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Modelling Academic Achievement among Selected Public and Private Schools in Ghana: A Bayesian and Artificial Neural Network Approach

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Abstract:- In the evolving landscape of basic education in Ghana, both public and private basic schools face the challenge of remaining competitive. This study employs Bayesian Loglinear Regression and Artificial Neural Networks (ANN) to identify factors influencing Basic Education Certificate Examination (BECE) outcomes in Ghana's public and private schools. Data collected from randomly selected schools in two districts in Ghana includes teacher, student, and administrative variables. Bayes factor analysis aids model selection, emphasizing predictive accuracy while balancing complexity. ANN, employing three partitions (6-2-2, 5-3-2, and 7-2-1) for batch training, ranks factors based on normalized importance. The results show superior performance of ANN3, achieving the highest AUC values and efficient generalization to new data. The analysis ranks factors based on normalized importance using ANN, revealing quality supervision, conducive teaching/learning environment, and parents' support as top priorities. These factors significantly impact success rates in both public and private schools. Further investigation highlights the importance of timely provision of teaching and learning materials, consideration of students' interests, and differentiated tasks based on ability levels. Gender and Social Inclusion (GESI) compliance by teachers and the incorporation of critical thinking in lesson delivery also play crucial roles. The study underscores the need for teacher training to enhance critical thinking promotion and the effective use of assessment as a learning strategy. The findings provide a comprehensive understanding of factors influencing academic achievement, offering valuable insights for stakeholders to prioritize and enhance different aspects of the educational system in Ghana.

Keywords: *ANN, Bayesian, Basic Education Certificate Examination (BECE), School Performance, Academic Achievement.*

1. Introduction

In Ghana's ever-changing basic education landscape, both public and private basic schools are striving to remain competitive. The challenge lies in efficiently allocating limited resources to areas believed to generate desired outcomes. However, there is a scarcity of research providing guidance to these stakeholders on resource allocation without compromising quality. This underscores the need for continuous research to identify prioritized factors that support all students in achieving at least the minimum learning outcomes set by the national government, without exacerbating existing disparities. Numerous studies have focused on academic achievement gaps between public and private basic schools in Ghana and other countries, particularly highlighting the superior performance of private primary schools on external exams like the BECE. While these studies explore factors contributing to the disparities, they fall short of assessing the implications or offering measurements to guide stakeholders in allocating their constrained resources (Endeley, 2017; Lubienski et al., 2006a,Lubienski et al., 2006b). Based on conventional findings and previous research, it is widely suggested that private basic schools exhibit higher academic performance. The belief in the superiority of the private basic school model over the public basic school model is apparent in the No Child Left Behind policy, which serves as the organizational framework for private schools. Reforms in private schools operate on the assumption that by placing parents at the forefront of their children's academic success, schools will be compelled to compete more intensely with other educational institutions boasting higher test scores (Dangara et al., 2019; Hussain et al., 2018; Endeley, 2017; Adamu, 2015; and Adediwura et al., 2007).

The Bayes factor serves as a tool for selecting the model that aligns most closely with observed behavior in terms of average prediction accuracy. It achieves this by accommodating any observed data while maintaining an optimal balance between a model's complexity and its fit. Another primary objective in cognitive modeling involves utilizing Bayes factors for hypothesis testing on the estimated model parameters (Hech et al., 2023; Van et al., 2019; Vanpaemel, 2020). Whether engaged in exploratory model building or confirmatory model validation, researchers commonly aim to evaluate the impact of continuous variables or experimental manipulations on latent processes. In cognitive modeling, there is a third primary goal, which is to categorize participants using Bayes factors. Mixture models are based on the premise that distinct individuals are more accurately characterized by unique models, rather than assuming that a single model universally applies to all individuals. Unlike well-known model-selection indices like AIC and BIC, the Bayes factor considers the functional flexibility of models. It favors the more parsimonious model that provides more accurate predictions when two models exhibit an equal level of fit (Hech et al., 2023; Van et al., 2019; Vanpaemel, 2020). Utilizing the area under the receiver operating characteristic curve (AUC) as an effect size metric offers several advantages. Firstly, it maintains a direct correlation with traditional statistics and indices integral to standard inference, applicable in both non-parametric and parametric scenarios, including cases involving categorical variables. Secondly, the AUC is a widely recognized index that remains independent of units and possesses a clear probability interpretation, aligning with the p-value. Thirdly, extensive theoretical and practical studies on the AUC have resulted in various generalizations, expanding its application to areas such as time-dependent problems (Pablo et al., 2020; Martínez-Camblor, 2017).

Performance disparities in both private and public primary schools in Ghana have been linked to significant factors. However, there is a lack of comprehensive research addressing the relative contributions of these factors to academic achievement. It is crucial to ascertain the relative importance and impact of each component to effectively allocate limited resources for high-quality education. Although scholarly literature extensively explores the reasons for these variations, the dynamic effects of these influences on BECE performance remain unclear. Thorough understanding of these dynamics would enable stakeholders to intentionally manipulate specific variables to enhance learning outcomes. The current study aims to investigate the utilization of Artificial Neural Networks (ANN) and the Bayesian Loglinear Regression Model to prioritize factors influencing BECE achievement in Ghana. The goal is to improve learning outcomes in public basic schools and elucidate the factors contributing to the performance gap between private and public schools, as discussed in scholarly literature.

2. Method

The study collected data from randomly selected schools in two districts of Ghana through a multistage sampling technique, with a total of 198 respondents participating. The investigation focused on factors influencing achievement gaps in Basic Education Certificate Examination (BECE) results, considering teacher, student, and administrative variables in both private and public schools in Ghana. Bayesian Logistic Regression and Neural Network Models were employed to analyze the data. The study used Bayesian analysis to measure the success rates of public and private schools in the BECE, assuming a bivariate normal distribution with an unknown correlation, ρ. The Bayesian log-linear regression model was established with specific parameters and a 95% credible interval. For the artificial neural network (ANN), three partitions (6-2-2, 5-3-2, and 7-2-1) were utilized for batch training, aiming to rank factors based on their normalized importance. The multilayer perceptron neural network, trained using the back-propagation algorithm, identified key factors significantly impacting the success rates of basic school students in both public and private schools. The receiver operating characteristic (ROC) curve was employed to determine effect size, allowing predictions of educational success risk based on BECE performance. Cochran's sample size estimator was used to determine the required sample size of 198 respondents. The study followed rigorous protocols for questionnaire development, including focus groups with specialists and validation procedures. Internal consistency was computed to assess dependability. Bayes Factor analysis was then employed to identify factors influencing academic performance in private and public school models, considering 70 factors in total.

Consider the x covariates required to compare academic achievement levels in the two models using the dataset.

Consider $P_1 : f_1\left(x|\theta_1\right)$ and $P_2 : f_2\left(x|\theta_2\right)$ with specified prior distributions of $p_1\left(\theta_1\right)$ and $p_2\left(\theta_2\right)$ and respective prior probanilities $p\left(P_1\right)$ and $p\left(P_2\right)$.

According to Bayes' Law, Model 1 has the following posterior odds over Model 2:

$$\frac{\pi\left(P_1|x\right)}{\pi\left(P_1|x\right)} = \frac{p\left(P_1\right)}{p\left(P_2\right)} \cdot \frac{\int_{\varphi 1} p_1(f_1\left(x|\theta_1\right) p_1(\theta_1) d\theta_1}{\int_{\varphi 2} p_2(f_2\left(x|\theta_2\right) p_2(\theta_2) d\theta_2} = \left[prior\ odds\right] \times \left[Bayes\ Factor\ B\left(x\right)\right] \tag{1}$$

$$B\left(x\right) = \frac{\pi\left(P_1 \mid x\right)}{\pi\left(P_2 \mid x\right)} \times \frac{p\left(P_2\right)}{p\left(P_1\right)} = \frac{\pi\left(x \mid P_1\right)}{\pi\left(x \mid P_2\right)} \tag{2}$$

It is evident that a Bayes Factor significantly higher than 1 favors Model 1 over Model 2.

In a scenario where there are only two viable models, P1 and P2, we can determine the posterior probability of Model 1 using the Bayes Factor B(x) as follows:

$$P\left(P_1 \mid x\right) = \frac{1}{1 + \frac{1}{B\left(x\right)} \frac{p\left(P_2\right)}{p\left(P_1\right)}} \tag{3}$$

The Bayes theorem updates our current understanding of a physical system by integrating information from prior sources. A probability estimate, such as a binomial, multinomial, beta, Laplace, or Bernoulli distribution, can be utilized as the prior. The likelihood is multiplied by the prior distribution to obtain the posterior or predicted probabilities of the facies distribution, according to the Bayes rule (Al-Mudhafer, 2014).

