Case Study
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PREDICTIVE ANALYTICS OF ACADEMIC PERFORMANCE OF SENIOR HIGH SCHOOL (SHS) STUDENTS: A CASE STUDY OF SUNYANI SHS

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ABSTRACT

Due to the availability and increasing adoption of technology in learning management systems, online admission systems, school management systems, and educational databases have expanded in recent years.
Motivation/Background: Literature shows that these data contain vital and relevant information that could be used to monitor and advise students' so that their performance could be enhanced. In this study, the random forest algorithm is proposed to identify and examine the factors that influence students' performance in WASSCE. Also, predict the future performance of students in WASSCE.
Method: A total of one thousand five hundred and twenty students' data were selected from Sunyani SHS. The results revealed that demographic data (age and gender) do not influence the performance of students in their final WASSCE.
Results: However, an accuracy of 89.4% with error metrics (RMSE) 0.001639 and MAPE error of 0.001321 revealed that the proposed model could effectively predict the performance of students in the WASSCE.

Keywords: Learning Management, Demographic Data, Effectively Predict, Random Forest Algorithm

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1. INTRODUCTION

The size of the educational database keeps proliferating every three years and these databases contain useful information that can be effectively employed to improve the academic performance of students Yadav and Pal (2012). There is a growing focus on institutional data mining by administrators, educational planners, and managers due to the exponential growth of educational data. (Anuradha & Velmurugan, 2015). Data mining techniques have been applied in educational systems to increase the understanding of the process of learning by concentrating on key issues such as identifying, mining, and evaluating parameters and variables which are associated with the learning progress of students Yadav and Pal (2012). Students' academic performance is a critical factor in every educational setting, especially in senior high learning institutes, because educational institutions are rated based on the academic excellence achieved by their students and academic staff Mohamed et al. (2016). Forecasting the academic performance of students in the real world has many challenges, but this has been made easy with the growth in information and communication technologies granting access to a large amount of information that could facilitate the critical decision-making process. Knowledge Discovery in

Databases (KDD) also called Data Mining (DM) is the process of extracting hidden patterns and discovering of associations between parameters in a massive amount of data (Ahmad et al., 2015; Kaur et al., 2015). DM techniques have made numerous achievements in areas such as marketing, education, engineering, finance, healthcare, and sports by helping decision-makers in finding a solution to everyday problems in these fields. This study focused on predicting final WASSCE score of SHS students' using random forest algorithm based on their Demographic Data and Past Exams records. Undoubtedly, this investigation will lead to students' performance prediction based on their demographic data and previous final examinations score, and this will ensure an immense benefit as follows: By knowing this information, teachers will be able to take the needed actions of the learning activities in the classroom to enhance students' skills. Enhance better arrangement of sitting position in class to maintain a balanced education and promote students to student interaction among fast and slow learners. Knowing the performance of students at the early stage helps teachers and schools' authorities to take charge and provide the needed assistance to the students involved

General Factors Affecting the Academic Performance of Students: Literature has shown that academic is affected by four main factors and that includes: the effect of teaching and learning materials on students' academic performance, the effect of administrative power of organizational practices on students' academic performance, the consequence of teacher related factors on students' academic performance, and finally the effect of socioeconomic background on students' academic performance. Teaching and learning resources, and environment have great impact on students' Academic Performance. According to Kieti (2017) educational creativity of teachers and students is believed to be a dependent of available facilities within the educational settlement or environments. Abundance in teaching and learning facilities and resources such as physical facilities, which include the habitable state-of-class and lecture-rooms, computer-room, equipped-library, laboratories, better dining halls, qualified and experienced teachers, teaching and learning materials (TLMs) contributes immensely to the success of students. As stated by Kieti (2017), Tran et al. (2017), Tuen et al. (2019) sufficiency current textbooks, learning videos and software, and other materials coincidental to learning have a good reflection on students' performance when these studying materials are supplied or provided sufficiently. As proposed by (Bydovska & Popelinsky, 2013, Li et al. (2013) concluded that an excellent illumination, clean and fresh air, safe, quiet, and comfortable learning environs are essential factors for positive achievement academically by students. It has been confirmed by (James et al., 2015, Morrison, 2017, Tuen et al. (2019) that, encouraging physical exercises, diminishing stress, decreasing air and noise pollution, and exposure to heat is excellent teaching and learning atmosphere. Studies have presented those organizational practices have effects on students' academic performance such practice include but not limited to instructions, leadership, and management Kieti (2017), Buabeng-Andoh, 2015, Egbenya and Halm (2016) Academic scholars have presented in literature that teacher-related factors such as the teacher's commitment, motivation, workload, and frequency of absenteeism (Affum-osei et al., 2014) have effects on students' academic performance.

