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Research Article

PREDICTING ICT INTEGRATION IN TEACHING AND LEARNING IN SOUTHWESTERN NIGERIA POLYTECHNIC USING ENSEMBLE-BASED MODELS

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Abstract

This study systematically examines the factors that affect the integration of Information and Communication Technology (ICT) into educational institutions in Southwestern Nigeria, using ensemble models. ICT continues to offer important benefits for teaching and learning, even though challenges remain. We used a mixed-methods approach to identify what influences ICT adoption, build and compare ensemble-based models, and carefully assess their performance using standard classification metrics. Data were collected from structured questionnaires administered to academic staff and students at selected Southwestern Polytechnics in Nigeria. After preprocessing, the research adopt feature selection methods like Principal Component Analysis (PCA), Sequential Backward Feature Selection (SBFS), Sequential Forward Feature Selection (SFFS), and Central Tendency Feature Selection (CTFS). The data analysed with AdaBoost, Gradient Boosting Machine (GBM), Stacking, and Voting ensemble models. The Voting ensemble model performed best, reaching 98.77% accuracy and a 98.81% F1-score when Sequential Backward Feature Selection was used. These results show that combining several base learners can improve prediction performance. The study also identifies key barriers to ICT integration, helping educational stakeholders create targeted strategies to encourage ICT adoption and support inclusive, high-quality education.

Keywords: Central Tendency Feature Selection, Ensemble-Based Models, Information & Communication Technology, Principal Component Analysis, Sequential Backward Feature Selection, Sequential Forward Feature Selection.

INTRODUCTION

Information and Communication Technology (ICT) is now an inextricable part of life, including education (Oyedokun & Adeolu, 2022). This plays a vital role in education by improving teaching and enriching learning (Anastasopoulou *et al.,* 2024). Nonetheless, it is noteworthy to know that the rate of ICT incorporation differs across institutions. The following barriers are largely responsible for difference in ICT integration: infrastructure unavailability, epileptic power outages, institutional policies, to mention just a few. Notably, ICT is essential to achieving the Sustainable Development Goal 4 (SDG 4) (UNESCO, 2020). This goal intent to ensure all-encompassing, equitable, quality education and promote lifelong learning (Zawacki-Richter *et al.,* 2019). ICT provides flexible, interactive, and personalized learning opportunities which enhances educational access, and its integration into tertiary education. This modernizes teaching, and administrative practices, thereby aid students to gain digital competencies vital for knowledge-based society (Mushimiyimana *et al.,* 2022). Studies have convincingly and consistently shown that more than half of the technical education teachers agree that integrating technology into the teaching and learning process makes instructional delivery easier, more engaging, and efficient than conventional teaching methods (Abedi, 2024; Cattaneo *et al.,* 2022; Shamim & Raihan, 2016). However, educational institutions encounter major difficulties in implementing ICT in pedagogical practice and numerous barriers to ICT usage. Therefore, the next logical and important step is to systematically identify the specific factors inhibiting adoption using analytical methods.

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In order to deal with the identified gap, this study adopts a clearly laid-out, systematic methodological strategy: first, questionnaires are used to gather data on barriers to ICT adoption from key stakeholders and ICT practitioners at Southwestern Nigeria Polytechnics, then the collected responses are converted into structured datasets appropriate for analysis with ensemble-based models. Since ensemble models perform exceptionally well on noisy, complex datasets and educational data typically contains qualitative and contextual variables, this choice is both logical and well justified (Dong *et al.,* 2020; Ghimire *et al.,* 2024). Traditional methods do not take into account the complicated relationships among the factors affecting ICT integration, it is natural and advantageous to use ensemble models which combine several weak learners to make better predictions exceptionally well on noisy, complex datasets and educational data typically contains qualitative and contextual variables, this choice is both logical and well justified (Dong *et al.,* 2020; Ghimire *et al.,* 2024). Because traditional methods do not take into account the complicated relationships among the factors affecting ICT integration, it is natural and advantageous to use ensemble models which combine several weak learners to make better predictions. This study makes use of computational techniques, by systematically identifying patterns and factors of influence to ICT integration in teaching and learning thus yielding actionable intelligence for educational administrators, policymakers, and IT practitioners to design interventions that tackle the most significant impediments, ultimately promoting effective ICT adoption and better educational outcomes in today's technology-rich academic context. Hence, the development of an ensemble-based framework for ICT integration in Southwestern Polytechnics in Nigeria has been made, since previous studies relied on predictive statistics or single-model prediction. Thus, the study uses multiple feature selection techniques and ensemble classifiers to identify ICT barriers and predict integration levels.