In this study, the input layer of an ANN model included features derived from the student, teacher, and administrative characteristics of both public and private schools in Ghana. The general model equation of an artificial neural network (ANN) is given by Equation 4.

$$\rho = f\left(\sum_{i=1}^{N} \omega_i \mathrm{P}_i\right) + b \tag{4}$$

Where p is the predicted output, f is the transfer function, w is the weight of the first input, b is the bias, and P represents the inputs (variables). The MLP predictor model was evaluated using the 50-30-20, 60-20-20, and 70-20-10 partitions for training, testing, and validation sets. This study presents a comparative analysis of the significance of independent variables in predicting basic education performance using MLP.

The area under the ROC curve is given by Equation 5.

$$A = \int_0^1 R(t)dt = 1 - \int F_\xi(t)dF_\chi(t) = 1 - \mathrm{E}\left[\mathrm{P}\{\xi \le t | \chi = t\}\right] = \mathrm{P}\{\chi \le \xi\} \tag{5}$$

Where, χ and ξ are any two random variables representing the values under a continuous measure. $\mathscr{R}(\cdot)$ represents a plot of the sensitivity. (·) and (·) represent the cumulative distribution function (CDF) for χ and ξ, respectively, for each t∈[0,1] (Pablo et al., 2020).

The Bayesian log-linear regression model is represented by Equation 6.

$$\log(\mu) = Adm_{fac} + Tch_{fac} + Stu_{fac} + E(prior) \tag{6}$$

Administration factors (Admfac), teacher factors (Tchfac), and student factors (Stufac) are categorical in nature.

Equation (6) can be summarised in Equation (7).

$$\log[f(x)] = \sum_{n=1}^{m} g\left(Adm_{fac_n}, Tch_{fac_n}, Stu_{fac_n}\right) + E(prior) \tag{7}$$

According to Andraszewicz et al. (2015), the interpretations of Bayes factors are as follows:

Bayes Factor	Interpretation
> 100	Strong evidence supporting the alternative hypothesis
30–100	There is very strong evidence for the alternative hypothesis.
10-30	Strong evidence supports the alternative hypothesis.
3-10	Moderate evidence supports the alternative hypothesis.
1-3	Anecdotal evidence supporting the alternative hypothesis
1	No evidence

3. Analysis

Table 1 presents the outcomes of the Bayesian log-linear regression model. The Bayes factor, known for its enhanced reliability compared to the p-value, facilitates a clearer comprehension of the probability level of variations in attainment rates for each relevant component concerning the dependent variable (performance in a private or public school model). Details such as the Bayes factor score, its strength, interpretation, variance, and confidence interval are provided in Table 1.

Table 1. Parameter Estimates from Bayesian Loglinear Regression

Parameter	Bayes Factor (BF)	BF Interpretation	Variance	95% Confidence Interval
Quality Supervision	176.741	Extreme Evidence	2.304	-3.338 - 5.005
Conducive Teaching /Learning Environment	126.817	Extreme Evidence	0.737	-2.549 - 1.959
Parents' support to schools progress	91.982	Very strong Evidence	2.059	-2.22-5.395
Timely Provision TLM and TLRs	65.685	Very strong Evidence	1.319	-3.651- 0.08

Student Interest	52.552	Very strong Evidence	0.815	-1.168-3.464
Differentiated Task	37.654	Very strong Evidence	1.953	-1.744-5.558
GESI compliance	33.651	Very strong Evidence	1.067	-2.809-2.667
Critical thinking	29.435	Strong Evidence	0.651	-3.629 - 0.859
Assessment as learning	26.123	Strong Evidence	1.941	-1.058- 6.192
Teacher Punctuality	23.64	Strong Evidence	0.477	-2.232-1.231
Home Tutor effect	19.955	Strong Evidence	1.87	-0.878 - 6.326
Prep Time Culture	18.725	Strong Evidence	1.073	-2.774-2.463
School Culture	17.708	Strong Evidence	2.027	-2.277-5.117
Meaningfully communicates progress	16.992	Strong Evidence	1.332	-3.783-1.993
Class competition	15.688	Strong Evidence	0.884	-1.718-3.254
Remediates Learners misconceptions	14.586	Strong Evidence	2.111	-2.311-9.216
SEL	12.727	Strong Evidence	1.903	-1.033-5.949
ICT integration	12.578	Strong Evidence	0.16	-0.293-1.468
Teacher regular in Sch	12.239	Strong Evidence	0.526	-0.838-2.867
Enhanced Parent-Teacher Relationship	11.623	Strong Evidence	0.391	-1.262-1.848
Extra Classes	10.59	Strong Evidence	0.403	-2.35-0.85

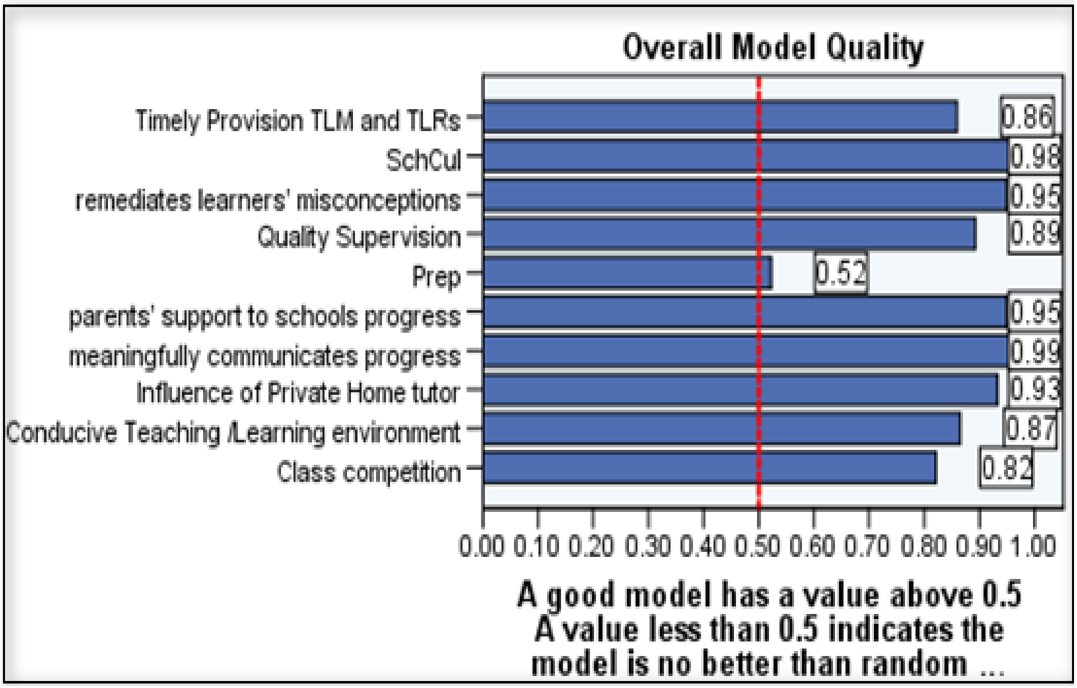

Figure 1(a). Overall Model Quality effect size effect

Figure 1 illustrates the performance of ten educational parameters. All nine components, except for preparation culture, demonstrated remarkably high levels of performance in the overall model quality, slightly exceeding the 0.5 threshold. The robust model incorporating all nine variables suggests their strong contribution to closing achievement gaps. Regarding prep culture, the model indicates a significant effect size but a relatively low strength, standing at 52%.

Table 2. Effect Size Determination for Figure 1(a)

Area Under the ROC Curve (Effect Size Determination of Parameter Estimates)					
Test Result Variable(s)	Area	Std. Errora	Asymptotic Sig.b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Timely Provision TLM and TLRs	0.906	0.024	0.00	0.86	0.953
Quality Supervision	0.936	0.022	0.00	0.893	0.978
Class competition	0.888	0.034	0.00	0.822	0.954
Conducive Teaching /Learning environment	0.917	0.026	0.00	0.866	0.969
Influence of Private Home tutor	0.963	0.015	0.00	0.933	0.992
parents' support to schools progress	0.976	0.014	0.00	0.949	1.003
meaningfully communicates progress	0.997	0.004	0.00	0.989	1.005
remediates learners' misconceptions	0.973	0.012	0.00	0.949	0.997
SchCul	0.992	0.008	0.00	0.976	1.008
Prep	0.594	0.036	0.01	0.522	0.665

Table 2 provides the effect sizes of the ten parameters outlined in Table 1, as measured by the area under a receiver operating characteristic (ROC) curve. The table includes standard error, p-values, and confidence intervals for each factor. Eight factors exhibit notable effect sizes, with their area under the curve ranging from 1 to 0.9 ($1 \leq AUC \leq 0.9$). Variables with an AUC value of $0.8 \leq AUC < 0.9$ display exceptionally strong correlations. The variable with an effect size falling within the range of $0.7 \leq AUC < 0.8$ demonstrates a robust ability to address achievement gaps. Additionally, educational components with effect sizes in the range of $0.6 \leq AUC < 0.7$ are found to be less effective at closing achievement gaps. Finally, the capacity to control achievement gaps is weakest for educational characteristics with effect sizes falling within the $AUC < 0.7$ range.

