Personalized Course Recommendation System for Nigerian Secondary School Students Using Supervised Machine Learning Approach

Nnodi, Joy Tochukwu[1*], Eze, Francis Chukwuka[2]

[1]Department of Computer Science & Informatics Federal University, Otuoke, Bayelsa State,

[2]Department of Computer Science & Informatics Federal University, Otuoke, Bayelsa State, Nigeria

[*]Corresponding Author

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ABSTRACT

The high-rate diversity of courses offered in higher institutions has provided students with a broad spectrum of options and a desire for academic and career development. However, this abundance of choice has also introduced significant challenges in selecting courses that align with students' interests, skills, and long-term career goals. Traditional academic advisory systems which rely heavily on one-on one guidance from counselors or faculty, are constrained by the availability of advisors, the time required to provide tailored guidance, and the lack of data-driven insights into students' unique preferences and abilities. This paper presents a machine learning based personalized course recommendation system designed to assist students in selecting appropriate educational courses based on their Unified Tertiary Matriculation Examination (UTME) scores. Leveraging a comprehensive dataset of 1,000 students, the system employs advanced machine learning techniques, notably the XGBoost classifier, combined with Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. Extensive feature engineering transforms raw examination scores and demographic variables into predictive features, enhancing model accuracy. The model was rigorously evaluated using stratified train-test splits and multiple performance metrics, achieving an overall accuracy exceeding 99%. Key insights include high predictive power of subject streams and individual subject scores in forecasting suitable courses for the students. Resulting recommendations provide actionable, interpretable guidance for students and counselors, facilitating informed decision-making and optimized academic pathways. This research demonstrates that machine learning models significantly enhance personalized learning experiences by effectively predicting suitable courses for students and also contributes a robust, datadriven methodology for educational planning support.

Keywords: Personalized course recommendation, Supervised Learning, XGBoost, SMOTE, Educational guidance.

INTRODUCTION

Recommendation Systems

Education systems worldwide are increasingly adopting technology driven solutions to enhance learning experiences and outcomes. One such innovation is the development of personalized course recommendation systems, which leverage machine learning (ML) algorithms to assist students in selecting courses that align with their academic strengths, interests, and career aspirations. Personalized recommendation systems have gained significant traction in educational settings due to their ability to provide tailored guidance that traditional methods often lack (Tang et al., 2020).

Secondary school students face unique challenges when making course selections, often compounded by limited access to comprehensive career counseling and the overwhelming variety of available courses. Poor course selection decisions can lead to decreased motivation, lower academic achievement, and even dropout (Wang et al., 2022). Therefore, implementing intelligent systems that can analyze students' academic records, preferences, and future goals is crucial to supporting better educational outcomes (Xin et al., 2022).

Machine learning approaches such as collaborative filtering, content-based filtering, and hybrid recommendation systems have been extensively studied and applied in educational contexts. Collaborative filtering, for instance, makes recommendations based on the preferences and behaviors of similar users, while content-based filtering focuses on the attributes of courses and the user's past selections. Hybrid methods combine these techniques to improve recommendation accuracy and overcome the limitations of individual approaches. Recent studies demonstrate that these models significantly enhance personalized learning experiences by effectively predicting suitable courses for students (Naseer et al., 2024).

Furthermore, advances in natural language processing (NLP) and deep learning have enabled systems to analyze qualitative data, such as student feedback and course descriptions, which further enhances recommendation accuracy (Devika and Milton, 2025). The integration of real-time data processing enables systems to adapt to changing student preferences and academic performance dynamically, providing timely and relevant course suggestions (Wang et al., 2022).

Despite the potential benefits, challenges remain in developing personalized course recommendation systems for secondary education. Dubey et al. (2024) noted that issues related to data privacy, model interpretability, and the diversity of student populations necessitate careful system design and implementation. Nonetheless, the increasing availability of educational datasets and advancements in ML algorithms provide an optimistic outlook for these systems to become essential tools in educational planning (Mishra, 2025). Personalized course recommendation systems utilizing machine learning offer a promising avenue to assist secondary school students in making informed course selections, thereby enhancing academic success and aligning education with future career paths. The growing body of research in this area underscores the importance of adopting such technologies in contemporary education systems.