LITERATURE REVIEW

Machine learning (ML) and information and communication technology (ICT) are becoming increasingly important in education, attracting significant attention from researchers. Recent studies show that ML helps predict academic performance, identify at-risk students early, support personalised learning, and guide data-driven decisions in higher education (Latif *et al.,* 2023; Chong *et al.,* 2025; Ahmed *et al.,* 2025). ICT is also seen as a way to improve access to education, streamline processes, boost student engagement, and help institutions run more effectively. However, challenges like infrastructure gaps, limited staff skills, digital readiness, and other barriers often slow its adoption (Ahmed *et al.,* 2025). This review brings together recent research on ML and ICT in education, focusing on predictive modelling, technology adoption, institutional readiness, infrastructure issues, and algorithmic complexity. Okaforcha (2024) demonstrated that machine learning has the potential to transform higher education in developing countries by reducing administrative workload, enabling personalized learning, and facilitating early identification of students requiring additional support. The study involved a survey of 197 lecturers from two public universities in Anambra State, Nigeria, and identified several barriers to implementation, such as inadequate ICT infrastructure, unreliable electricity, high technology costs, limited technical skills, insufficient institutional policies, and data management concerns. Additionally, lecturers with prior technological experience perceived greater benefits from machine learning. The author recommended increased investment in ICT facilities, continuous staff training, and the promotion of international collaboration to enhance technology adoption and knowledge sharing. Parallel research has clearly and systematically explored the limitations of traditional forecasting methods in education, namely their poor accuracy and sluggish responsiveness, and has convincingly argued that machine learning provides a powerful alternative for identifying student learning patterns. ML algorithms excel at detecting complex trends, processing large datasets, and improving predictions through adaptive learning, hence making them well suited for early identification of at-risk students, cost reduction, and enhancing institutional resilience to disruptions. That said, it is also acknowledged that challenges such as algorithmic errors, lack of sufficient training data, and the computational expense of model development still exist. Therefore, recent literature has naturally and appropriately led to the proposal of using Artificial Neural Networks (ANNs) to predict academic outcomes in Nigerian secondary schools (Alberto *et al.,* 2024; Onyema *et al.,* 2022). Besides prediction, ML has been nicely applied to the problem of assessing user satisfaction with ICT in educational settings, with one recent study going far beyond conventional survey methods by building predictive models to evaluate ICT satisfaction. The authors analysed quantitative survey data with five different ML algorithms and clearly showed that Random Forest performed best, leading to direct, robust conclusions: ICT tool quality, frequency of use, and user training are the most important determinants of satisfaction. Therefore, they logically recommend expanding datasets, employing more sophisticated ML techniques, and incorporating real-time feedback mechanisms to improve ICT service delivery (Almaghrabi *et al.,* 2024). The Indian higher education literature has examined ICT adoption through the Technology Acceptance Model (TAM) with several added constructs, and the analysis using Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM) yielded clear, robust results: perceived usefulness, ease of use, ICT competency, and infrastructure support all significantly influence adoption, with perceived usefulness being the most important determinant. Therefore, the validated model offers concrete guidance for improving ICT integration. Future research is naturally suggested to consider cultural, institutional, and faculty-level factors, as well as to adopt comparative and longitudinal designs (Rosaline & Wesley, 2017).

Nyako et al. (2023) conducted a survey of 569 participants at the Federal College of Education in Yola, Nigeria, to examine the integration of technology in teaching and learning. The study found that computers and e-libraries facilitate lesson delivery, enhance student engagement, and improve learning outcomes. However, challenges such as unreliable electricity, insufficient resources, negative attitudes, and limited administrative support hinder effective technology adoption. The authors concluded that technology is essential for educational improvement and recommended the development of robust infrastructure, the implementation of comprehensive ICT policies, and increased funding to address these barriers.

Collectively, these studies underscore the dual promise and complexity of integrating ML and ICT into educational systems. While predictive modeling and advanced algorithms offer substantial opportunities for enhancing learning outcomes, institutional readiness, robust datasets, and sustainable infrastructure remain critical prerequisites for effective implementation Since the research proceeds in that way, it is natural to expect that it will deal with the following:

- Identify factors affecting ICT integration in teaching and learning, as discussed by earlier researchers.
- Adopt ensemble-based techniques to predict ICT integration based on dataset formulated from responses.
- Assess the performance of the models using the following metrics: accuracy, precision, recall, and F1 – score.
- Formulate policy-oriented recommendations based on model performance.

METHODOLOGY

The study obtained its dataset from the responses from the IT professionals and academic Staff of Nigeria Polytechnic. The dataset underwent various preprocessing techniques and feature selection techniques were also used to select significant features. Two sets of experiment were carried out with dataset split into 70% training and 30% testing set and also 10% validation. The experiments were carried out using various ensemble models such as Adaboost, Gradient, Stacking, and Voting.

Dataset

The questionnaire responses were based on a five-point Likert scale consisting of Strongly Agree, Agree, Disagree, Strongly Disagree, and No Comment. For the purpose of machine learning analysis, the responses were converted into numerical values using ordinal encoding.