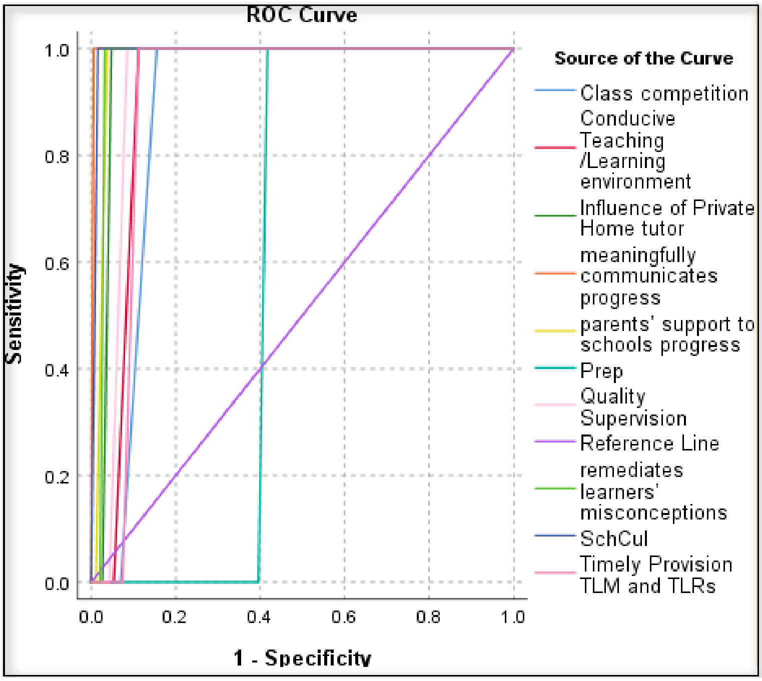

Figure 1(b). Effect Size Plot for Figure 1(a)

Figure 1(b) displays the effect size plot corresponding to Figure 1(a). The ROC curve for the nine factors illustrates that the area above the reference line surpasses the area below. In contrast, the scenario is reversed for the Preparation culture variable.

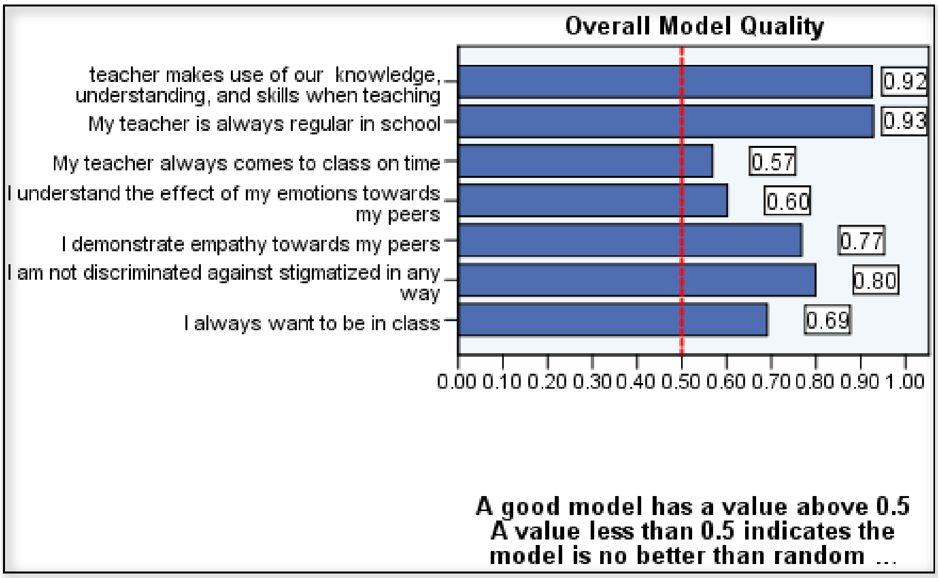

Figure 2(a) Overall Model Quality Effect Size Effect

The model indicates that organizing classes according to student characteristics by teachers in public and private basic schools can lead to a 92% improvement in learning, as shown in Figure 2(a). The data from Figure 2(a) highlights a high level of consistency (approximately 93%) among teachers in both public and private schools in the studied districts in Ghana. However, their punctuality in attending classes is notably low, hovering around 57%. The model further suggests that when teachers are tardy to class, there is a significant reduction in contact hours, emphasizing the importance of timely attendance for effective teaching.

Table 3. Effect size Determination for Figure 2(a)

Area Under the ROC Curve (Effect Size Determination of Parameter Estimates)					
Test Result Variable(s)	Area	Std. Errora	Asymptotic Sig.b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
I demonstrate empathy towards my peers	.853	.044	.000	.767	.939
teacher makes use of our knowledge, understanding, and skills when teaching	.960	.018	.000	.925	.995
I am not discriminated against stigmatized in any way	.869	.036	.000	.798	.939
My teacher is always regular in school	.965	.019	.000	.927	1.003
My teacher always comes to class on time	.765	.100	.008	.568	.961
I understand the effect of my emotions towards my peers	.791	.097	.003	.601	.982
I demonstrate empathy towards my peers	.853	.044	.000	.767	.939
I always want to be in class	.826	.069	.000	.691	.961

Table 3 presents the Area under the ROC Curve, indicating the effect size determination of parameter estimates for various test result variables related to students' experiences and teacher behaviors. The variables include the demonstration of empathy towards peers, the teacher's utilization of students' knowledge, understanding, and skills in teaching, the absence of discrimination or stigma, teacher's regularity in school, teacher's punctuality to class, understanding of the emotional impact on peers, and students' eagerness to be in class. The values include the area under the curve, standard error, significance level, and asymptotic 95% confidence interval for each variable, offering insights into their impact on students' experiences and perceptions.

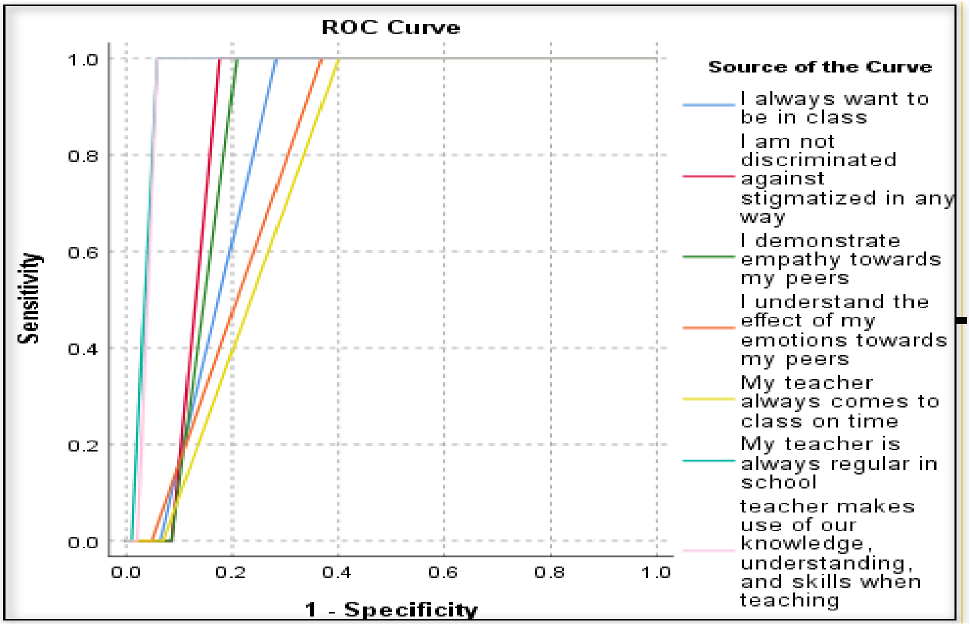

Figure 2(b) ROC Curve Analysis

The projected success rate for emotional intelligence is relatively constrained, standing at 60% according to Figure 2(b). Consequently, it is imperative for teachers in both educational sectors to undergo training in emotional intelligence to adeptly manage their students' emotions. The predicted achievement level of 69% underscores the substantial responsibility teachers bear in cultivating students' interest in the taught content. This is crucial for boosting their motivation to consistently attend classes and actively participate. Proficiency in group activities, involving skills such as tolerance, cooperation, teamwork, and collaboration, becomes achievable when students comprehend how their emotions impact the teaching and learning process. The emphasis on specific 21st-century skills is notable in the new curriculum.