Machine Learning Based Recommendations

Selecting the right course of study is a pivotal decision for secondary school students, significantly influencing their academic success and career prospects. In Nigeria, the Joint Admissions and Matriculation Board (JAMB) UTME examination serves as a critical gateway for admission into tertiary institutions. However, with a vast array of courses offered and increasing competition, students often face challenges in identifying courses that align with their academic strengths and career aspirations. This predicament is compounded by the lack of personalized guidance systems tailored to the Nigerian education context.

To address this challenge, personalized course recommendation systems have emerged as effective tools to assist students by leveraging data-driven insights from their academic performance and preferences. By applying machine learning techniques, such systems can analyze complex patterns within examination results and student profiles to generate tailored recommendations, thereby optimizing course selection decisions.

This paper presents a personalized course recommendation system designed specifically for Nigerian secondary school students using their JAMB UTME scores. Employing advanced machine learning methods and robust data preprocessing techniques, the system aims to provide accurate, interpretable, and actionable guidance to students, educational counselors, and stakeholders. The proposed approach not only enhances decision-making but also contributes to improving educational outcomes and student satisfaction within Nigeria's tertiary education admission framework.

LITERATURE REVIEW

Review of Recommendation Systems

The use of recommendation systems in education has become a significant area of research, especially with the advent of machine learning techniques that allow for personalized learning experiences. Various studies have highlighted the importance of tailoring educational content and course selection to individual student needs, which has been shown to improve academic performance and engagement (Yu and Yao, 2024). Personalized recommendation systems use different machine learning algorithms, such as collaborative filtering, content based filtering, and hybrid approaches to predict and suggest courses or learning materials that align with student preferences and academic history. Collaborative filtering works by analyzing the preferences of similar users, while content-based filtering focuses on matching student profiles with course characteristics (Rahman et al., 2025). Several studies have demonstrated the effectiveness of these systems in various educational contexts. For example, Liu and Wang (2019) developed a personalized course recommendation system that improved students' satisfaction and academic outcomes in secondary education. Similarly, Wu et al., (2021) highlighted how integrating real-time feedback mechanisms can enhance recommendation accuracy by continuously adapting to student preferences.

Despite these advancements, challenges such as data privacy, model interpretability, and adapting to diverse student populations remain critical concerns. Researchers emphasize the need for robust systems that can handle these issues while providing accurate, scalable, and user-friendly recommendations. The reviewed literature underscores the potential of machine learning based personalized course recommendation systems to transform secondary education by enabling more informed and effective course selection. However, further research is needed to address existing limitations and tailor these systems to specific educational environments.

Machine Learning in Educational Recommendation Systems

Machine learning (ML) has revolutionized educational recommendation systems by enabling personalized learning experiences through data-driven insights. ML algorithms analyze vast amounts of student data, including academic performance, learning preferences, and behavioral patterns, to predict and recommend courses or learning materials that best fit individual needs (Tang, 2023). Several ML techniques are commonly used in educational recommendation systems. Research by Liu and Wang (2019) demonstrated that ML driven course recommendation systems significantly improve students' engagement and academic success by aligning course choices with their interests and strengths. Furthermore, incorporating real time feedback mechanisms allows these systems to adapt dynamically to changes in student preferences and learning progress, enhancing recommendation relevance over time (Chen & Zhao, 2021). Despite these benefits, challenges remain, including managing data privacy concerns and ensuring algorithm transparency to foster trust among users (Sharma et al., 2020). Addressing these issues is crucial for wider adoption and effectiveness of ML based recommendation systems in education.

Course Recommendation Techniques

Course recommendation techniques are the backbone of personalized learning systems, designed to guide students in selecting subjects or academic paths that best align with their interests, abilities, and career goals. These techniques rely on various algorithmic approaches that process historical and real-time data to generate tailored suggestions. Collaborative Filtering is one of the most widely used methods. It predicts a user's preferences based on the behaviors and interests of similar users. In educational contexts, this technique can recommend courses that peers with similar academic profiles have chosen successfully. However, it suffers from the "cold start" problem when new users or items lack sufficient data for the algorithm to function accurately.