Table 1. Dataset Description

Feature	Description
ICT Evolving (IEV)	ICT tools are evolving so fast
ICT Integration (IIN)	The Integration of ICT tools into teaching requires more time and effort
Incentives (INC)	Management does not offer incentives to encourage lecturers
Unstable Network (UNE)	An unstable network connectivity in teaching environments
Network coverage (NCO)	There is no network coverage within the teaching environment
Evaluation (EV)	Management does not evaluate the effectiveness of ICT integration in teaching
Reliability (RE)	ICT tools are reliable
Training (TR)	Difficulty to access practical training programs on ICT integration and usage
Technical support (TES)	Difficulty in getting the required support from technical staff
Insufficient Hardware (INH)	Available hardware is insufficient to support ICT-based teaching.
Outdated hardware (OUS)	Available hardware is outdated to support ICT-based teaching
Insufficient Software (INS)	Available software is insufficient to accommodate ICT-based teaching
Unlicensed Software (UNS)	Unlicensed software available is inadequate to accommodate ICT-based teaching
Software Usability Issues (SUI)	Certain software is difficult to learn and use
Software application (SAP)	Software applications are difficult to learn and use.
ICT Policy (IPO)	Management does not provide ICT policy on how to integrate ICT tools into teaching
Programs (PR)	Management does not organize any programs to promote ICT-based teaching
Vision (VS)	Management lacks a clear vision for integrating ICT tools in teaching
Negative View (NV)	Colleagues have expressed negative views about using ICT tools in teaching
Negative attitude (NA)	Students have provided negative feedback on ICT-based teaching
Computer illiteracy (CIL)	Students lack basic computer literacy skills
Adaptation (ADP)	Adaptation Difficulty from my current teaching practices to integrate ICT tools.
Insufficient Space (ITS)	There is insufficient space to accommodate ICT tools in the classroom
Epileptic Power Supply (EPS)	Unstable power supply discourages the integration of ICT tools into teaching

Table 2. Statistical Analysis of the Dataset

Feature	Mean	Standard Deviation	Q1(25%)	Q2(50%)	Q3(75%)	Missing values
IEV	4.295	0.746	4	4	5	0
IIN	3.978	0.97	3	4	5	29
INC	4.078	0.918	4	4	5	6
UNE	4.443	0.852	4	5	5	4
NCO	4.27	0.866	4	5	5	22
EV	3.724	1.119	3	4	5	0
RE	4.039	0.98	3	4	5	17
TR	3.794	0.919	3	4	4	31
TES	3.583	1.045	3	4	4	4
INH	4.097	1.086	4	4	5	23
OUS	3.970	0.918	3	4	5	14
INS	4.116	0.873	3	4	5	8
UNS	3.795	1.093	3	4	5	6
SUI	3.835	0.969	3	4	5	31
SAP	3.846	1.253	3	4	5	8
IPO	3.728	1.136	3	4	5	25
PR	3.392	1.166	3	3	4	33
VS	3.729	0.924	3	3.5	5	46
NV	3.768	0.917	3	4	4.75	46
NA	3.621	0.876	3	4	4	46
CIL	3.712	0.723	3	4	4	36
ADP	3.711	1.085	3	3	5	110
ITS	3.361	0.568	3	3	4	86
EPS	4.623	0.807	4	5	5	10

Specifically, Strongly Agree was coded as 5, Agree as 4, Disagree as 3, Strongly Disagree as 2, and No Comment as 1. The target variable, referred to as ICT Adoption Level (ICT_AL), was designed to represent the overall level of ICT integration in teaching and learning. The target variable was formulated as a binary classification problem, where respondents classified under the high ICT adoption category were coded as 1, while respondents classified under the low ICT adoption category were coded as 0. The dataset contained twenty-four (24) features, as depicted in Table 1, and also 352 records

The study applied ordinal encoding to convert the dataset into numerical data. The statistical analysis of the dataset is presented in Table 2

In this study, missing values were filled using the mean. Equation (1) depicts the process where x stands for a single data point, and n is the total number of values in the column.

$$\text{Mean} = \frac{\sum x}{n} \tag{1}$$

From the correlation heatmap presented in Figure 1, it is straightforward and clearly documented that training, technical support, ICT policy, software applications, and infrastructure all have moderate to strong positive correlations; hence they are all important factors favouring ICT integration in teaching and learning. In marked contrast, computer illiteracy has a weak negative correlation with ICT adoption, so higher computer illiteracy tends to hinder ICT integration.

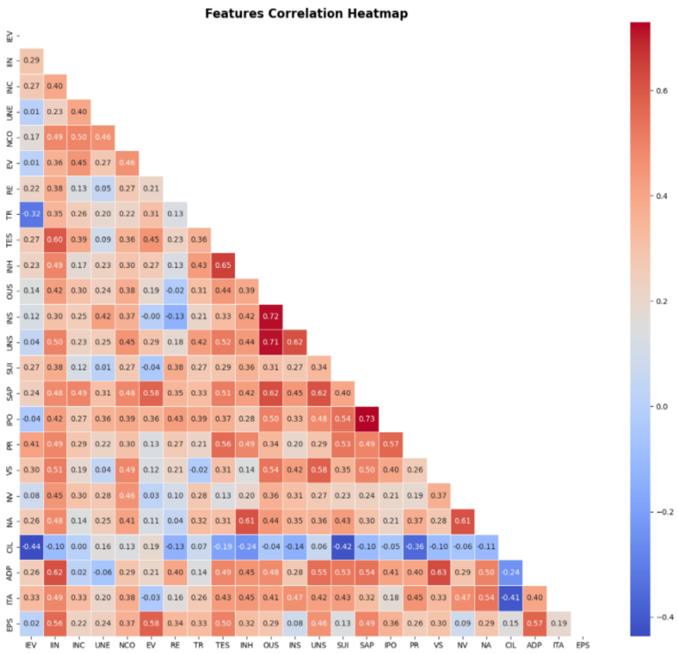


Figure 1. Correlation heatmap

Problem Formulation

The main objective of the study is to classify levels of ICT integration in Polytechnic tertiary institutions in Nigeria, and accordingly, machine learning models are built to predict the outcome variable, ICT adoption level (ICT_AL), using variables that measure infrastructural, institutional, and user-related barriers to ICT implementation. The ICT_AL is defined as a quantitative indicator of the overall effectiveness of ICT use in teaching and learning, hence it naturally serves as the dependent variable in the modelling framework. By predicting for a clear, well-defined outcome, the learning algorithms are optimally tuned, the results are easier to interpret, the research objectives are more directly addressed, and model performance can be reliably validated. Thus, the formulation enhances the scientific rigour and reproducibility of the machine learning-based analysis.