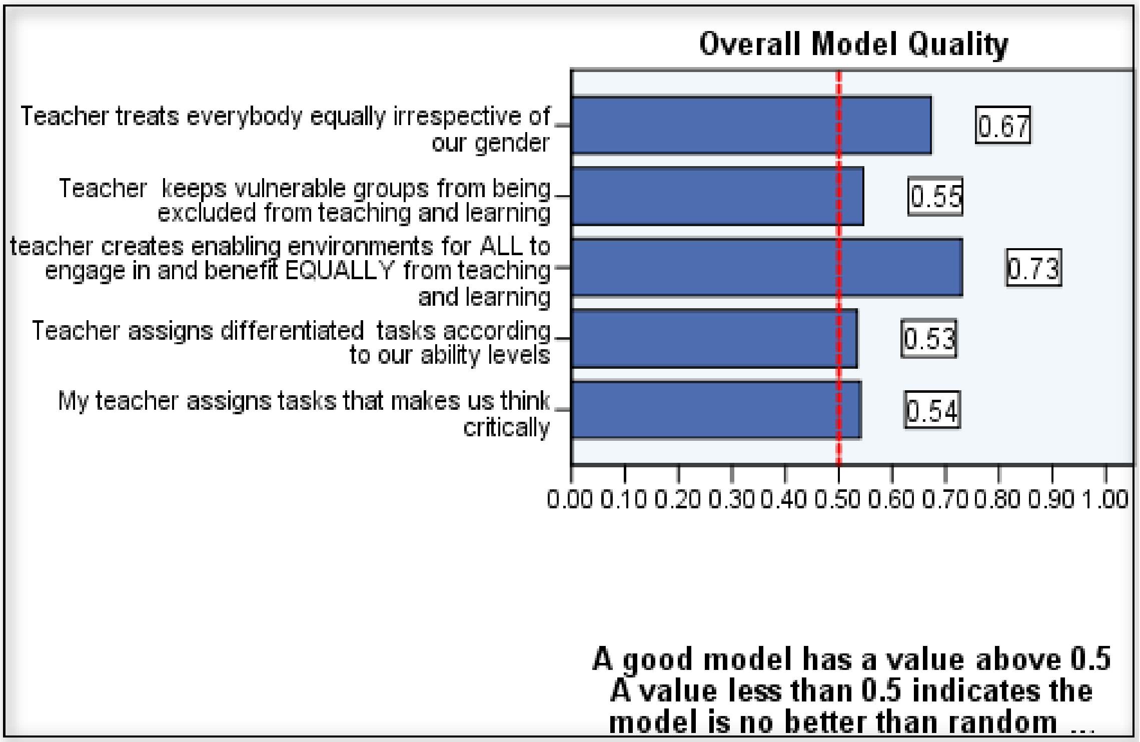

Figure 3(a) Overall Model Quality

Table 4. Effect Size Determination for Figure 3 (a)

Area Under the ROC Curve (Effect Size Determination of Parameter Estimates)					
Test Result Variable(s)	Area	Std. Errora	Asymptotic Sig.b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Teacher assigns differentiated tasks according to our ability levels	.743	.107	.022	.535	.952
teacher creates enabling environments for ALL to engage in and benefit EQUALLY from teaching and learning	.864	.068	.000	.730	.997
Teacher keeps vulnerable groups from being excluded from teaching and learning	.741	.099	.015	.546	.935
Teacher treats everybody equally irrespective of our gender	.783	.056	.000	.673	.894

Area Under the ROC Curve (Effect Size Determination of Parameter Estimates)					
Test Result Variable(s)	Area	Std. Errora	Asymptotic Sig.b	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
My teacher assigns tasks that makes us think critically	.746	.105	.019	.540	.952
Teacher assigns differentiated tasks according to our ability levels	.743	.107	.022	.535	.952
teacher creates enabling environments for ALL to engage in and benefit EQUALLY from teaching and learning	.864	.068	.000	.730	.997
Teacher keeps vulnerable groups from being excluded from teaching and learning	.741	.099	.015	.546	.935
Teacher treats everybody equally irrespective of our gender	.783	.056	.000	.673	.894
My teacher assigns tasks that makes us think critically	.746	.105	.019	.540	.952

Table 4 provides information on the Area Under the ROC Curve, serving as a measure to determine the effect size of parameter estimates for various test result variables related to teaching practices. The variables include the teacher's assignment of differentiated tasks based on students' ability levels, creation of inclusive environments for equal engagement and benefit in teaching and learning, prevention of exclusion of vulnerable groups, equal treatment regardless of gender, and assignment of tasks encouraging critical thinking. The values indicate the area under the curve, standard error, significance level, and asymptotic 95% confidence interval for each variable, providing insights into the effectiveness of these teaching practices.
The data presented in Figure 3 and Table 4 indicates that, while the overall quality of the model is good, there are areas where teachers can enhance their practices. Specifically, there is room for improvement in engaging students in differentiated tasks and critical thinking exercises, with effect sizes of 53% and 54%, respectively. The data also suggest that teachers may not be effectively preventing the exclusion of vulnerable groups from the teaching and learning process, with an effect size of 55%. Regarding efforts to treat everyone equally regardless of gender, there is a 67% effect size. Although satisfactory, the effectiveness of this aspect remains below 70%, indicating the need for further improvement. On a positive note, the model with a 73% effect size indicates that teachers are successfully facilitating learning and teaching, ensuring equal participation and benefit for all students.

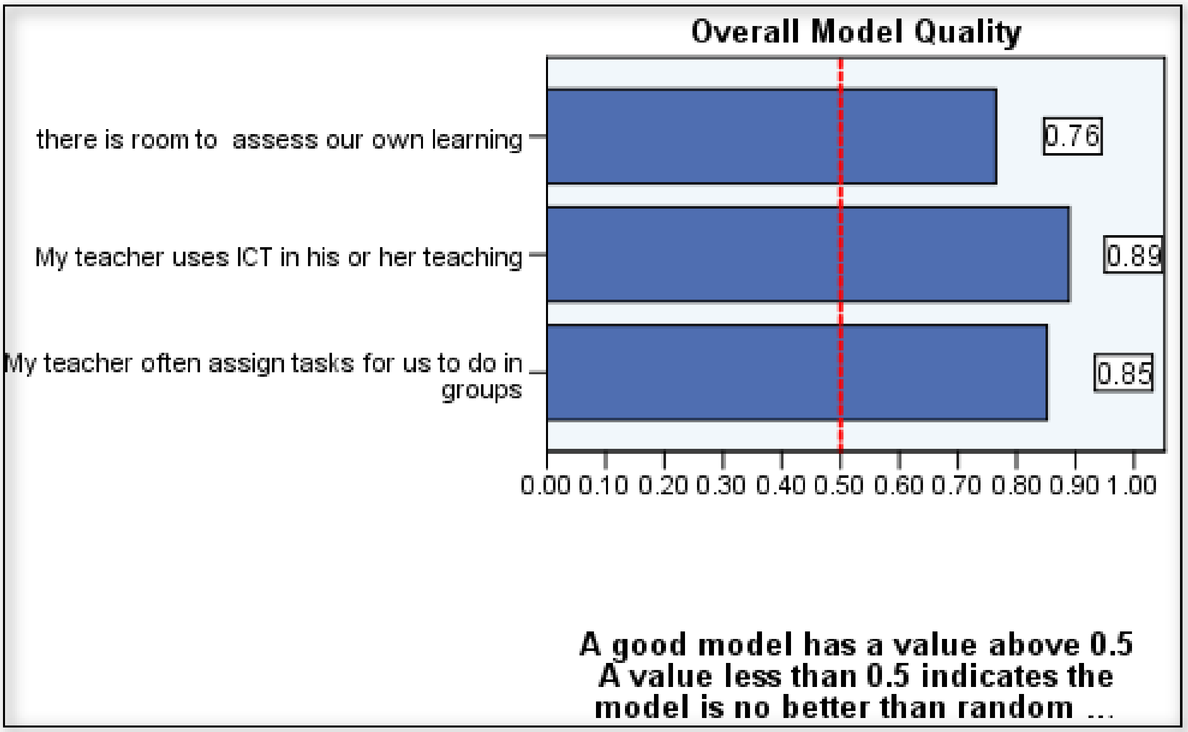

Figure 4a. Overall Model Quality

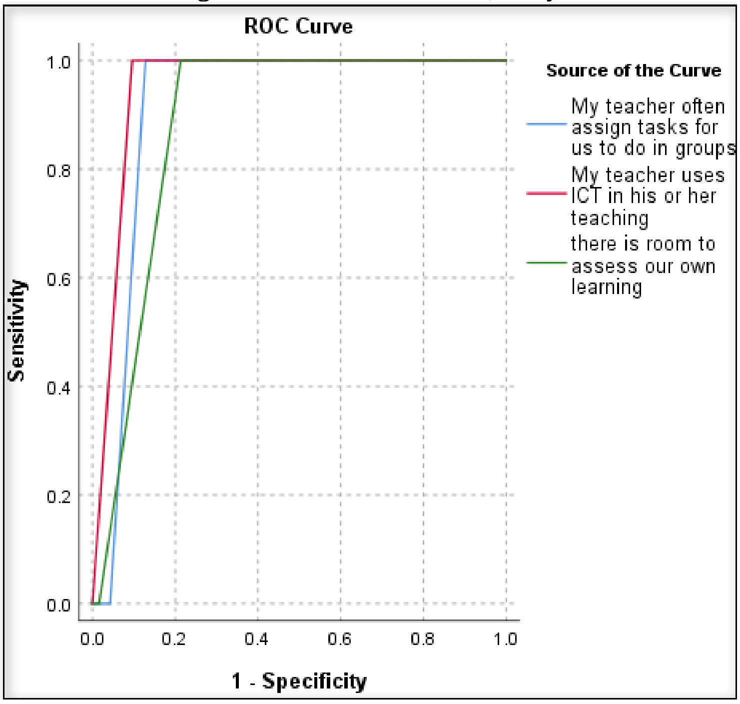

Figure 4(a) ROC Curve Analysis for Figure 4 (a)