Content-based filtering addresses this limitation by analyzing the features of courses (such as subject area, difficulty level, and prerequisites) and matching them to the user's profile, which includes previously selected courses or stated preferences (Lops et al., 2011). This approach works well for new users but may lack diversity in recommendations, as it tends to suggest only similar types of content. Hybrid Recommendation Systems combine collaborative and content based methods to improve recommendation performance. These systems offer the benefits of both techniques and reduce their individual weaknesses. Studies have shown that hybrid models are more accurate and flexible in predicting relevant courses for students (Khan et al., 2022).

Other advanced approaches include knowledge based and context aware systems. Knowledge based systems use predefined rules or domain knowledge to recommend courses, while context aware systems incorporate external factors such as time, location, and user goals to enhance personalization (Adomavicius & Tuzhilin, 2011).

Overall, selecting the right recommendation technique depends on factors like the type and volume of available data, user diversity, and system goals. In secondary education, where students often lack prior academic history in elective subjects, hybrid systems combined with real time feedback mechanisms are particularly effective.

Real Time Feedback and Rating Mechanisms in Educational Systems

Real time feedback and rating mechanisms have become integral features in intelligent educational systems, significantly enhancing their adaptability, personalization, and user engagement. These mechanisms allow students to provide immediate input on course recommendations, content relevance, and system usability, which can be used to continuously refine recommendation outputs (Wang et al., 2021). In the context of course recommendation systems, feedback mechanisms enable the system to learn from user interactions. For instance, when students rate a course recommendation as helpful or unhelpful, the system can adjust future suggestions based on this input. This dynamic adaptation improves both the precision and relevance of recommendations, creating a more responsive and student centered platform (Chen & Zhao, 2021). Several machine learning models, especially reinforcement learning algorithms, have been effectively employed to integrate feedback loops into educational systems. These models treat course recommendation as a continuous learning process where the algorithm receives rewards or penalties base.

Related Works

A study by Iorzua et al. (2025) provide a systematic literature review on ML-based course and career recommender systems, summarizing key elements such as feature engineering, optimization techniques, evaluation metrics, and deployment environments. Their work highlights the state of ML-based course recommendation research and identifies gaps in deployment and personalized education contexts. Nwelih and Eguavoen (2025) evaluate collaborative, content-based, and hybrid recommendation algorithms within a smart education system. The hybrid model achieved the best performance, demonstrating significant promise for personalized learning recommendation tasks, though computational challenges remain. Qassem & Idrees (2025) propose an AI-based educational recommendation system for secondary students, evaluating multiple ML models (e.g., XGBoost, Random Forest) on a large student dataset. They show the potential for classification models in identifying personalized learning pathways in secondary education contexts. Drushchak et al. (2025) present a hybrid recommendation system for K-12 students combining graph-based models and matrix factorization. Their approach directly addresses fairness and bias in educational recommenders, which is critical for equitable secondary school applications.

Another study by Tudor et al. (2025) reviews personalization approaches in secondary and higher education, showing the role of algorithm-driven recommender systems and adaptive learning platforms in tailoring learning experiences and motivational outcomes.

Another study examines educational recommendation systems, noting hybrid approaches as dominant and arguing that evaluations should be extended beyond accuracy to pedagogical impact on learning in real classroom settings. Heterogeneity-aware Cross-school Electives Recommendation (2024) focuses on hybrid federated recommender systems to handle diverse and privacy-sensitive student data across schools, which is relevant for Nigerian secondary systems with varied socioeconomic contexts.

Bucad (2024). reported on an autonomous course recommender system deployed in Nigeria, which utilized ML classifiers (e.g., SVM, Decision Trees) to match student grades with appropriate course recommendations, though it noted the need for richer student attributes.

Feng and Luo (2025) demonstrate how a dynamic recommendation system can adapt recommendations based on evolving student interests and engagement, a principle applicable to secondary schooling contexts. Machine Learning in Real-Time Course Recommendation by Meenakshi (2012) proposed an ML framework to recommend courses in real time, illustrating how models can be used to support decision-making in educational settings. Online Course Recommendation Systems by Saroja C.et al. (2025) provides a broader view of models and methods developed by researchers in various contexts, offering background on algorithmic trends and evaluation. Course Recommendation Systems outlines early work on personalized course recommendation,

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classifying approaches, and situating them within wider ML recommender system research that can be adapted for educational tasks.