Model Learning Formulation

Since the goal is to improve the structure of the predictive modelling process, the present paper naturally and appropriately employs a supervised machine learning framework to explore the relationship between input variables representing IT-related barriers and the degree of ICT integration, and the dataset is organized accordingly

$$D = \{(x_{i,}y_i)\}i_1^N \quad (2)$$

Such that $x_i \in \mathbb{R}^d$ represents a feature vector for the i^{th} observation. This comprises the variables such as infrastructure availability, institutional support and user competence. The target variable, $y \in \{0,1\}$ implies ICT adoption (ICT_AL), where 0 indicates low adoption, and 1 indicates high adoption.
The objective of the learning algorithm is to estimate an unknown function.

$$f: R^d \rightarrow \{0,1\} \quad (3)$$

such that $\hat{y}_i = f(x_i)$

where:
$\hat{y_i}$ = Predicted Class
f^* = Optimal function

$$= \arg\min_f \frac{1}{N}\sum_{i=1}^{N} \mathscr{L}(y_{i,}\ f(x_i)) \quad (4)$$

Where: N = All training samples
x_i = input feature for the i^{th} observation
y_i = class label

$$\mathscr{L}(y_i, f(x_i)) = \text{loss function} \quad (5)$$

The loss function metric quantifies the difference between the actual label and the predicted output.

The expression, $\arg\min_f$ indicates that the learning algorithm evaluates all possible candidate functions f to identify the one that yields the minimum average loss. The function f* denotes the optimal model, which most accurately captures the relationship between ICT-related factors and the level of ICT adoption. This approach ensures that the selected model generalises effectively to unseen data by minimising prediction errors during training.

In probabilistic models, the output is represented as follows:

$$P\ (y = 1|x) = f(x) \quad (6)$$

Classification is performed by applying a decision threshold:

$$\hat{y} = \begin{cases} 1, & if\ P\ (y = 1|x) \geq \tau \\ 0, & otherwise \end{cases} \quad (7)$$

Where τ is set at $^1/_2$

Ensemble learning techniques, such as AdaBoost, stacking, Voting and Gradient Boosting, are employed to improve predictive performance. These models integrate multiple base learners to reduce variance, address overfitting, and increase classification accuracy.

The performance of the trained models is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and specificity. This approach provides a comprehensive assessment of predictive capability across multiple dimensions of model effectiveness.

RESULTS AND DISCUSSION

Feature Selection Results

The study adopts four feature selection techniques to select significant attributes of the dataset: Principal Component Analysis (PCA), Sequential Backward Feature Selection (SBFS), Sequential Forward Feature Selection (SFFS) and Central Tendency Feature Selection (CTFS). The results of the feature selection are presented in the table 1 below.

Table 3 shows that PCA selects 13 significant features, SFS selects 12 features, SBS selects 12 features while CTRS selects 10 features.

Table 3. Feature Selection Results

S/N	Selection Techniques	Selection Features
1.	PCA	IEV, INC, TR, TES, INH, INS, SUI, PR, NV, NA, ADP, ITA & EPS
2.	SBFS	RE, TES, INH, OUS, INS, SAP, PR, VS, NA, CIL, ADP, & EPS
3.	SFFS	IEV, INC, EV, RE, TR, UNS, SUI, SAP, PR, VS, ADP & EPS
4.	CTRS	INC, EV, TR, TES, IPO, PR, NV, NA, CIL & ITA