On the other hand, socio-economic background of the student: the Socio-Economic Status (SES) of a child is generally determined by merging parents' occupational status, educational level, and income level. Research has confirmed over and over that, SES affects students' academic performance and that students' who have a low SES earn lower exams and quiz scores and are more likely to be school dropout (Al-Rahmi & Zeki, 2017; Oladejo et al., 2011; Seah et al., 2015). The consequence of SES on students' academic performance has been found to dominate other educational influential factors, like parental involvement. There are highly negative associations with low SES and academic performance of students. Other scholars have argued that, economically some parents are less capable of paying for the cost of education of their children at advanced levels and subsequently, their children do not work at their maximum potentials (Nguyen, 2017). The home environs have a remarkably significant part to play on the academic performance of every child.

Application of Data Mining in Academic Performance Prediction: Knowledge of students' performance in advance is key in the educational settings Bhardwaj and Pal (2011), Kaur et al., 2015; Ming et al., 2014). The performance of a student is pivoted on many dynamics like personal, psychological, social, and other environmental features. An effective and efficient way to achieve students' academic performance prediction is the use of the technique of Data Mining (DM) mostly referred to as Knowledge Discovery in Databases (KDD) (Ahmad et al., 2015; Kaur et al., 2015). DM techniques are applied in an extensive database to notice unseen relationships and patterns helpful in decision making (Argiddi & Apte, 2012; Kaur et al., 2015; Khasanah and Harwati (2017), Ramesh et al., 2013). DM can also be employed in educational institutions to promote understanding of the pedagogical and learning process to focus on discovery and evaluating the variables related to students learning Bhardwaj and Pal (2011), Devasia et al. (2016). DM applies to Artificial Intelligence (AI) and machine learning algorithms in discovering these hidden details in the educational database.

Numerous researchers have applied machine learning (ML) algorithms for predicting and detecting factors that influence student academic performance. Literature shows that the academic success of students is dependent on one factor or the other. Hence, there is no dependable agreement among different studies Table 1 present details of input data for prediction students' academic performance.

Here are some of these studies. The student performance prediction system based on a decision support system (DSS) was proposed by (Dole & Rajurkar, 2014) using the Naïve Bayes algorithm. A novel DSS framework for predicting students' performance concerning their final examinations of a school was carried out in (Livieris et al., 2015) using a hybrid machine learning algorithm. A hybrid classifier consisting of three parallel algorithms, namely DT, KNN, and Aggregating One-Dependence Estimators (AODE) in Pandey and Taruna (2016) was implemented for accurate prediction of students' performance. An assembling of three DT (C4-5, ID3, and CART) algorithms were applied on the data of students studying engineering to predict their performance in their final examinations in Yadav and Pal (2012).

Engineering students' academic performance was carried out in Li et al. (2013) by lump together machine learning algorithms namely principal component analysis, K-means, and hierarchical clustering, and KNN and NB classifiers. The intellectual and non-intellectual actions of students, together with demographic information was used as input parameters to a predictive framework proposed by Musso et al. (2013) to predict students' academic performance based on Artificial Neural Networks (ANN). A combination of NB, Multilayer Perceptron (MLP), and DT algorithms was proposed in Osmanbegović et al. (2014), Osmanbegovic and Suljic (2012) to predict students' academic performance. A decision tree classifier was implemented to predict the performance of students in Berhanu (2015).

Students' performance prediction model using Multi-Agent Data Mining was proposed in (AlMalaise et al., 2014) to predict the performance of the students based on their past academic records. ANN model, for predicting the probable performance of an applicant of university admissions was implemented and tested Oladokun et al. (2008). Similarly, ANN-based student academic performance predictive framework with two meta-heuristic algorithms motivated by cuckoo birds and their lifestyle, namely, Cuckoo Search (CS) and Cuckoo Optimization Algorithm (COA) is proposed in Chen et al. (2014).

A Neural Network model is proposed to predict the performance of students in an academic organization Agrawal and Mavani (2015). A combination of ANN, DT, and Support Vector Machines (SVMs) was assembled in Tran et al. (2017) to predict students' academic performance. The precise predictions of learners' academic performance at the early stages of the academic programme aids in the identification of the weak students and assist management and teachers in taking the counteractive measures to prevent them from failure. The performance of a Senior High School (SHS) student is a matter of importance because this determines whether the student will get a better grade to further his/her education in a higher learning institution.

