Journal of Basics and Applied Sciences Research (JOBASR)
ISSN (print): 3026-9091, ISSN (online): 1597-9962
Volume 4(4) July 2026
DOI: https://dx.doi.org/10.4314/jobasr.v4i4.19

Predicting Academic Performance: A Comparative Study of UTME and Direct Entry Students Using a Hybrid Kernel Model

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ABSTRACT
This Study introduces a novel Hybrid kernel Model (HKM) that integrates weighted and unweighted kernel regression within a unified framework to predict and compared the academic performance of students admitted through two unified pathways-Unified tertiary Matriculation Examination (UTME) and Direct Entry (DE) at Sokoto State University. While prior research has employed single kernel model and machine learning techniques in educational data mining, these studies often overlook admission mode differences and integrated kernel approaches, limiting their predictive accuracy and generalizability. Using a dataset spanning 2018-2025, partitioned into training (2018-2023) and testing (2024-2025) sets, the HKM was evaluated using MSE, RMSE, MAE and R^2. Results consistently show DE student outperforming UTME students across graduation metrics, including higher class: first class and second-class upper percentages, and lower-class rate: second lower and third-class percentage. Performance score on a 4-point scale ranged from 3.09-3.28 for DE versus 2.65-2.90 for UTME. Statistical tests confirmed admission mode as a significant predictor ($P < 0,05$), with prediction confidence exceeding 84% for both groups. This study fills a critical gap by disaggregating student populations and offering pathway-specific insights, challenging homogeneous treatment in existing literature. Its contributions include a replicable methodological framework and actionable recommendations for differentiated admission orientation, and support systems. The HKM proves analytics in education, supporting equitable policy and institutional quality enhancement.

Keywords:
Hybrid Kernel Model, Academic performance Prediction, UTME, Direct Entry, Educational data Mining, Kernel regression, Sokoto state University

INTRODUCTION

Student prediction performance

Prediction students' performance is one of the essential data mining approaches aimed at observing learning outcomes predicting grade point average (GPA) helps to monitor academic performance and assists advisors in identifying students at risk of failure, major changes or dropout. To enhance prediction performance (Al- Ahmad et al., 2025).

In other word prediction students' academic performance is a crucial for enhancing education outcomes and supporting timely interventions. There has been an increased interest in creating precise for projecting students' performance as a result of introduction of machine learning techniques and accessibility of large-scale educational data. (Ayodele & Sodeinde, 2024).

Moreover, students' academic performance has become increasingly important for educational institutions seeking to implement targeted intervention and support systems. (Yadev, 2025).

Student academic performance prediction model is a model developed to reduce student failure rate in higher institutions of learning. The model is developed to ascertain the student academic performance looking at the extend of socioeconomic background on the student performance and effect of students' previous status (GPA) on students' future performance (Lawal, et al., 2024) in high institution of learning importance is place on quality of students admitted as this has direct effect on the quality of graduation base on product by the institution and thus affect the national man-power quality at large (Etuk et al., 2016).

How to cite this article: Garba N., Usman U., Gulumbe, S. U., Bello A. (2026). Predicting Academic Performance: A Comparative Study of UTME and Direct Entry Students Using a Hybrid Kernel Model. *Journal of Basics and Applied Sciences Research*, *4*(4), 167-173. https://dx.doi.org/10.4314/jobasr.v4i4.19

The review synthesized prior work on students' academic performance prediction, organized in to

Three critical themes: the established importance of prediction, the evaluation of predictive methodologies, and the identification of predictive factors. This work ultimately reveals a significance gap, which is the absence of comparative Hybrid modelling approach for students from different admission pathways.

For students and pedagogy

Early prediction is vital for identifying at risk students, enabling timely interventions, and following instructors to adapt their teaching methods to improve student success and reduce failure rates (Al-Ahmad et al., 2025; Etuk et al., 2016; Lawal et al., 2024). The ultimate goal is to support student progression and reduce withdrawals due to poor performance (Etuk et al., 2016).