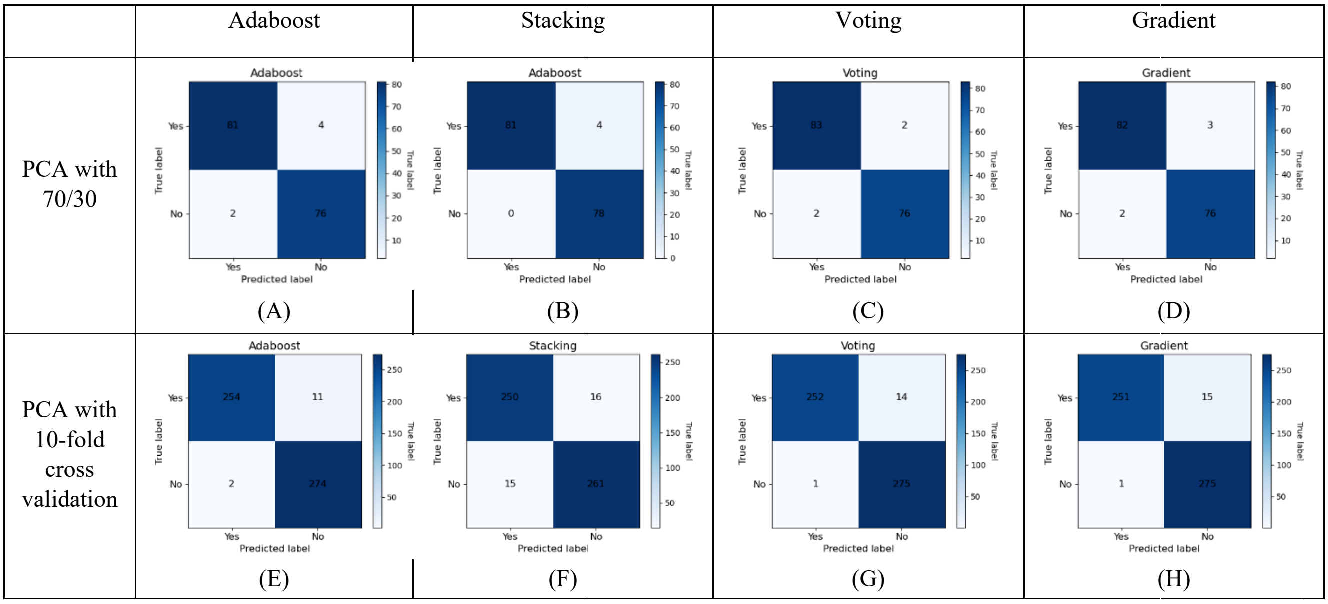


Figure 2. Confusion Matrix of Ensemble Classification Models Using PCA Feature Selection under 70/30 Split and 10-Fold Cross-Validation

Classification Results

This section presents the classification of ensemble models (Adaboost, Stacking, Voting and gradient) used for the classification.

Classification Results based on PCA Feature selection: This section presents the classification results obtained after applying Principal Component Analysis (PCA) feature selection to the obtained dataset.

Figure 2. Confusion Matrix of Ensemble Classification Models Using PCA Feature Selection under 70/30 Split and 10-Fold Cross-Validation

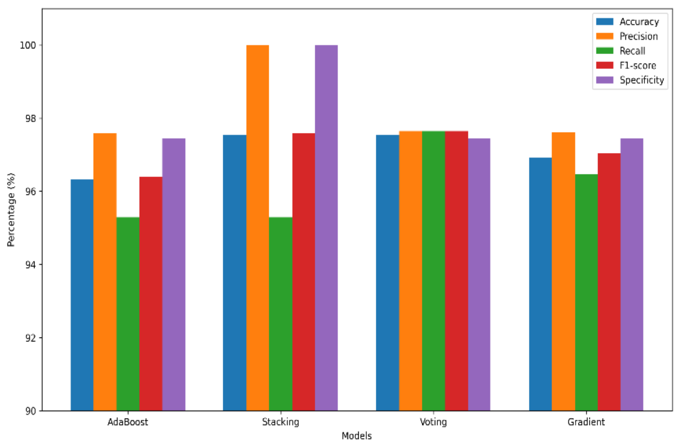


Figure 3. Classification Results with PCA Using 70/30 split

Figure 2 presents Confusion Matrix of Ensemble Classification Models Using PCA Feature Selection under 70/30 Split and 10-Fold Cross-Validation while figures 3 & 4 depict classification Results with PCA Feature Selection Based on 70/30 Training–Testing Split and 10-Fold Cross-Validation. From the results, the Voting ensemble model demonstrates superior performance among all models under the 70/30 split, achieving the highest F1-score of 97.65% and an accuracy of 97.55% (see figure. In the 10-fold cross-validation setting, Adaboost emerges as the best-performing model, achieving an F1 score and accuracy of 97.32%.

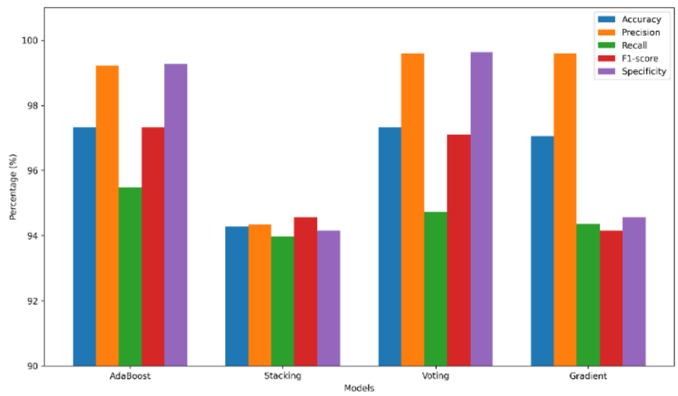


Figure 4. Classification Results with PCA Using 10-fold cross validation

Classification Results based on Sequential Backward Feature Selection: This section presents the classification results obtained after applying Sequential Backward Feature Selections (SBFS) to the obtained dataset.