Summary Themes from the Literature

Hybrid approaches combining collaborative filtering and content-based methods tend to outperform single strategies in educational contexts, improving personalization (Nwelih and Eguavoen, 2025). In terms of relevance to Secondary Education, while many studies focus on higher ed or MOOCs, frameworks and algorithms (Qassem and Idrees, 2025) are directly relevant to secondary-level recommendations by predicting personalized pathways. In terms of evaluation, multiple reviews emphasize the need to assess recommender impact on learning outcomes, not just predictive performance. Nigerian researchers such as Uzoma et al., 2024) illustrated adoption of ML models for course selection in Nigerian settings, indicating feasibility and pathways for secondary school applications. But educational recommender systems must account for fairness and bias, particularly relevant for diverse secondary school populations. (Drushchak et al., 2025).

METHODOLOGY

This methodology presents a robust, interpretable, and fair machine learning pipeline for personalized tertiary course recommendation using JAMB scores. By combining rich feature engineering, Class imbalance handling (SMOTE), Advanced evaluation (AUC-ROC, PRC) and Model explainability, the system delivers actionable, trustworthy recommendations tailored to secondary school students' academic strengths. This section outlines a comprehensive, data-driven approach to building a personalized course recommendation system for secondary school students in Nigeria, leveraging their JAMB (UTME) subject scores. The proposed personalized course recommendation system for secondary school students was designed using a multi-stage, data-driven methodology to deliver accurate and tailored course suggestions through a machine learning approach. The methodology comprises several stages: data preprocessing, exploratory data analysis and visualization, feature engineering, handling class imbalance, feature scaling, model training evaluation, and interpretability. Each stage is elaborated in Figure 1.