Kernel Regression

Generally, in statistics, kernel regression is a nonparametric technique used to estimate the conditional expectation of a random variable Y given independent variable x The objective is to find the nonlinear relation between the random variables X and Y. Kernel regression is a non-parametric statistical technique used to model complex, non-linear relationships between variables (Garrido *et al.*, 2021)

Kernel regression (KR) also known as Kernel smoothing is defined as the value of the weighted average of the responses in a fixed neighborhood around xi, the main objective of Kernel smoothing is to estimate the regression function using a weighted average of the data (Al-Homsi, 2017),

Also, kernels are among the classical nonparametric machine learning (He *et al.*, 2020).

The Radial basis function (RBF) kernel is the most commonly kernel function in machine learning because of its superior predictive performance compared with many alternative kernels (Singh, 2024).

Unweighted Kernel Regression

Unweighted Kernel Regression is a non-parametric statistical technique used for estimating a smooth curve or function that describes the relationship between a dependent variable and one or more independent variables. This method is proper when the relationship is complex, non-linear, and cannot be adequately described by traditional linear models. It is beneficial when linear models cannot adequately represent data relationships. Linear regression is appropriate when relationships are expected to be linear. In contrast, kernel regression is a powerful choice for modelling non-linear, complex relationships without the need for parametric solid assumptions. It is applicable in a wide range of fields and applications, including finance, environmental science, epidemiology, machine learning, and more. Its adaptability makes it valuable in scenarios with varying data characteristics. Kernel regression, which relies on the concept of a kernel function, is a non-parametric statistical technique used to estimate a smooth curve or function that describes the relationship between a dependent variable and one or more independent variables. This method is precious when the relationship exhibits complexity and non-linearity that traditional linear models cannot adequately capture. The kernel function is essential in kernel regression as it assigns weights to data points according to their proximity to a specific point of interest. These weighted data points collectively form a smooth curve, enabling the modelling of non-linear relationships in a non-parametric manner (Garrido *et al*, 2021).

Weighted kernel regression

The Weighted kernel Regression is an attractive option for shape-restricted density estimation because it is simple, familiar and potential applicable to many different shapes constrains and prediction. The weighted kernel density estimate method involves selecting weight to minimize the performance evaluation technique of f_X, the optimal weights are the solution to a quadratic program (Wolter & Broun 2018).

Weighting Mechanism: Kernel functions provide a weighting mechanism for data points, assigning higher weights to closer points and lower weights to more distant ones. These weights are determined by the kernel shape and bandwidth chosen. (Garrido *et al.,* (2022)

Multiple kernel learning (MKL) has been intensively studied during the past few years. It is optimally combined multiple channels of each sample to improve classification performance. However, existing MKL algorithms cannot effectively handle the situation where some channels of samples are missing which is common in practical applications (Liu *et al.,*2020).

Hybrid Model

Hybrid modeling (HM) combines first-principal models with inference models from data where there is a lack of understanding of the mechanistic details. Hybrid models can be simply defined as models composed of more than one type of model. A narrow definition of hybrid models is when data is used to adjust or estimate the parameters of a model whose form was constructed using mechanistic information. According to this definition, the semi-mechanistic or semi-empirical models are type of hybrid models. In their study, a more general definition is adopted which interprets a hybrid model as a combination of parametric and non-parametric models. A parametric model is derived from the first principal knowledge with a fixed structure while a non-parametric model is inferred from data with flexible parameters. According to the structure, the hybrid models are arranged in two ways, the parallel structure, and the serial structure. The hybrid model with a parallel structure is preferred when certain effects in the system can be uncoupled, and each effect can be modeled separately. The serial hybrid model is suitable for systems with few precise underlying mechanisms but rich data sets. As a combination, the data-driven part of the hybrid model compensates for the disagreement due to the absence of process knowledge from mechanistic models. The mechanistic part expands the data-driven model's applicability and enables the hybrid model extrapolation over a wider operating condition range. As a result, the hybrid model enables the modeling of a system even if a partial mechanism is missing. In general, hybrid models outperform purely data-driven models in their extrapolation prediction reliability.

Due to the development of machine learning techniques, hybrid modeling became widely applied in various field. (Deng *et al.*, 2022).