Table 1 Input Data for ML in Predicting Students' Academic Performance

Reference	Inputs variable	Description
Kieti (2017), Musso et al. (2013)	Age	Demographic Data
Chen et al. (2014), Musso et al. (2013), Oladokun et al. (2008)	Gender	
Devasia et al. (2016), Goga et al. (2015), Musso et al. (2013), Yadav and Pal (2012), Yusif et al. (2011)	Father's occupation and Mother's occupation	
Adejo and Connolly (2018), Attuquayefio et al. (2014), Tuen et al. (2019)	Ethnicity	
Cortez and Silva (2008), Goga et al. (2015)	Parents' marital status	
Agrawal and Mavani (2015), Bhardwaj and Pal (2011), Devasia et al. (2016), Goga et al. (2015), Khasanah and Harwati (2017), Osmanbegović et al. (2014), Osmanbegovic and Suljic (2012), Yadav and Pal (2012), Yeboah (2014), Yusif et al. (2011)	Family size	
Egbenya and Halm (2016), Fleischer (2015), Mohamed et al. (2016), Oladokun et al. (2008)	Exam's score	Past Exams records
Proposed Model	Age, Gender, Exam's score, Ethnicity	Demographic Data & Past Exams records

2. MATERIALS AND METHODS

This study focused is to build an efficient predictive model for final WASSCE score of SHS students' using random forest algorithm based on their Demographic Data and Past Exams records. The methods, procedures and techniques adopted are organized into the following sections study design, area of the study, the population of the study, sample and sampling technique, instruments for data collection, the validity of the instruments, reliability of the instruments, method of data collection/instrument, and method of data presentation/analysis.

3. PROPOSED CONCEPTUAL FRAMEWORK

The framework for predicting the academic performance of students' using the RF algorithm, as shown in Figure 1. The framework illustrates the steps involved in developing models to predict final exams score for SHS final year students. There are three main phases involved in this research which are data-collection, data-integration, data-transformation, and pattern extraction. To apply DM algorithms on any data, it is essential to carry out some data pre-processing tasks such as data-cleaning, integration, discretization, and data-transformation Berhanu (2015).

Data Collection and Integration: 1520 participants from records of student's offering Business, General Art, Visual Art, Home Economics, and Science, which consisted of both demographic and past academic performance were integrated into one file using SQL database server at this stage as shown in Figure 1.

Data Transformation: At this stage, the integrated data was passed through three distinct stages, (i) data cleaning which includes filling in missing values, smoothing noise, identification, and removing of outliers where necessary and resolving data inconsistency. (ii) Data normalization and aggregation (iii) data reduction, where volumes of data were reduced but produce the same or similar analytical results using feature selection and feature extraction. All data transformation process was carried out with Python. Patterns Extraction: Weka, an open-source data mining program, was used to construct the predictive model using the RF regressor.

Data Partitioning: 1500 out of the 1520 clean data was partitioned into two, thus training dataset *(Train_D)* which accounted for 75% of the dataset (DS) and the remaining 25% was apportioned for testing *(Test_D)* the proposed model as shown in figure 3.2. The reaming 20 records were the records of students who are still in school (SHS 3) preparing to write their final WASSCE.