Based on the information depicted in Figures 4a and 4b, it is evident that teachers in basic schools have successfully incorporated Information and Communication Technology (ICT) into their lessons. This accomplishment indicates the success of the Ghanaian government's initiative to equip teachers with laptops for instructional support. Additionally, the findings suggest that teachers have implemented efficient assessment methods, enabling students to assess their own learning. Moreover, the results highlight the commendable efforts of teachers in integrating students into group work projects, fostering the development of their cooperative and collaborative skills.

Table 5. Summary for Designed Models

	Layer Description	ANN1	ANN2	ANN3
[1] Training	Cross Entropy Error Percent Incorrect Predictions Training Time	18.022 20.3% 0:00:00.21	25.056 25.9% 0:00:00.17	8.957 14.3% 0:00:00.15
Testing	Cross Entropy Error Percent Incorrect Predictions	7.786 35.3%	5.481 17.6%	11.904 22.2%
Holdout	Percent Incorrect Predictions	29.4%	26.7%	21.9%

[1] Notes: Stopping rule used = consecutive step(s) with no decrease in error. Dependent variable: school type performance: 0 = public school, 1 = private school, Error computations are based on the testing sample.

Table 6 Prediction with ANN3

Sample	**Observed**	**Predicted**		
		Private	Public	**Percent Correct**
[1] Training	1 Private 0 Public Overall Percent	51 8 70.2%	4 21 29.8%	92.7% 72.4% 85.7%
Testing	1 Private 0 Public Overall Percent	39 9 76.2%	5 10 23.8%	88.6% 52.6% 77.8%
Holdout	1 Private 0 Public Overall Percent	21 4 78.1%	3 4 21.9%	87.5% 50.0% 78.1%

Table 7. Area under the ROC Curve of Tentative Models

	School type	**ANN1 60% 20%20%**	**ANN2 50% 30% 20%**	**ANN3 70% 20% 10%**
		Area	**Area**	**Area**
School type performance	1 private	0.808308	0.784493	0.845960
	0 Public	0.808308	0.784493	0.845960

The AUC values indicate that all three ANN models perform well in distinguishing between private and public schools. During the training phase, ANN3 surpasses ANN1 and ANN2, exhibiting the lowest Cross Entropy Error and Percent Incorrect Predictions. Moreover, ANN3 requires the shortest training time, making it the most efficient model. In the holdout phase, ANN3 continues to demonstrate superior performance, maintaining its efficiency in generalizing to new, unseen data. The training configuration of ANN3, with 70% training, 20% testing, and 10% holdout, achieves the highest AUC values, suggesting better overall discrimination performance.

Table 5 summarizes the designed models, providing information on the holdout samples and the training (and testing) results. During the training phase, ANN3 minimizes the cross-entropy error, with the lowest value (8.957) among the models, indicating its ability to predict the optimal level of academic success. The study reveals that the ANN3 model produces incorrect predictions in the training and testing samples at rates of 14.3% and 22.2%, respectively, while the holdout dataset has an error rate of 21.9%. The training process continues until the error function decreases in a single successive step. If the predicted probability for each case's forecast outcome by the ANN3 model is greater than 0.5, it is considered correct. Overall, the ANN3 model correctly classifies 85.7% of the training cases and 77.8% of the testing cases.

After further processing, the ROC curve validates the ANN3 model, displaying its classification performance for all possible cutoffs. The Private School model, with a training configuration of 70%, testing at 20%, and

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holdout at 10%, achieves the best area under the ROC curve (0.846). The lift graph, utilizing a subset of the data, illustrates the advantages of using the model compared to not using one. The lift factor (benefit) is calculated as 100% / 10% = 10% for academic achievement.

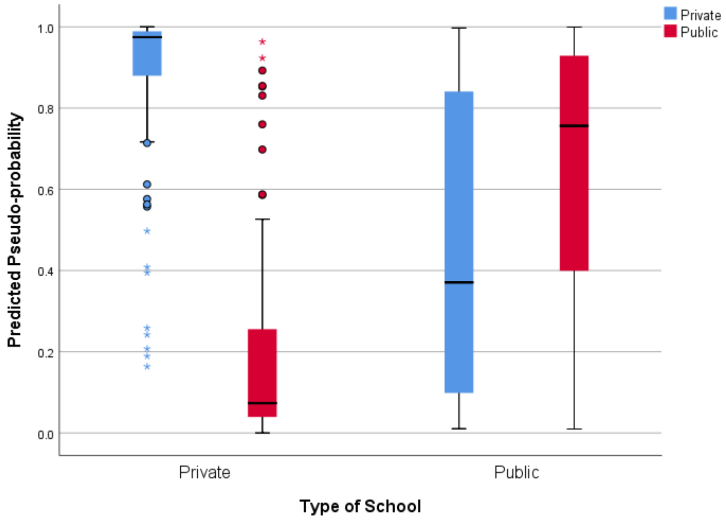

Figure 5. Predicted Pseudo-probability Plot for Robust Model

The initial set of boxplots in Figure5 highlights a notable distinction in the medians between private and public schools, indicating a discernible contrast in the model's confidence when predicting classes for these two school types. The shorter whisker indicates a more concentrated or narrow range of predicted values suggesting higher confidence or precision in the model's predictions for the private school category. The model is more certain about the outcomes and expects less variation. The median value for the private school model is in close proximity to 1, implying a higher confidence in predicting favorable educational outcomes. Conversely, the median for the public school model is nearer to zero, suggesting lower predicted educational outcomes. It is important to observe that the private school model exhibits a limited number of outliers beyond the high-performance range, indicating a few instances of lower performance, though not statistically significant. Similarly, despite the predicted value range for poor performance in the public school model, there are a few instances of exceptionally high predicted performance for some students, although these occurrences are numerically insignificant. The substantial difference in medians underscores the model's varied levels of confidence in predicting outcomes for private and public schools. This divergence may reflect inherent disparities in the educational environments or factors influencing predictions for the two school types. The proximity of the median to 1 for the private school model suggests a robust prediction of higher educational outcomes. However, the presence of a few outliers with lower performance indicates potential areas for improvement or nuances in prediction accuracy. Despite the generally lower predicted outcomes for public schools, the existence of some high-performance records implies the model's ability to identify exceptional cases. Addressing the predicted value range for poor performance and understanding the factors influencing both ends of the performance spectrum is crucial. The presence of outliers in both models, though minimal, necessitates attention. Investigating the factors contributing to these outliers can provide insights into the model's limitations and areas for refinement.

The boxplots for the second category pertaining to public schools expose notable misclassification challenges, with a substantial portion of the box extending below the 0.5 mark. The increased length of the whiskers and boxes signifies that the public school model faces difficulties in accurately predicting optimal educational outcomes, resulting in a broader distribution of predicted values. This observation suggests a potential need for refinement in the model or indicates inherent complexities in predicting instances within this particular category. The elongated whiskers and boxes in the public school model give rise to concerns regarding the reliability of the model in forecasting specific outcomes.