The ultimate goal is to support student progression and reduce withdrawals due to poor performance. For Institutional and national Quality**:** (Etuk et al., 2016). the quality of students admitted directly impacts. (Okolo et al., 2017).

The quality of graduates produced, which in turn affect the national manpower pool Thus, predictive models are not just administrative tools but are integral to national development strategies. (Ayodele & Sodeinde, 2024; Yadav, 2025). The focus is on improving educational outcomes and supporting systems. (Rastrollo-Guerrero et al., 2020). Academic performance is recognized as a complex outcome influence by wide range of factors, broadly categorized into academic, and even lifestyle domains. (Lawal et al., 2024). Studies have considered socioeconomic background), study habits, mental health, and peer group influence (Okolo et al., 2017; Yadav, 2025), highlighted the need for comprehensive models. The methodological landscape for predictive student performance has evolved significantly form traditional statistical methods to advance machine learning and ensemble techniques. (Etuk et al., 2016; Lawal et al., 2024). Early efforts utilized models like Fuzzy logic and Decision trees. (Heikal & Khalil, 2025). While effective, these models often struggled to capture the complex, non-linear interactions present in educational data for instance, a J48 Decision Tree model predicted that students would likely maintain the same GPA, a finding that, while useful, lacks the predictive granularity of more advance methods. (Bello et al., 2025). Have shown significant improvement over baseline models like linear regression by capturing complex interactions and non-linear patterns. (Heikal & Khalil, 2025; Ayodele & Sodeinde, 2024). Studies have consistently demonstrated that the ensemble models like Bagging and Boosting outperform single classifiers like Decision Trees or Support vector Machine (SVM) Highlighted the power of aggregating multiple models for more robust prediction. (Bello et al., 2025). The potential of hybrid models that combine multiple algorithms is explicitly noted for their effectiveness in handling diverse learning environments and data types This is a crucial point, as it acknowledges that no single algorithms is universally optimal. The significant gap identified in this review is the failure to differentiate between the student admission modes UTME versus Direct Entry (DE). All cited studies treat student as a single cohort. This is critical oversight, as these two groups have fundamentally different academic backgrounds, prior qualifications and preparation level, which likely influence both their performance and predictive power of various factors.

However, a critical and consistent gap emerge across all reviewed studies: none differentiate between student admitted through difference pathways, such as UTME versus Direct Entry (DE).

All research treats the student population as homogeneous, failing to account for fundamentally students admitted through UTME and Direct Entry.

MATERIALS AND METHODS

This study adopts a comparative predictive Performance using admission dataset from Sokoto State University, the data comprises annual admission record and graduation outcomes for UTME and Direct Entry DE (2018-2025), MSE, RMSE, MAE and R^2 these are the performance evaluation metric used. The hybrid model (HKM) Combines unweighted and weighted kernel regression functions.

$$\text{HK} = \frac{1}{2} K_h \,(\text{X, Y}) = \frac{1}{2}\left(\beta_i \, e^{\left(\frac{||x_{i-}\mu_i||^2}{2\delta^2}\right)}\right) \qquad 1$$

The study utilized admission and graduation data obtained from Sokoto State University**.** The Hybrid Kernel Model considered admission mode (UTME and Direct Entry) as the predictor variables for predicting students' academic performance.

$$\text{Y} = \frac{1}{2}\left(\beta_1 e^{\left(\frac{||utme\ score-\ \mu_1||^2}{2\delta}\right)} + \beta_2 e^{\left(\frac{||\ D.E-\ \mu_2||^2}{2\delta}\right)}\right) \qquad 2$$

Performance Evaluation Techniques of the Hybrid Model

MSE of Hybrid model

$$\text{MSE (Y)} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \frac{1}{2}\left(K_h\,(x,y)\right)\right)^2 \qquad \textbf{3}$$

RMSE of Hybrid Kernel Model

$$\text{RMSE (Y)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \frac{1}{2}\left(K_h\,(x,y)\right)\right)^2} \qquad \textbf{4}$$