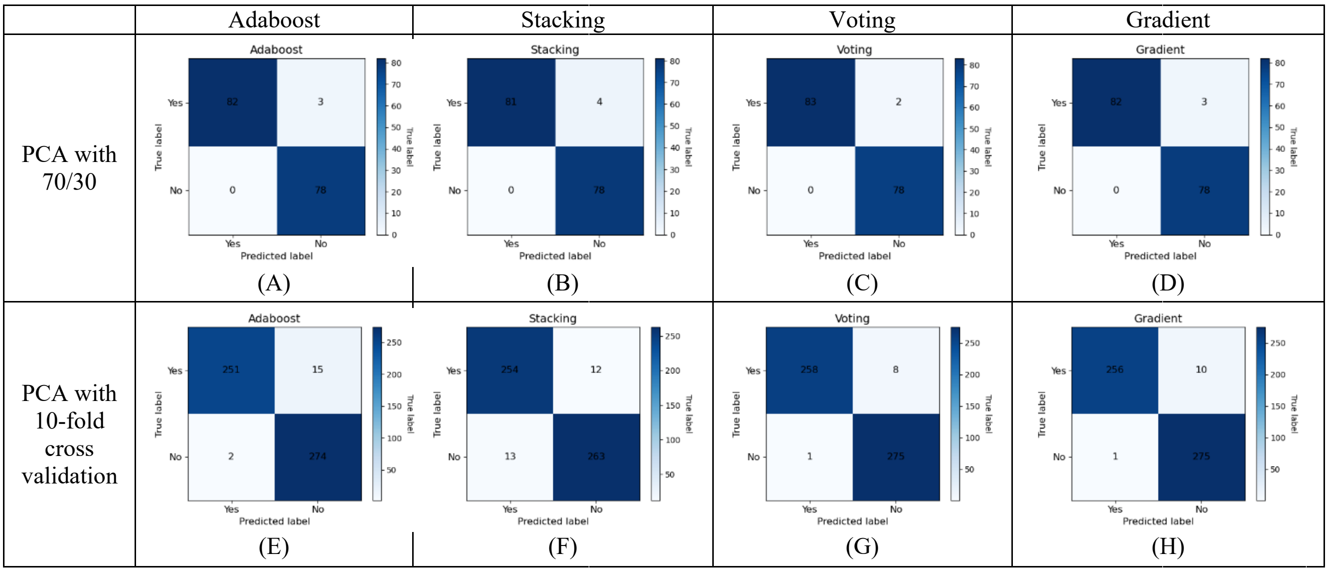


Figure 5. Confusion Matrix of Ensemble Classification Models Using SBFS Under 70/30 Split and 10-Fold Cross-Validation

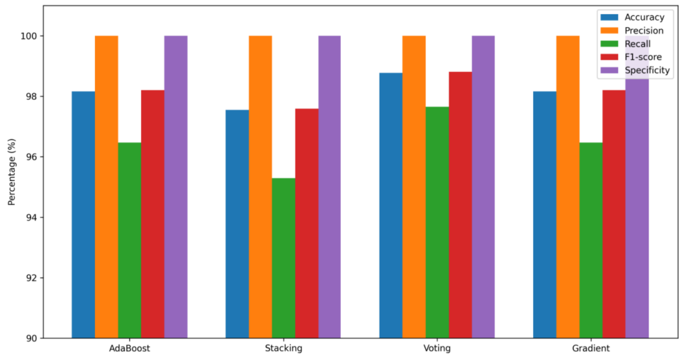


Figure 6. Classification Results with SBFS using 70/30 split

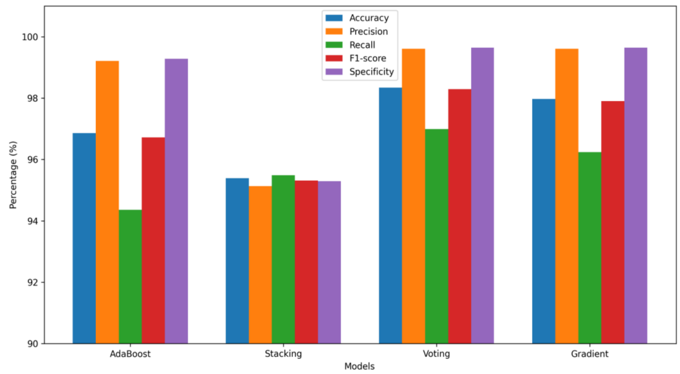


Figure 7. Classification Results with SBFS Using 710-fold cross validation

Figure 5 presents Confusion Matrix of Ensemble Classification Models Using SBFS Feature Selection under 70/30 Split and 10-Fold Cross-Validation while figures 6 & 7 depict classification Results with SBFS on 70/30 Training–Testing Split and 10-Fold Cross-Validation. From the results, the Voting ensemble model demonstrates superior performance among all models under the 70/30 split, achieving the highest F1-score of 98.81% and an accuracy of 98.77%. In the 10-fold cross-validation setting, voting ensemble emerges as the best-performing model, achieving an F1 score of 98.29% and accuracy of 98.34%

Classification Results based on Sequential Forward Feature Selection: This section presents the classification results obtained after applying Sequential Forward Feature Selections (SFFS) to the obtained dataset.