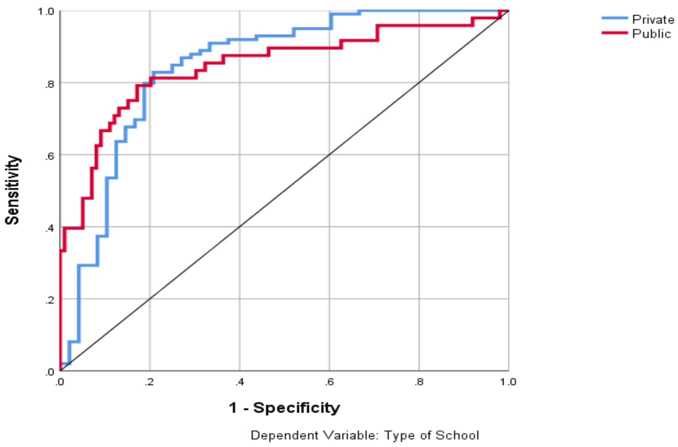

Figure 6. ROC Curve plot to Identify the Extent of Robustness

The analysis of the Receiver Operating Characteristic (ROC) curve in Figure 6 has yielded a noteworthy Area under the Curve (AUC) value of 0.845960. This metric is indicative of the model's discriminatory power in distinguishing between private and public schools. Among the three sets of partitions examined—comprising 70% training, 20% testing, and 10% validation—the optimal result was observed, as summarized in Table 7. The AUC value of 0.845960 for both private and public schools is particularly significant. It suggests that the two fundamental school models can achieve equally optimized academic achievement levels when adhering to the normalized factor importance, as depicted in Figure 9. The ROC curve analysis underscores the model's ability to balance sensitivity and specificity, effectively capturing the trade-off between true positive and false positive rates. This implies that the chosen partitioning strategy, specifically the allocation of 70% for training, 20% for testing, and 10% for validation, contributes to a robust and well-generalized model. The model's performance is consistent across both private and public school categories, signifying its reliability in predicting academic achievement levels. The normalized factor importance, as illustrated in Figure 9, plays a crucial role in achieving optimal outcomes for both private and public schools. The factors contributing to academic achievement are appropriately weighted, ensuring a balanced representation of key features in the model. The ROC curve analysis, coupled with partitioning strategies and factor importance considerations, indicates a well-performing model capable of achieving optimized academic predictions for both private and public schools. The chosen partitioning ratio of 70-20-10 has proven to be particularly effective in achieving this balance, contributing to the overall reliability and robustness of the model.

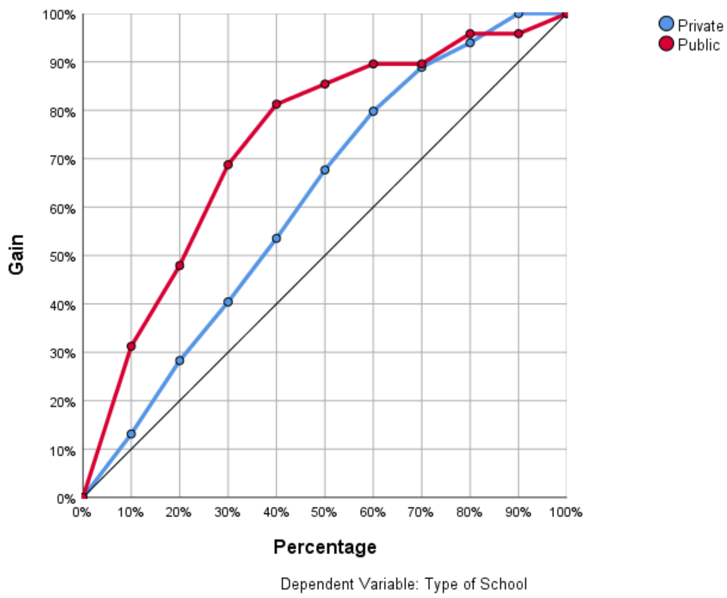

Figure7. Cumulative Gain Plot

Figure 7 presents Cumulative Gain plots designed to evaluate the chosen model's performance by contrasting its predictions with those of a random or baseline model. The x-axis delineates the percentage of the dataset, distributed into uniform intervals, with each point representing a cumulative percentage of the data. On the y-axis, the cumulative gain achieved by the model is depicted—a metric expressing the ratio of positive instances captured by the model to the expected number without the model. This measurement gauges the extent to which the model outperforms a random or baseline model. The baseline, represented by a straight diagonal line in the figure, embodies the cumulative gain of a random model. The objective is for the model's cumulative gain curve to significantly diverge from this baseline, indicating superior performance. In the case of the private school model, the steeper curve suggests effective early identification of positive instances in predictions. Within the realm of Artificial Neural Networks (ANNs), this implies accurate predictions and a higher gain compared to random chance. The consistent outperformance of the private school model against the baseline underscores its valuable predictive capabilities.

Examining the cumulative gain curve for the public school model reveals sudden changes or inflection points, highlighting specific thresholds where the model encounters challenges. These fluctuations underscore potential complexities or limitations in the model's performance for public schools. The implication of these results is that while the private school model demonstrates robust predictive power, the public school model may require further refinement or consideration of inherent challenges in predicting positive instances. Understanding these nuances is essential for optimizing the model's performance and ensuring reliable predictions in different scenarios.

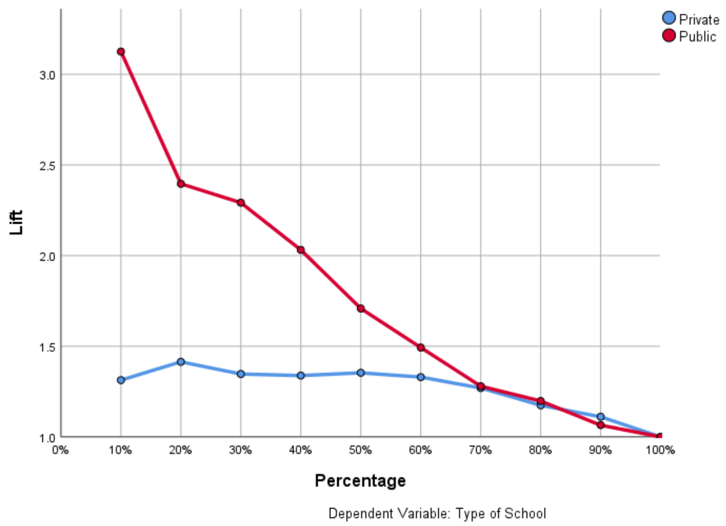

Figure8. Lift Diagram Plot

The Lift Plot presented in Figure 8 within the context of ANNs offers a visual representation of the model's capacity to distinguish between positive and negative instances. The diagram illustrates a high-performing model that displays superior predictive effectiveness compared to the baseline.

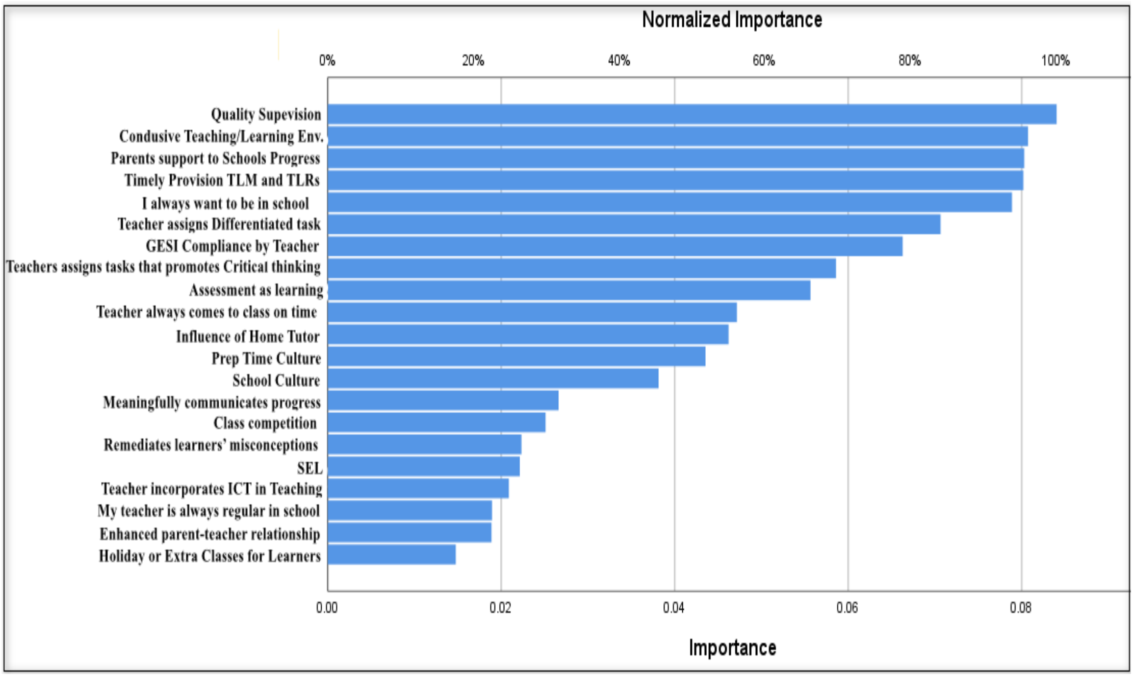

Figure 9: Plot of Normalised Importance of Variables

The values in Table 8 are arranged in descending order of importance and depicted in a bar chart in Figure 9. It is evident that factors related to administration (such as effective supervision, a conducive teaching and learning environment, parental support for academic progress, and timely provision of teaching and learning materials) and teachers (considering learners' interests in lesson delivery, providing differentiated tasks, promoting gender and social inclusion, and integrating critical thinking) have the most significant impact on how the network assesses student achievement.