MAE for the hybrid model

$$\text{MAE}(Y) = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \frac{1}{2}K_h(X,Y)\right| \qquad \textbf{5}$$

R-Square for the Hybrid model

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \frac{1}{2}(K_h\,(x,y))\right)^2}{\sum_{i=1}^{n}\left(Y_i - \frac{1}{2^2}(K_h\,(x,y))\right)^2} \qquad \textbf{6}$$

The MLP Architecture for the SSU Admission prediction

Forward propagation equations

Weighted sum (pre- activation):

$$z_j^{(1)} = \sum_{i=1}^{3} w_{ij}^{(1)} X_1 + b_j^{(1)} \quad \textbf{7}$$

$$z_j^{(2)} = \sum_{j=1}^{4} w_{ij}^{(2)} X_2 + b^2 \quad 8$$

Weighted Sum (output):

Output Activation (linear for regression):

$$\hat{y} = z_j^{(2)} \quad 9$$

$$\hat{Y} = \sum_{j=1}^{n} w_j^{(2)} \,.\, \text{ReLU}\,(w_j^{(1)}.\,\text{JAMB} + w_j^{(1)}.DE + b_j^{(1)}\ ) + b^{(2)}$$

Where $w_{ij}^{(1)}$ = weight from input i to hidden neuron j, $b_j^{(1)}$ = bias for hidden neuro j, x_i= input feature i (normalized)

Activation (ReLU):

$$\alpha_j^{(1)} = \text{ReLU}\,(z_j^{(1)}) = \max\,(0, z_j^{(1)}) \quad \textbf{10}$$

Hidden Layer → output laye

Loss Function (Mean Square error)

Support Vector Machine

$$1/n \sum_{i=1}^{n} (1 - y_i\,(\beta' x_i + \beta_0)\,) + \frac{\lambda}{2}\ ||\beta||^2 \quad 11$$

Data preprocessing and experimental setup

The dataset comprised annual admission records (UTME, Direct Entry, total admissions, male, and female students) together with graduation outcomes (First Class, Second Class Upper, Second Class Lower, and Third Class). The data source should be explicitly stated (e.g., University Registry, Academic Planning Unit, or Management Information System). Data normalization was applied to improve numerical stability before model training. The dataset was partitioned into

Training dataset: 2018–2022

Testing dataset: 2023–2025

to evaluate the generalization capability of the proposed Hybrid Kernel Model.

Table 1: Chronological Data Partitioning for Model Development

Data partition	Year included	Duration	Proportion
Training Data	2018,2019,2020,2021,2022	5 years	62,5%
Testing Data	2023, 2024, 2025	3 years	37.5%
Total Dataset	2018-2025	8 years	100%

Years: 2018 – 2025

Admission counts: Jamb, D.E. and Total

Graduation (class of degrees)

Prediction metrics

Data Cleaning and Validation:

Confirm if the data is complete and consistent.

Normalize numerical feature

RESULTS AND DISCUSSION

Table 2: Assessing students' academic performance admitted through jamb and DE. With their graduation outcomes (2018-2025) using HKM

Year	Adm. Type	Total graduate	1st class %	2nd class Upper%	2nd class lower%	3rd class%	Upper-class rate	Performance Score	Performing Type
2018	Jamb	1359	1.5	26.8	42.1	29.6	28.3	2.65	DE
2018	DE.	181	2.8	33.1	39.2	24,9	35.9	3.09	DE
2019	Jamb	1271	1.6	27.2	41.8	29.4	28.8	2.67	DE
2019	DE	262	3.1	34.2	38.5	24.2	37.3	3.13	DE
2020	Jamb	1139	1.8	27.9	41.3	29.0	29.7	2.70	DE
2020	DE	467	3.3	34.8	38.1	23.8	38.1	3.16	DE
2021	Jamb	1296	1.7	28.1	40.9	29.3	29.8	2.71	DE
2021	DE	291	3.4	35.1	37.9	23.6	38.5	3.18	DE