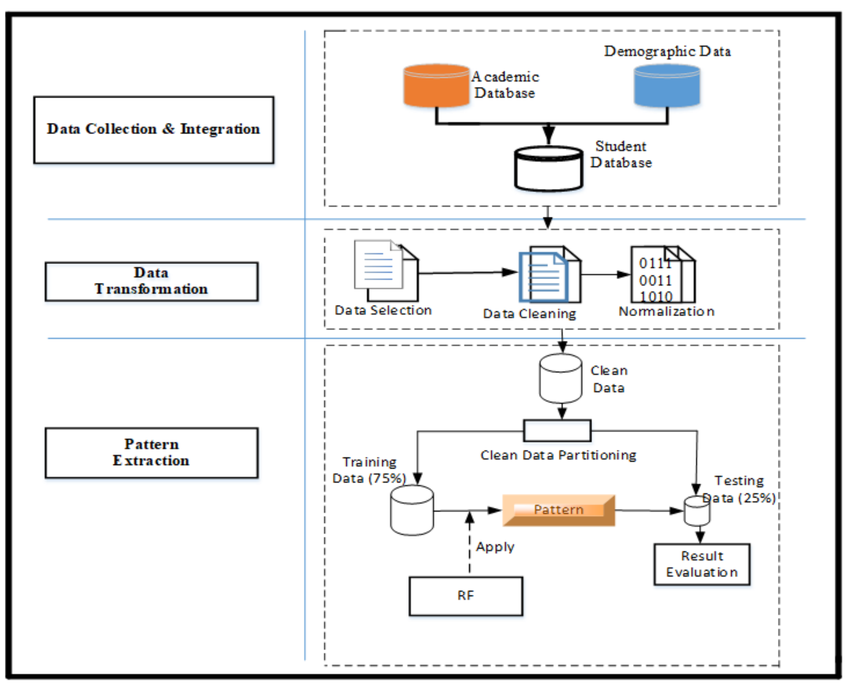


Figure 1 Conceptual Framework

3.1. DATASET AND STUDY AREA

The population (N) for the current study is two thousand four hundred (2,400) students from Sunyani Senior High school, which constitute two thousand past students and four hundred (400) continue students in SHS 3. The study adopted a simple random sampling technique stated in algorithm 1 to select one thousand five hundred (1,500) students (75%) out of 2,000 past students' records and 5% (20) out of the 400 continue students, making the sample size for the study to be 1520. The 20 continue students were taken to make predictions against the pending 2020 WASSCE exams. The study records consist of student's continuous assessment for SHS 1 and SHS 2 (6 terms) and demographic data from students offering business, general art, visual arts, science, and home economics courses.

Algorithm 1 simple random sampling
1. Make a list of classes (C) $c = \{c_1, c_2, \ldots, c_t\}$ where t is the total class, for this study t = 5
2. For each c_i in c, where $i = (1, 2, \ldots, t)$
3. Make a list of all the students (population) (N) in the class (c_i) (the list contains their index numbers)
4. Assign a sequential number to each student (1,2,3…n) in the class (c_i). This represents the sampling frame (percentage of students for a class). The list from which the study draws its random sample
5. Initialize the sample size *(k)* for the class (c_i), $k = (0.75 \times N)\ or\ (0.05 \times N)$ for past students and continue students' class respectively
6. Select the sample (k) of (c_i) using a random number generator (rand ()), based on the sampling frame (population size of (c_i))
$//\ Generates\ k\ random\ number\ within\ 1 - \mathrm{n}.$ $Initialise\ random\ number\ generator\ rand\ (1 : \mathrm{N})$ $Initialise\ an\ array\ (A)\ of\ size\ (k)\ to\ hold\ generated\ numbers$ $For\ int\ i = 0\ to\ (k-1)$ $A[i] = rand.Next\ (1, N)$ end
7. Associate every generated number in *(A)* with its *(n)* equivalent number and select the index number of students in (c_i)
8. Repeat steps 3 to 7 for all c_i in c

Training Techniques: The training technique adopted for the current study is a supervised machine learning technique, where the intended input variables (demographic and past terminal exams record) are entered into the network to produce the required output variable (WASSCE score).

The RF is applied to the *Train_D* and the model learning the pattern hidden in the dataset, we measure the accuracy and error metrics and determine if they are within the accepted values. If they are, then the learned pattern is then applied to the *(Test_D)* to make a prediction.

Random forest (RF): This is an ensemble-learning technique that integrates the performance of several decision tree algorithms to predict or classify the value of a variable Rodriguez-Galiano et al. (2015), Wakefield, 2013). RF can be used for both classification and regression ML tasks. In the RF technique, many DTs are created, with each observation fed into every single DT. The optimal result in each observation is used as the final output. A different observation is served into all the trees and a majority vote is computed for each classification model. An error estimate is made for the cases, which were not used throughout the tree building. This is known as OOB (Out-of-bag) error estimate, which is stated as a percentage. When an RF receives an input of (x), where x is a vector consisting of variables of different evidential features examined for a given training area, the RF builds several regression trees (N) and averages the results. Therefore, that for N tress {T(x)} ^N the RF regression predictor is given by equation Equation 1.

$$\boldsymbol{f_{rf}^{N}(x) = \frac{1}{N}\sum_{N=1}^{N} T(x)}$$ **Equation 1**

Algorithm 2 Random Forest Algorithm

Input : *DatasetTrain _ D, number of trees in the ensemble n*
Output : *a composite model M **
1 → *for j = 1 to k do*
2 → Construct boostrap sample Train_{Dj} by sampling S with replacement
3 → Select 4 features randomly
4 → *UseTrain _ D_j and unsystematically selected 4 features to develop a regression tree M_j*
5 → end for
6 → return M^*