Table 8. Normalised Importance of Variables by Rank

Parameter	Importance	Normalised Importance	Rank
Quality Supervision	0.084	100.0%	1
Conducive Teaching /Learning Environment	0.081	96.1%	2
Parents' support to schools progress	0.080	95.6%	3
Timely Provision TLM and TLRs	0.080	95.4%	4
Student Interest	0.079	93.9%	5
Differentiated Task	0 .071	84.1%	6
GESI compliance	0.066	78.9%	7
Critical thinking	0.059	69.7%	8
Assessment as learning	0.056	66.2%	9
Teacher Punctuality	0.047	56.1%	10

Home Tutor effect	0.046	55.0%	11
Prep Time Culture	0 .044	51.8%	12
School Culture	0.038	45.4%	13
Meaningfully communicates progress	0.027	31.7%	14
Class competition	0.025	29.9%	15

The importance of each independent variable identified in the designed neural network models (ANN1, ANN2, and ANN3) is presented in Table 7 and illustrated in Figure 8 to provide a clear overview of the factors and their significance for optimized learning outcomes.

Upon analyzing the results, it was observed that quality supervision stood out with the highest indication among all predictors, attaining a normalized importance of 100% in the designed neural network models when assessing the significance of independent variables. Other notable predictors included a conducive teaching and learning environment (normalized importance = 96.1%), timely provision of teaching and learning materials and resources (normalized importance = 95.6%), learner interest (normalized importance = 95.4%), and teachers assigning differentiated tasks based on students' ability levels (normalized importance = 93.9%). Following in the order of importance were gender and social inclusion compliance by the teacher (normalized importance = 84.1%), administering tasks that promote critical thinking (normalized importance = 78.9%), among others as detailed in Table 8 and visually represented in Figure 9.

Table 8 provides a comprehensive overview of the normalized importance of various parameters in an educational context, offering valuable insights for prioritizing and enhancing different aspects of the educational system. Quality supervision, conducive teaching/learning environment, and parents' support are identified as the top three priorities, having the highest normalized importance percentages and corresponding ranks. The list covers a diverse range of parameters, including teaching methods, parental involvement, infrastructure, and cultural aspects of the educational environment. While some factors like quality supervision are ranked high, others such as class competition and meaningful communication of progress also hold significance. Decision-makers can use this information to allocate resources and focus on areas that contribute most significantly to overall educational effectiveness.

4. Discussions

4.1 Quality Supervision

Quality supervision takes precedence in terms of normalized importance, with strong evidence indicating a 177-fold increase in the likelihood (variance = 2.304, CI: -3.338-5.005) that effective supervision of teachers and head teachers can improve success rates by approximately 89% in both private and public basic schools in Ghana. The effect size of 0.936, documented through the area under the receiver operating characteristic curve (AUC), supports this conclusion (CI: 0.893–0.978, $p < 0.01$). The Bayes factor strength (greater than 1) upholds the hypothesis that private schools outperform public schools in this aspect. The predicted pseudo-probability plot (Figure 5) further underscores the reliability of the private school model. The results indicate that students at public basic schools face a higher risk of academic underachievement due to a lack of quality supervision. To address this issue, circuit supervisors should intensify their efforts to monitor instruction in public schools, while the district education directorate can investigate the reasons behind consistently less effective oversight compared to the private sector.

Effective supervision entails motivating the right individuals to perform the right tasks with the right knowledge at the right time to achieve the intended outcome. This finding is supported by various studies. According to Dangara (2015), regular monitoring of education, effective supervision techniques, administrator visits and classroom inspections, review of lesson plans and teacher notes, and assessment of teachers' record-keeping are positively correlated with the academic achievement of secondary school students and the performance of teachers. Mustapha et al. (2020) also identified a significant difference in the degree of quality supervision between private and public schools, with private schools receiving higher ratings.

4.2 Conducive Teaching /Learning Environment

In the rankings, a favorable teaching and learning environment secured the second position in terms of normalized importance. The Bayes factor strongly indicates a 127-fold increase in the likelihood (variance = 0.737, CI: -2.549-1.959) that improvements in the success rates of basic school students in both public and private schools in Ghana can reach 87%. The results suggest that private schools are more adept at mobilizing resources at exceptional levels, creating an environment conducive to effective teaching and learning. The effect size for this factor, measured by the area under the receiver operation characteristic curve, is reported as (AUC=0.917, $p<0.01$, CI: 0.866–0.969). The findings highlight that private schools outperform public schools in this aspect, supported by the Bayes factor strength (greater than 1) and the predicted pseudo-probability plot shown in Figure 5. The evidence suggests that private schools are more capable of establishing environments that support effective teaching and learning compared to public basic schools.

The attitudes of children are profoundly influenced by a nurturing and healthy school environment, which, in turn, enhances student achievement (Ihekoronye, 2020). Private schools, in comparison to public schools, boast highly efficient and superior-quality facilities, including reading nooks, computer labs, libraries, and well-maintained restrooms (Day et al., 2014). The provision of suitable infrastructure ensures a conducive learning environment for students. Private schools are more inclined to regularly update their facilities, staying current with technological advancements and providing students with access to the latest knowledge and high-quality instruction. The primary objective of most private schools is to deliver a high-quality education, justifying their higher cost as the investment is considered worthwhile (Day et al., 2014).

4.3 Parents' Support for School's Progress

The third factor of significant importance, according to Artificial Neural Network (ANN) analysis, is parents' involvement and support for the school's advancement, particularly through the support of the Parent-Teacher Association (PTA). When considering this factor, the Bayes factor strongly supports a 92-fold increase in the likelihood of improving differences in basic school student success rates by 95% in both Ghanaian public and private basic schools. The effect size recorded for this factor is 0.906 (variance = 2.059, 95% CI: -2.22 to 5.395). The findings suggest that the private school model outperforms the public school model, attributed to the typically more active Parent-Teacher Associations (PTAs) in private schools, as indicated by the predicted pseudo-probability plot and a Bayes factor score greater than one.

An effective strategy to foster greater collaboration between parents and teachers is through the Parent-Teacher Association (PTA). Research has consistently shown that PTAs have a significant positive impact on overall school performance, contributing to happier teachers, improved student performance, and increased parent participation in school activities. PTAs also play a crucial role in advocating for enhancements in the educational system. Together, parents and educators can influence decisions that impact the school, ensuring a positive learning environment for all children. Armed with this information, parents are better equipped to make informed decisions about their children's education and advocate for necessary adjustments or advancements. Furthermore, PTAs enhance fundraising efforts by providing a structured framework for parents and contributors to support their child's educational institution. This support can lead to fundraising for essential supplies such as new books, technology, and even field trips (Wangeci et al., 2018).

4.4 Timely Provision TLM and TLRs

The provision of teaching-learning materials (TLM) and resources (TLRs) in a timely manner is of significant importance, ranking fourth in normalized importance. Strong evidence from Bayes factor analysis suggests a 66-fold likelihood of improving differences in basic school student success rates by 87% in both private and public basic schools in Ghana. The recorded effect size for this factor is 0.906, with a standard error of 0.024 and a 95% confidence interval of 0.86–0.953. The hypothesis that private schools outperform public schools in this aspect is supported by a Bayes factor strength exceeding 1. The anticipated pseudo-probability plot further indicates the private basic school model's greater resilience compared to the public school model. These findings provide evidence that public schools may be less proficient in creating, obtaining, or utilizing teaching and learning materials (TLMs) and resources (TLRs) in a timely manner.

Published research reveals that students in the West African Subregion, including Ghana, faced challenges in achieving positive outcomes due to the unavailability, inadequacy, and improper usage of Teaching and Learning Materials (TLMs) and Teaching and Learning Resources (TLRs). This situation hindered children's academic progress and the effective delivery of instruction in basic school settings (Oppong, 2021). There exists a strong, positive, and significant relationship between academic achievement and instructional resources. Schools with more resources tend to outperform those with fewer resources. The availability and quality of teaching and learning resources contribute to the superior academic performance of private schools over public ones. The caliber and volume of instructional resources significantly impact students' academic achievement, with schools possessing adequate resources, such as textbooks, demonstrating a higher probability of success in exams compared to those lacking resources. Consequently, insufficient tools and resources for instruction and learning may be a contributing factor to subpar academic results (Okongo et al., 2015). Moreover, research indicates that private schools utilize classroom instructional materials and resources at a considerably higher rate than public schools (Mustapha et al., 2020).