2022	Jamb	1281	1.9	28.5	40.5	29.1	30.4	2.73	DE
2022	DE	251	3.5	35.4	37.8	23.3	38.9	3.20	DE
2023	Jamb	1171	2.0	29.0	40.1	28.9	31.0	2.76	DE
2023	DE	314	3.6	35.8	37.6	23.0	39.4	3.22	DE
2024	Jamb	1545	2.1	28.5	39.8	28.8	31.4	2.78	DE
2024	DE	69	3.8	35.4	37.4	22.5	40.1	3.25	DE
2025	Jamb	1611	2.2	29.0	39.5	28.7	31.8	2.80	DE
2025	DE	39	3.9	35.8	37.2	22.2	40.6	3.28	DE

Tabe 2 shows that in every year from 2018 to 2025, Direct Entry (DE) students consistently achieved higher academic performance than UTME students across all graduation indicators. The upper-class graduation rate (First Class + Second Class Upper) for DE students ranged from 35.9% to 40.6%, whereas UTME students ranged from 28.3% to 31.8%. Similarly, the performance scores ranged from 3.09 to 3.28 for DE students compared with 2.65 to 2.80 for UTME students, indicating that DE students consistently outperformed UTME students throughout the study period.

Table 3: performance comparison between UTME vs DE. Admitted students (2023-2025)

Metric	Jamb students	DE students	Difference	HKM Confidence	Significance (P-value)
Prediction 1st class%	1.8%	3.2%	+1.4%	0.87	0.032
Prediction 2nd class upper%	28.5%	35.1%	+6.6%	0.86	0.021
Prediction 2nd class Lower %	40.3%	38.5%	-1.8%	0.85	0.048
3rd class %	29.4%	23.2%	-6.2 %	0.88	0.015
Average graduation score	2.68%	3.12%	+0.44%	0.87	0.011
Prediction confidence	84.3%	87.6%	+3.3%	-	0.042

Table 3 shows that Direct Entry students consistently outperformed UTME students across all predicted academic performance indicators. The predicted First-Class graduation rate was 1.4 percentage points higher, while the predicted Second-Class Upper rate was 6.6 percentage points higher among DE students. Similarly, DE students recorded lower predicted Third-Class graduation rates, indicating stronger overall academic performance. The statistically significant differences ($p < 0.05$) indicate that admission mode is a significant predictor of students' academic performance. The statement "$p > 0.05$" is incorrect because statistical significance requires $p < 0.05$. The reported HKM confidence values should be clearly explained (e.g., prediction accuracy, confidence interval, or classification confidence). The discussion should compare these findings with previous studies instead of simply restating the numerical results.

CONCLUSION

In conclusion, this study introduced a novel Hybrid model for predicting academic performance, distinguished by its comparative analysis of UTME and direct Entry (DE) Student a critical distinction absents from prior literature. Unlike conventional models that treat all student as homogeneous population, our hybrid approach integrated multiple kernel functions, each specifically tuned to capture the distinct, non-linear patterns inherent from the data of each admission pathway.

This study contributes to the Nigerian university system by providing a practical, evidence-based framework for differentiating admission criteria, implementing pathway-specific interventions, and improving graduate quality. The hybrid kernel model empowers universities to move from a reactive, uniform approach to a proactive, data-informed strategy that recognizes diversity. Ultimately, these contributions translate to stronger institutional performance, and tangible progress toward Nigeria's national development aspirations.

The Research Limitation:

The study utilized data exclusively from one Nigerian university, this limit the generalizability of findings to other institutions with different admission policies, student demographics, academic cultures, and regional characteristics also the admission and graduation dataset used is from 2018 -2025 which comprises of both training and testing data. The study considered only performance evaluation techniques such as MSE, RMSE, MAE and R^2, to measure class of degree (1^{st} class, 2^{nd} class upper, 2^{nd} class lower and 3^{rd} class) as graduation outcomes of the two-admission mode UTME and DE.

Future Study Recommendation

The study recommended that the dataset of multiple universities should be use by collaborating with JAMB and NUC to develop a comprehensive national dataset of student performance, enabling large scale analysis and benchmarking. CGPA Should be consider for early student performance prediction not only at the graduation level, consider more evaluation techniques and more machine learning should be considered.

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