$Train_D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ The Bootstrap Aggregating (Bagging) technique was used in assembling the decision trees for this study. Given a *Train_D* as given in equation Equation 2, the bagging technique generates a New_Di new training dataset of size denoted by N which is sampled from the original training dataset Train_D with replacement. New_Di is referred to as the bootstrap sample. By bootstrapping, some observations may be recurrent in each *New_D$_i$*. This approach assists to reduce variance and circumvents overfitting. Users specify the number of regression trees (T), in the current study, two hundred (200) trees were specified.

$$\mathrm{Train_D} = \{(x_1, y_1), (x_2, y_2),, \ldots.., (x_N, y_N),\}$$ **Equation 2**

Choosing Variables to Split On: grow unpruned regression tree using the steps for each of the bootstrap samples: At the individual node, indiscriminately sample K variables and select the most exceptional split among those variables (K) rather than picking the most excellent split amid all predictors. This practice is sometimes called “feature bagging.” We select a random subset of the predictors or features because the correlation of the trees in a standard bootstrap sample can be reduced. In this study K=p/3.

The splitting principle, let assume that a partition is divided into T constituencies R_1, R_2..., R_T. We model the response as a constant ck in each constituency as proposed by Wu et al. (2017) in equation Equation 3. The splitting principle at each node is to minimize the sum of squares. Hence, the best c ̂_t_tis the average of y_i in region Rt as given in equation Equation 4.

$$\boldsymbol{f(x) = \sum_{t=1}^{T} c_t I(x \in R_t)}$$ **Equation 3**

(c_t)^=ave (y_i | x_i∈R_t) **Equation 4**

Let a splitting feature j and split point *s*, and express the pair of half-planes

$$R_1(j,s) = \{X|X_j \le s\} \; and \; R_2(j,s) = \{X|X_j \ge s\}$$ **Equation 5**

Where j and s satisfy equation Equation 6.

$$\left[\frac{min}{c^1}\sum_{x_i \in R_{1(j,s)}}(y_i - c1)^2 + \frac{min}{c^2}\sum_{x_i \in R_{2(j,s)}}(y_i - c2)^2\right]$$ **Equation 6**

When the best split is obtained, the dataset is partitioned into two resulting segments and echo the splitting procedure on each of the two segments. This splitting procedure is reiterated until a predefined ending criterion (threshold) is satisfied, five was set as the threshold for this study.

3.2. EVALUATION METRICS

Several criteria are available for measuring the performance of a predictive model; however, for this study, the following criteria were used: Root means squared error (RMSE): This index evaluation the residual between the actual-value and predicted-value. A model has better performance if it has a smaller RMSE. An RMSE equal to zero represents a perfect fit.

$$RMSE = \sqrt{\frac{1}{m}\sum_{v=1}^{m}(t_v - y_v)^2}$$ **Equation 7**

Mean absolute percentage error (MAPE): This index shows an average of the absolute percentage errors, the lower the MAPE, the better.

$$\boldsymbol{MAPE = \frac{1}{m}\sum_{v=1}^{m}\left|\frac{t_v - y_v}{t_v}\right|} \qquad \textbf{Equation 8}$$

t_v is the actual value, yv is the predicted value produced by the model, and m is the total number of observations. The correlation coefficient (R): This criterion reveals that the strength of associations between actual-values and predicted-values. The correlation coefficient has a range from 0 to 1, and a model with a higher R means it has better performance.

$$R = \frac{\sum_{v=1}^{m}(t_v - \bar{t})(y_v - \bar{y})}{\sqrt{\sum_{v=1}^{m}(t_v - \bar{t})^2 . \sum_{v=1}^{m}(y_v - \bar{y})^2}} \qquad \textbf{Equation 9}$$

In addition to the mentioned criteria, output accuracy is also used to evaluate the performance of the predictive model.

4. ANALYSIS OF RESULTS AND DISCUSSION

4.1. DEMOGRAPHIC CHARACTERISTICS OF THE STUDENTS

The background data of the students were sought. The data elicited relate to gender, age distribution, and classes/forms. The background data of students formed no part of the principal analysis. The reason for presenting the background data of respondents was to have an idea about the over-all information of students but not for the principal scrutiny. The results are discussed in the form of frequency and percentages as shown in Table 2

Table 2 Demographic Features of the Students

Variable	Sub-scale	Frequency	Percentage (%)
			(n = 1520)
Gender	Male	670	44.07
	Female	850	55.9
Age Distribution	14 -15 Years	180	11.8
	16 - 18Years	950	62.5
	≥19 Years	390	25.7

Table 2 shows the students' demographic information. It was observed that out of one thousand five hundred and twenty (1520) students, a majority (n = 850; 55.9%) were females while 670 (44.07%) were males. This outcome shows that the female students were 26% more than their male counterparts were. The majority (n = 950; 55.9%) of the students were within the age group of 16 – 18 years, which confirms the normal age for one to be in SHS, while 180 of them representing 11.8% were found to be in the age group of 14-15 years and 390 representing (25.7%) were found with 19 years or more.