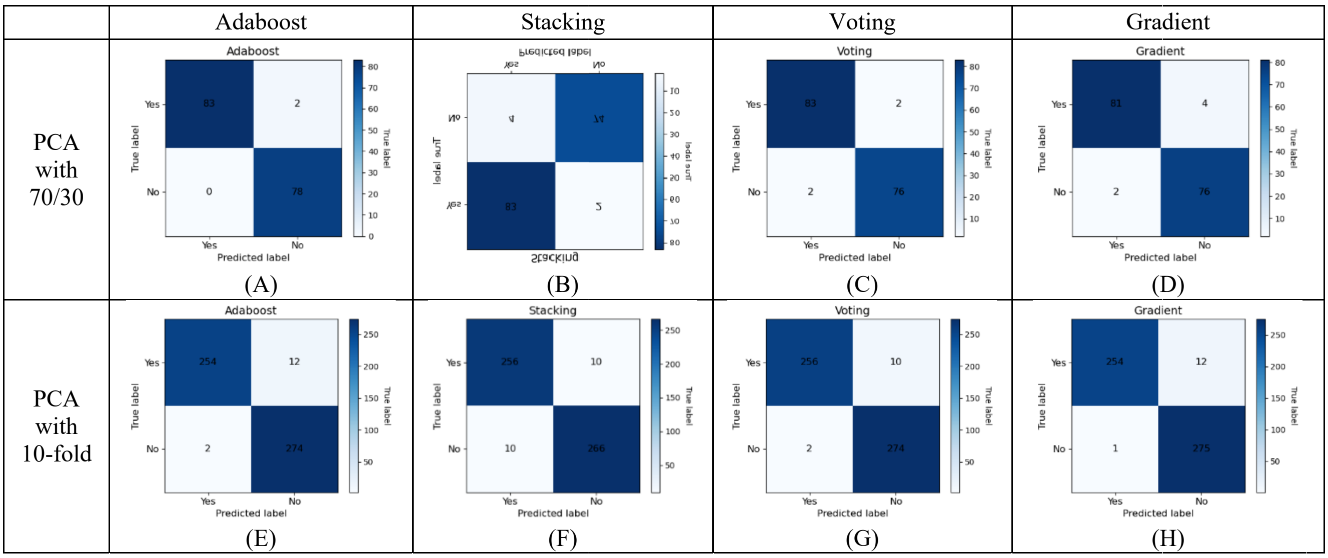


Figure 8. Confusion Matrix of Ensemble Classification Models Using SFFS Under 70/30 Split and 10-Fold Cross-Validation

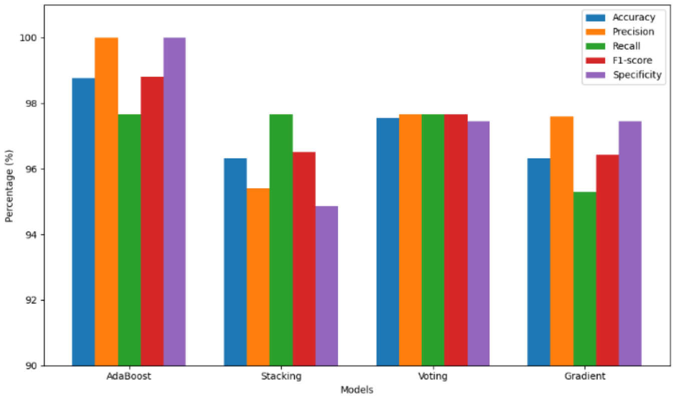


Figure 9. Classification Results with SFFS using 70/30 split

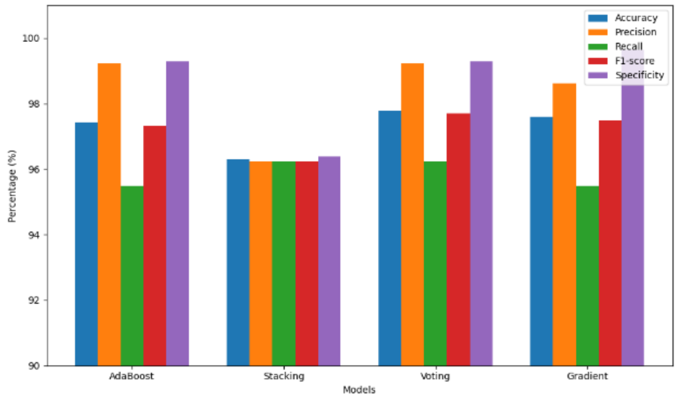


Figure 10. Classification Results with SFFS Using 10-fold cross validation

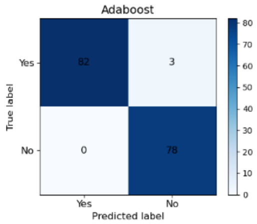
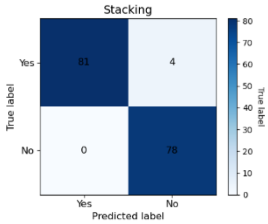
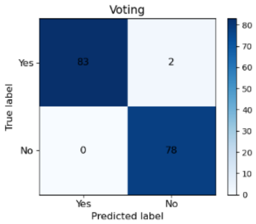
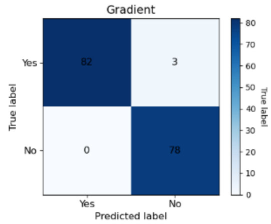
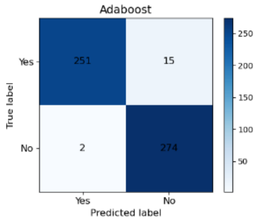
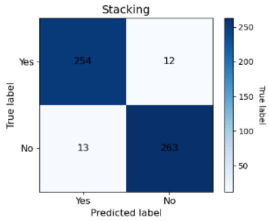
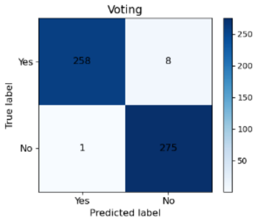
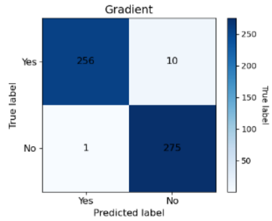
	Adaboost	Stacking	Voting	Gradient
PCA with 70/30	 (A)	 (B)	 (C)	 (D)
PCA with 10-fold cross validation	 (E)	 (F)	 (G)	 (H)