4.5 Teacher considers the Interest of students in lesson planning

The importance of students' engagement in the teaching and learning process is ranked fifth in terms of normalized relevance, as indicated by an artificial neural network. Strong support from the Bayes factor suggests that enhancing students' interest in the teaching and learning process can significantly increase the likelihood of improving the success rates of basic school students in both public and private schools during the BECE by 69%, with a 53-fold possibility. The effect size for this factor is 0.826 ($p<0.01$, CI: 0.691–0.961). Analysis of pseudo-probability plots and a positive Bayes factor indicates that incorporating students' interests into lesson planning allows teachers to provide high-quality learning opportunities and support students in pursuing their interests. This approach fosters increased student engagement in the teaching and learning process, contributing to the development of knowledge, practical, analytical, and creative skills crucial for success in their chosen pursuits.

Academic success is closely tied to interest, a potent motivator that shapes learning experiences and guides career and academic trajectories. Various strategies aimed at enhancing interest, such as creating attention-grabbing environments, aligning situations with past interests, implementing problem-based learning, and increasing the utility value, have proven to be beneficial. Elevating students' interest levels can result in more motivated and involved learning experiences (Harackiewicz et al., 2016).

4.6 Teacher assigns differentiated tasks according to ability levels of leaners

The utilization of differentiated instruction by teachers holds the sixth position in terms of normalized relevance, as assessed by an artificial neural network across various components. The Bayes factor suggests a strong likelihood, 38 times greater (variance = 1.953, CI: -1.744-5.558), that employing differentiated tasks can enhance success rates by 53%. The effect size, measured by the area under the receiver operating characteristic curve, is 0.743 (CI: 0.535–0.952, $p = 0.022$). There is a clear need for comprehensive training for teachers in both public and private schools in Ghana concerning the implementation of differentiated instruction. This need is underscored by the comparatively low projected value compared to other variables. Teachers who undergo sufficient training in differentiated teaching are more likely to develop the necessary skills to customize their lessons, tailoring them to each student's unique needs, interests, and strengths while incorporating differentiated assignments throughout the lesson.

According to data supported by Leballo et al. (2021), teachers in private schools show a greater inclination towards incorporating differentiated instruction, with time constraints identified as the primary hindrance. In contrast, teachers in government schools employ differentiated instruction less frequently, citing various challenges such as resource shortages and high student-teacher ratios.

4.7 Gender and Social Inclusion (GESI) complaince by Teacher

Teachers' adherence to Gender and Social Inclusion (GESI) is ranked seventh in terms of normalized relevance, with the Bayes factor providing compelling evidence that fostering an environment supportive of Gender and Social Inclusion could potentially increase the success rates of basic school students during the Basic Education Certificate Examination (BECE) by 34 times (variance = 1.067, CI: -2.809 - 2.667). According to the comprehensive quality model, when teachers establish an inclusive atmosphere where ALL students can actively participate and benefit equally from teaching and learning, the success rates of private schools see an approximately 73% higher improvement. The effect size for this aspect, depicted as the area under the receiver operation characteristic curve, is 0.864 ($p<0.01$, CI: 0.730–0.730).

The overall quality model also reveals that ensuring the prevention of the exclusion of vulnerable groups in the teaching and learning process leads to an approximate 55% increase in the success rates of private schools. The findings indicate that eliminating discrimination or stigma against students results in an 80% improvement in learning outcomes, with an effect size of 0.869 ($p<0.01$, CI: 0.798–0.939). Additionally, creating enabling environments for ALL students to participate and benefit EQUALLY from teaching and learning leads to a 73% enhancement in learning outcomes, with an effect size of 0.864 ($p<0.01$, se=0.068, CI: 0.730–0.997). The study further reveals that when teachers ensure equal benefits for all learners in the lesson, irrespective of their gender, learning outcomes improve by 67% with an effect size of 0.783 ($p<0.01$, se=0.056, CI: 0.673–0.894).

It is emphasized that gender equality and social inclusion should serve as the foundation of any lesson plan aiming to instill respect for the dignity of each individual, diversity, tolerance, non-discrimination, equality of opportunity, solidarity, and the participation of all students, including those from disadvantaged and vulnerable groups (UN, 2013).

4.8 Teacher incoorpoartes critical thinking in Lesson delivery

Teachers' proficiency in integrating critical thinking into lesson delivery holds the eighth position in normalized importance. The Bayes factor presents compelling evidence, suggesting that the success rates of basic school students in both public and private schools during the BECE could potentially increase by 29 times (variance = 0.651, CI: -3.629-0.859), or by 54%, when teachers design lessons that encourage critical thinking. The effect size for this factor is indicated by the area under the receiver operation characteristic curve (AUC=0.864, $p<0.01$, CI: 0.730–0.730). The relatively low predicted success rates regarding this factor underscore the need for teacher training to enhance their ability to promote critical thinking in lessons.

A 2009 study conducted by Choy et al. highlights that teachers may lack sufficient knowledge about critical thinking and how to guide students in developing these skills. The research emphasizes the role of critical thinking in providing intellectual stimulation for students and fostering an environment conducive to learning. The findings also point to a lack of confidence among teachers in their students' capacity to independently develop critical thinking skills. Effectively teaching critical thinking requires educators with in-depth knowledge of critical thinking techniques and the ability to seamlessly integrate them into their teaching (Choy et al., 2009).

4.9 Assessment as Learning Strategy

Ranked ninth in normalized importance is teachers' proficiency in integrating assessment as a learning strategy. The Bayes factor parameter from a Bayesian model strongly indicates that effective utilization of assessment as a teaching strategy by teachers presents a 26-fold likelihood (variance = 1.941, CI: --1.058-6.192) of improving learning outcomes by 92%. The impact of this factor is measured by the area under the receiver operation characteristic curve (AUC=.960, $p<0.01$, CI: 0.925–0.995). A recent study conducted by Dann (2014) found that students' academic performance experiences enhancement when teachers skillfully leverage their knowledge, provide constructive feedback, and address learning gaps.

4.10 Other Factors

Enhanced student achievement is linked to teachers' punctual attendance, the impact of home tutors, and students' dedication to preparation, ranking 10th (with a 57% improvement), 11th (with a 93% improvement), and 12th (with a 52% improvement) in terms of normalized importance. The corresponding effect sizes were (AUC=0.765, p<0.01, CI: 0.568–0.961), (AUC=0.963, p<0.01, CI: 0.933–0.992), and (AUC=0.594, p<0.01, CI: 0.522–0.665). Notably, projected performance values for punctuality and the culture of preparation are relatively low, indicating a potential loss of contact hours by teachers. Additionally, there is evidence suggesting that students at the basic school level may not effectively engage in personal studies at home.

Conclusions

In a time where resources are constrained and unable to meet all demands, education stakeholders grapple with the persistent challenge of prioritizing elements that enhance students' academic performance on standardized exams, notably the Basic Education Certificate Examination (BECE). Employing the Bayesian Logistic Regression method, this study evaluated the likelihood strength of various factors, revealing Bayes factors that suggest potential influences on the success rates of both private and public schools in the BECE. The construction of a comprehensive model, anchored in Bayes factor strength, utilized the area under the Receiver Operating Characteristic (ROC) curve as a pivotal benchmark for effect size.

The examination of three partition models through Multilayer Perceptron (MLP) artificial neural networks highlighted the ANN3 model, characterized by the lowest cross-entropy error value (8.957). Despite making incorrect predictions at rates of 14.3% and 22.2% in training and testing samples, respectively, and a 21.9% rate in the holdout dataset, the meticulously designed ANN3 model demonstrated significant accuracy, classifying 85.7% of training cases and 77.8% of testing cases. The model displayed a substantial effect size, reflected in the high area under the ROC curve (0.846) for both public and private school models.

The noteworthy area under the ROC curve underscores the importance of considering predicted normalized variables seriously in both educational sectors, offering the potential to narrow gaps in academic achievement. Administrative factors, such as qualitative supervision, a conducive learning environment, parental support, and timely provision of Teaching and Learning Materials (TLM) and Teaching and Learning Resources (TLR), emerged as crucial contributors. Teacher-related factors, including addressing students' interests, providing differentiated tasks, fostering social and gender inclusion, and integrating critical thinking into lesson delivery, closely followed.

Recognizing these factors as pivotal for narrowing achievement gaps in basic private and public schools, this research advocates for targeted interventions to optimize BECE outcomes in both sectors. The predicted pseudo-probability plot accentuates the superior predictions made by the private school model, reinforcing the notion that focused efforts in these identified areas have the potential to bring about more equitable and enhanced academic outcomes in the educational landscape.

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