4.2. DESCRIPTIVE STATISTICS

Table 3 shows the statistical analysis of candidate continuous assessment scores. The mean value range (63.67 - 66.36) for all subjects except core maths shows that the end of terms examination mark of the candidates was quite good.

However, the minimum score (0) and maximum score (80.02) for core maths indicates that the performance of a candidate in core maths need more improvement. This outcome affirms Ablakwa's reports that a high percentage of candidate fails in the core maths (Ablakwa, 2014).

Additional statistical analysis was performed on the students' continuous assessment scores. Table 4 shows a one-sample test of 95% confidence interval. Again, the difference in mean values in students' continuous assessment shows a close margin in the general performance of students.

Table 3 Statistical Analysis of Student Continuous Assessment

Descriptive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
CM	1520	0	80.02	66.2028	7.6342
EG	1520	44.33	81.2	66.3631	7.59182
IS	1520	46	84.25	63.672	6.46139
SS	1520	45.5	84.75	64.8148	7.96228
EL1	1520	39.17	87.6	63.8926	7.54045
EL2	1520	34.17	83	65.2059	6.88485
EL3	1520	46.5	84.8	66.0408	6.87008
EL4	1520	29.83	89.6	65.7409	7.50126
Valid N (listwise)	1520				

Table 4 One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	**df**	**Sig. (2-tailed)**	**Mean diff.**	**Lower**	**Upper**
CM	153.664	1520	0	66.20277	65.3551	67.0505
EG	174.377	1520	0	63.52882	62.812	64.2456
IS	144.143	1520	0	64.62707	63.7449	65.5092
SS	150.192	1520	0	63.70774	62.8731	64.5423
EL1	166.222	1520	0	65.05242	64.2824	65.8224
EL2	169.554	1520	0	65.97631	65.2107	66.7419
EL3	153.81	1520	0	65.6108	64.7715	66.4501
EL4	168.268	1520	0	65.36828	64.6039	66.1326

4.3. FEATURE IMPORTANCE RANKING

The correlation between each input feature and the expected output (WASSCE score) was tested. Figure 2 shows the feature's importance ranking. The result shows that the demographic data (age and gender) are of less significance. Thus, the gender and age of a candidate do not determine how good or bad he/she will pass the final WASSCE. Again, the program pursued by a candidate also is of less importance to one passing the WASSCE. However, students' performance in Integrated Science (IS) and Social Studies (SS) were seen to be the most significant determining factor of one passing his/her WASSCE. Furthermore, the results show that the average continuous assessment score of Core Math (CM) by a candidate was also highly related to the candidate success in the final WASSCE. This affirms the reason behind core math being one of the compulsory subjects in all areas of studies.

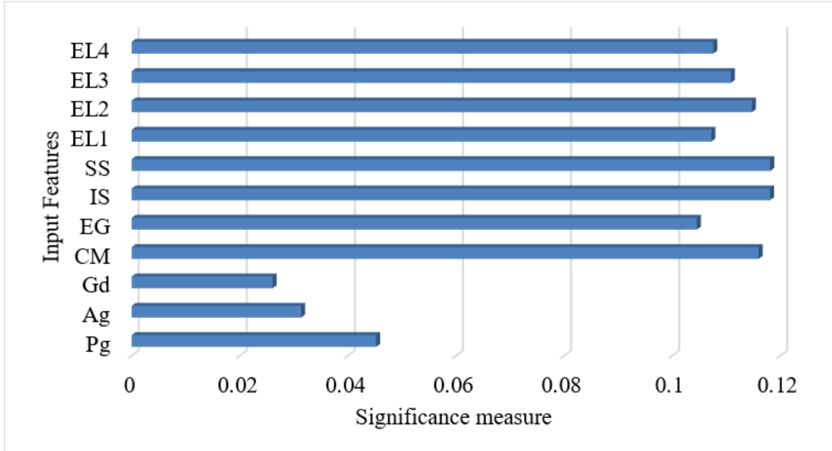


Figure 2 Features Importance

4.4. MODEL TRAINING AND TESTING

Figure 3 shows the Out-of-bag error rate of the proposed random forest regressor. The aim here was to obtain the right number of estimators that will offer fewer errors. The minimum number of estimators was set to fifteen (15) and the maximum to two hundred (200). The result shows that as the estimators increase in number, the error margin reduces. However, the error increased when the number of estimators increased above one hundred and seventy-five (175). Hence, for this study, the number of estimators was set to one hundred and sixty (160).