Figure 11. Confusion Matrix of Ensemble Classification Models Using CTFS Under 70/30 Split and 10-Fold Cross-Validation

Figure 8 presents Confusion Matrix of Ensemble Classification Models Using SFFS Feature Selection under 70/30 Split and 10-Fold Cross-Validation while figures 9 & 10 depict classification Results with SFFS on 70/30 Training–Testing Split and 10-Fold Cross-Validation. From the results, Adaboost ensemble model demonstrates superior performance among all models under the 70/30 split, achieving the highest F1-score of 98.81% and an accuracy of 98.77%. In the 10-fold cross-validation setting, voting ensemble emerges as the best-performing model, achieving an F1 score of 97.71.29% and accuracy of 97.79%.

Classification Results based on Central Tendency Feature Selection (CTFS): This section presents the classification results obtained after applying CentralTendency Feature Selection (CTFS) to the obtained dataset.

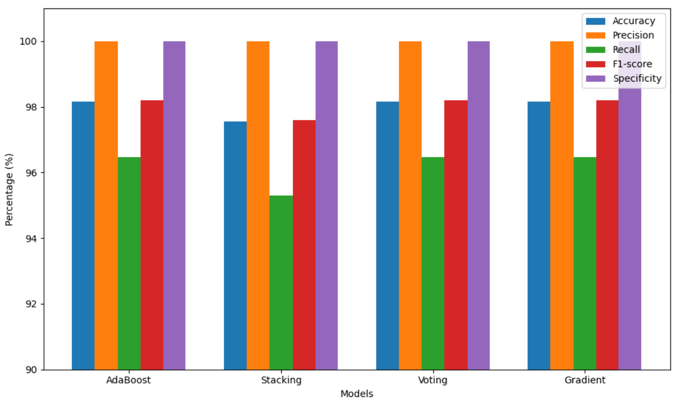


Figure 12. Classification Results with CTFS using 70/30 split

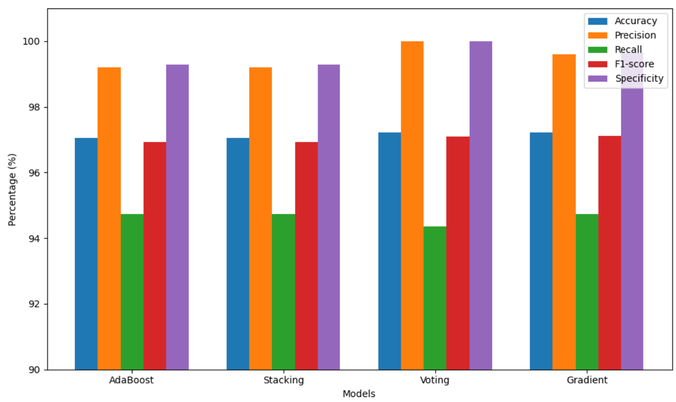


Figure 13. Classification Results with CTFS Using 10-fold cross validation

Figure 11 shows the Confusion Matrix of Ensemble Classification Models Using CTFS under 70/30 Split and 10 - Fold Cross - Validation, whereas figures 12 and 13 give the classification results with CTFS on 70/30 Training–Testing Split and 10 - Fold Cross - Validation. From the results it is very clearly established that Adaboost, Voting & Gradients ensemble models perform best under the 70/30 split, attaining the highest F1 - score of 98. 20% and accuracy of 98. 16%. In the 10 - fold cross - validation setting, the voting & Gradient ensemble model is the top performer, with an F1 score of 97. 11% and accuracy of 97. 23%.

Conclusion

The present paper introduces an ensemble-based learning framework for predicting the level of information and communication technology (ICT) integration in teaching and learning at polytechnics in Southwestern Nigeria, beginning with data collection via questionnaires and moving on to the construction of a structured dataset with 352 observations and 24 variables. The problem is naturally and appropriately formulated as a binary classification task, with ICT adoption level (ICT_AL) as the target variable. From the results it is clearly and convincingly shown that the Voting ensemble model outperforms other ensemble methods, attaining an accuracy of 98. 77% and an F1 - score of 98. 81% when Sequential Backward Feature Selection was used, hence providing strong evidence for the benefit of combining several base learners to improve prediction performance. The paper rightly points out the major factors affecting ICT integration, namely unreliable power supply, the rapid development of ICT tools, user attitudes, and the difficulty of adapting existing teaching practices to ICT. Since the proposed framework is intended as a decision-support tool for educational administrators in Polytechnics, as well as for IT practitioners and policymakers, it is very natural to use it for data-driven planning and to identify priorities for improving ICT integration. Since the paper points out future directions clearly, it is natural to recommend extending the framework to other educational settings, namely universities and colleges of education, in order to increase generalizability, and also to employ deep learning and explainable AI methods to improve both model performance and interpretability.

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