C), P, varies for the two models.

Table 9: Performance measure of the Models

| Models | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---------------------|--------------|---------------|------------|--------------|
| Logistic Regression | 78 | 0.85 | 0.85 | 0.85 |
| Random Forest | 98 | 1.00 | 1.00 | 1.00 |

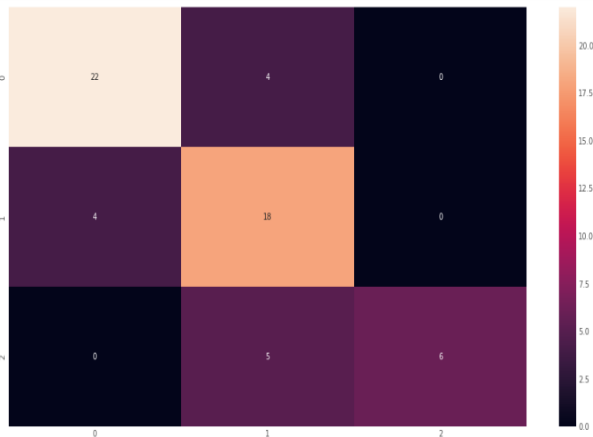


Figure 9: Confusion Matrix

The confusion matrix in Figure 9 showed 22 True positives, 5 False Negatives, 4 false positives, and 18 True Negatives. The number of False Negatives, which is not supposed to be high, is of particular concern because it indicates that the model predicted these instances where students are likely not to fail. This is unfortunate because it is impossible for all of the students to pass an external examination

Table 8: Reports Random Forest Results:

| Grade | Precision | Recall | F1-Score | Support |
|--------------|-----------|--------|----------|---------|
| A | 1.00 | 1.00 | 1.00 | 26 |
| B | 0.96 | 1.00 | 0.98 | 22 |
| C | 1.00 | 0.91 | 0.95 | 11 |
| Accuracy | - | - | 0.98 | 59 |
| Macro avg | 0.99 | 0.97 | 0.98 | 59 |
| Weighted avg | 0.982 | 0.98 | 0.98 | 59 |

Logistic Regression and the classification are mostly used to predict the outcome of model as fail/pass/excellent, or fail/pass. However, for this study the best model for this investigation, as determined by table 4.6 is Random Forest performance measure which has a 98% accuracy. Random Forest is the most accurate and best-performing model in the study by Rodriguez-Hernández et al., [8]. The optimal method for feature selection, according to Baliyan, 2020 [9] is Random Forest. Looking at the study as shown logistic regression correctly classified the highest number of students, and also misclassified the lowest number. Random Forest was third with 21 records less than logistic regression. The reverse is the case for this study

Table 10: Result of some Models. Source Mgala, (2016)

| Selected Item | LR | MLP | SMO | NB | J48 | RF |
|---|------|------|------|------|------|------|
| Students corrected | 1445 | 1372 | 1439 | 1249 | 1415 | 1424 |
| Students incorrectly classified | 251 | 324 | 257 | 456 | 281 | 272 |
| Correctly classified high intervention students | 1094 | 1034 | 1079 | 830 | 1072 | 1074 |
| Incorrectly classified high intervention students | 90 | 150 | 105 | 354 | 112 | 110 |
| Correctly classified low intervention student | 351 | 338 | 360 | 410 | 343 | 350 |
| Incorrectly classified low intervention students | 161 | 174 | 152 | 102 | 169 | 162 |



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Table 11: Result of some Models. Source (Dervenis, 2022)

| Algorithm | AUC | CA | F1 | Precision | Recall |
|-----------|-------|-------|-------|-----------|--------|
| KNN | 0.871 | 0.600 | 0.597 | 0.602 | 0.600 |
| SVN | 0.822 | 0.491 | 0.466 | 0.488 | 0.491 |
| RFL | 0.905 | 0.676 | 0.666 | 0.672 | 0.676 |

From Table 11 the results in this case were also satisfactory, with the best algorithm based on the AUC metric being Random Forest.

IV. CONCLUSION

The study evaluated the datasets using Logistic Regression and Random Forest to test the accuracy of the model. The prediction models investigate the parameters that can impact students' performance in mathematics. The prediction model was developed by fitting the datasets into Logistic Regression algorithm. Logistic Regression algorithm was implemented by using it to test for accuracy. Random Forest was also used to test the accuracy of the model. The Models were used to predict and classify the Grade and outcome of students result as Pass or Fail. In the other hand, the study also evaluated the performance of models using confusion matrix to reveal the numbers of accurately predicted samples and those that were not predicted accurately and generated a report. Finally, the accuracy of the models was compared and Random Forest has the highest accuracy of 98%. Therefore, it can be concluded that Random Forest is the best model for the prediction of students' academic performance of students in mathematics at BECE. Never the less, it can be concluded that the research objectives stated in chapter one of this study has been attained. For pupils entering primary school, there should be a proper common admission exam. As some children who are accepted into junior secondary school cannot read or write, this will help to address the issue that teachers are facing. In accordance with areas of need, the government must expand facilities, modernize school buildings, and hire additional teachers. Government needs to take a closer look at the issue of overcrowding in public schools and develop IT infrastructures so that public schools can compete with private schools in terms of computer proficiency. Their concerns and dread will significantly diminish as a result of their participation in and contact with the computer system. When two or more students are paired with a system, there will be less noise. In turn, this will help them get over their emotional instability and nervousness, which will increase their self-assurance and enthusiasm in the topic. Internet connectivity is required for computer systems. Internet use is one of the variables this study will examine since it might affect how pupils are affected because it allows them to engage and obtain local knowledge from all over the world. Pupils' health can have an impact on how well they do; thus parents, stakeholders, and teachers should make sure that unwell pupils are sent home for medical treatment.

Looking at the parameters that can influence students' academic performance language or mother tongue is one of them. This goes a long way in impacting the performance of students because most students encountered setback as a result of not understanding the language that was used in teaching. This study suggest teaching with mother tongue for more understanding.

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