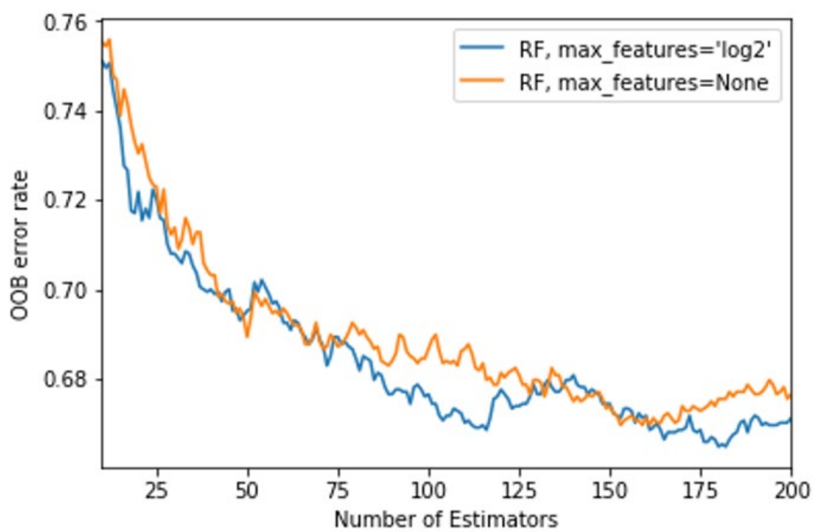


Figure 3 Out-of-bag Training Error

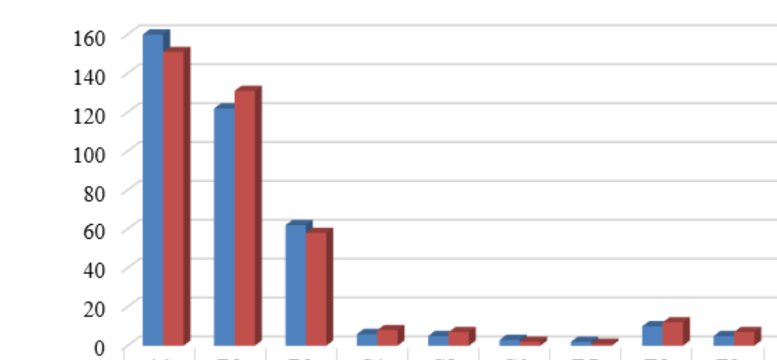
4.5. ACCURACY AND ERROR METRICS

Table 5 shows the error metrics and computational time of the proposed predictive model. With a training dataset of one thousand one hundred and twenty-five (1,125) rows eleven (11) columns, it took the proposed model 0.392 seconds to study all hidden patterns in the dataset. While 0.013 was taken to make predictions on three hundred and seventy-five (375) test data. The RMSE of 0.001639 and the MAE error of 0.001321 achieved by the proposed model show that the proposed model fits very well with the dataset. Again, the obtained error values indicate a close range in model estimated value compared with the actual (true) values and an indication that students' performance in the WASSCE can be effectively predicted based on student performance in continuous assessment.

Table 5 Model error metrics and computational time

RMSE	MAE	R^2	Training time	Testing Time
0.001639	0.001321	0.034323	0.392 secs	0.013 secs

Figure 4 shows the grade analysis based on model prediction against actuals on the test dataset. It was observed that a good number of the students records at least A1 in one or more of the subject grades for the final WASSCE. Also, the closeness of the model predicted to the actual grade confirms the accuracy of the proposed model (see Table 5 and 4.7). Based, on the outcome it can be inferred that a good predictive model can help school authority to ascertain the grade analysis of their students before the WAASCE exams.



	A1	B2	B3	C4	C5	C6	D7	E8	F9
Actual	160	122	62	6	5	3	2	10	5
Predicted	151	131	58	8	7	2	1	12	7

Figure 4 Grade analysis of predicted values

To further examine the proposed predictive framework, the continuous assessment records of 20 students that are in SHS 3 preparing for the final WASSCE was used to predict the outcome of their exams. Table 6 shows the model predicted values. Since the actual values were not available at the time of this study, there was no means to compare the predicted values for these 20 students to their actual results. However, based on the accuracy record by the model on the test data, it is hoped that the predicted results will not be far from right when these students take their final exams.

Table 6 Model predicted values for 20 students yet to write their WASSCE

Record	WCM Y'	WEG Y'	WIS Y'	WSS Y'	WEL1 Y'	WEL2 Y'	WEL3 Y'	WEL4 Y'
1.	6	5	5	4	4	4	4	4
2.	4	3	4	3	3	4	4	4
3.	4	4	4	3	4	4	4	5
4.	6	4	5	4	4	4	4	4
5.	5	4	5	4	5	5	4	4
6.	6	5	5	4	4	4	4	4
7.	6	5	6	4	4	4	5	5
8.	3	4	4	3	4	4	4	5
9.	4	4	4	3	4	4	4	4
10.	3	4	4	4	4	5	4	4
11.	4	4	4	3	4	4	4	4
12.	3	4	4	4	3	3	4	3
13.	5	5	5	4	4	4	4	4
14.	5	4	5	4	4	4	4	4
15.	5	4	5	3	4	4	4	4
16.	4	4	5	3	3	4	5	6
17.	4	4	4	3	4	4	4	5
18.	4	4	4	3	4	4	4	4
19.	4	4	4	3	4	4	4	4
20.	5	4	5	4	4	4	4	4

4.6. COMPARISON ANALYSIS OF RESULTS WITH RELATED WORKS

Table 7 shows a comparative analysis of the current study with related works. Pandey and Taruna (2016) obtained an accuracy of (86.76 – 98.86) % with 1000 respondents, Guo et al. (2015) an accuracy (63.2 – 88.4) % with 120000 participants. The results as shown in Table 7, indicates that the prediction accuracy (89.4%) with 1000 participant outperformed other state-of-the-art students on student's academic performance. This comparative analysis shows that there has been an enhancement in the current study to existing literature and a confirmation that the academic performance of students can effectively be predicted with a high accuracy rate.

Table 7 A comparative analysis of study results with related works

References	Predicted variable	Sample size	ML algorithm	Evaluation metrics. Accuracy	RMSE
Purwaningsih et al. (2018)	English score in WASSCE	72	Naïve Bayes	35-86%	Not Available
Bosson-Amedenu (2017)	Core Mathematics score in WASSCE	42	Linear regression	90 – 92 %	Not Available

Ahmed and Ibrahim (2014)	Not Stated	1547	Decision tree (ID3)	Not Available	Not Available
Pandey and Taruna (2016)	Not Stated	1000	Decision Tree, K-Nearest Neighbour, and Aggregating One-Dependence Estimators (AODE)	86.76 – 98.86 %	Not Available
Livieris et al. (2016)	Mathematics	279	Decision trees, Support vector machine and Sequential Minimal Optimization (SMO) algorithm	51.6 – 70.3 %	Not Available
Li et al. (2013)	Not stated	90	Principal Component Analysis	Not Available	Not Available
Musso et al. (2013)	Psychology, engineering, medicine, law, social communication, business, and marketing	786	Artificial Neural Networks	87 – 100%	Not Available
Guo et al. (2015)	Not stated	120,000	Deep neural networks	63.2 – 88.4%	Not Available
Osmanbegovic and Suljic (2012)		257	Naive Bayes algorithm, Multilayer Perceptron and Decision tree	71.2 – 76.65%	0.42 – 0.5
Osmanbegović et al. (2014)	Not stated	1410	Random Forest and Decision Trees (J48)	71%	Not Available
Berhanu (2015)	Not stated	199	Decision trees	84.95%	Not Available
Tran et al. (2017)	Not stated	1268	ANN, DT and Support Vector Machines (SVMs)	Not Available	1.668
Current study (Adjei 2020)	General Science Business Home Economics Visual Arts General Arts	1,520	Random Forest	89.40%	0.001639

5. CONCLUSIONS AND RECOMMENDATIONS

The study aimed at investigating the factors that affect student academic performance in the WASSCE. It also attempted to predict the final students' score in the WASSCE based on student's continuous assessment using the random forest algorithm. The considered factors were demographic factors such as age and gender, and continuous assessment score. Descriptive statistical (frequency and percentages, means, and standard deviation) and T-Test methods were used to analyse the details of one thousand (1000) randomly sampled students' records from the Education Database (ED). The study found that the demographic data (gender and age) has no effects on the performance of students in the WASSCE. A high correlation was found between Integrated Science (SI) and Social Studies (SS), and the performance of students in the WASSCE. The study found that students that score within (40-55) in core maths were likely not to perform well in the final WASSCE. The performance of students in the WASSCE is highly predictable at an accuracy of 89.4%.

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