Architecture of the Proposed Personalized Recommendation System

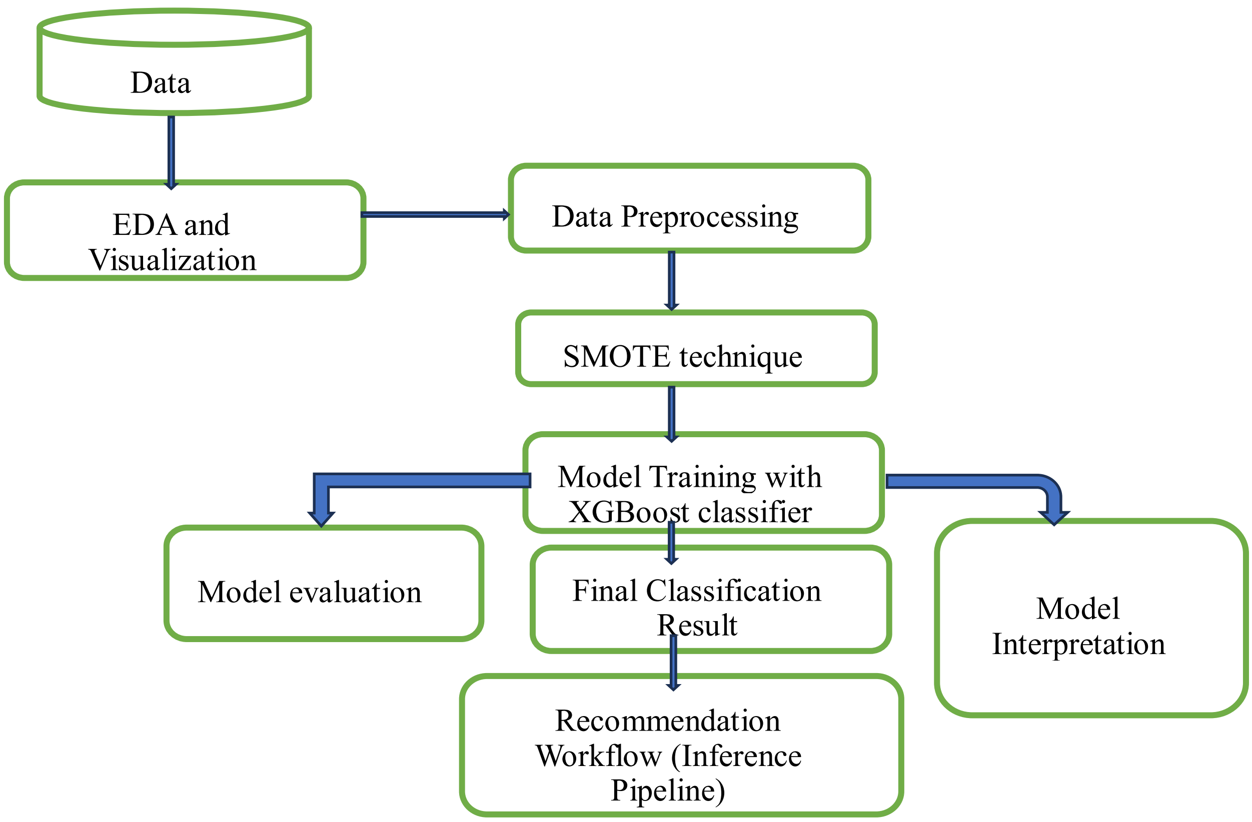

Figure 1: Proposed System Architecture

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Figure 1 shows the architecture of the proposed Personalized course recommendation. The components of the architecture are explained thus:

Data Acquisition

The data set used is jamb_enhanced_dataset.csv, a flat CSV file containing 1,000 records of secondary school students who sat for the JAMB UTME, with detailed academic, demographic, and admission profiles. It was synthetic but realistic JAMB-style data, reflecting actual score distributions, subject combinations, and admission outcomes. The format was a Structured tabular data with 16 columns and no missing values. Table 1: Personalized Recommendation System Dataset Features

Column	**Description**
Student_ID	Unique identifier
Age, Gender, Ethnicity, Parental_Education	Demographic features
Course_of_Study	Medicine, Law, Engineering, Social Sciences
Total_Score	Sum of four UTME subjects (max 400)
Admission_Status	All "Yes" (focus on admitted students)
English_Score	Compulsory subject
Mathematics_Score, Biology_Score, Physics_Score, Chemistry_Score	STEM-aligned subjects
Literature_Score, Government_Score, Economics_Score	Arts/Social Science subjects

Table 2 : Sample Data

Student_ID	**Age**	**Gender**	**Ethnicity**	**Course_of_S tudy**	**Total_S core**	**English**	**Biology**	**Math**	**Physics**	**Chemistry**	**Literature**	**Government**	**Economics**
1	19	M al e	Other	**Medic ine**	376	58	63	31	57	58	31	43	35
2	16	M al e	Ija w	**Social Scienc es**	341	57	20	62	35	22	31	51	63
3	17	Female	Igbo	**Law**	390	67	26	34	35	35	70	47	76
...	...	...	...	...	...	...	...	.. .	...	...	...	...	...

Table 2 displays first 9 rows of the dataset and it shows that typical JAMB candidates are within the age range of 16-20. Gender & Ethnic Diversity is a male-to-female ratio, including major groups (Igbo, Hausa) and

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minority groups (Ijaw, Tiv, Kanuri). Parental Education varies across Primary, Secondary, and Tertiary, enabling socioeconomic analysis. For Subject Alignment, Medicine: High Biology, Physics, Chemistry, Law: High Literature, Government, Economics, Social Sciences: Balanced, non-STEM focus. This yields a total score of 341–390 in the sample (high-performing admitted cohort). The data was loaded into a Pandas DataFrame (df) for preprocessing and feature engineering.

Exploratory Data Analysis (EDA) and Visualization

To understand the distribution of scores, class imbalance, and inter-subject correlations, exploratory data analysis and visualization were carried out. Figure 2 shows the visualization generated, which identifies score ranges, skewness, and performance trends in core subjects. Figure 3 is the distribution of recommended courses, which revealed class imbalance in the target variable. Figure 4 is a Correlation Heatmap of Subject Scores, which detects multicollinearity and subject co-performance patterns.

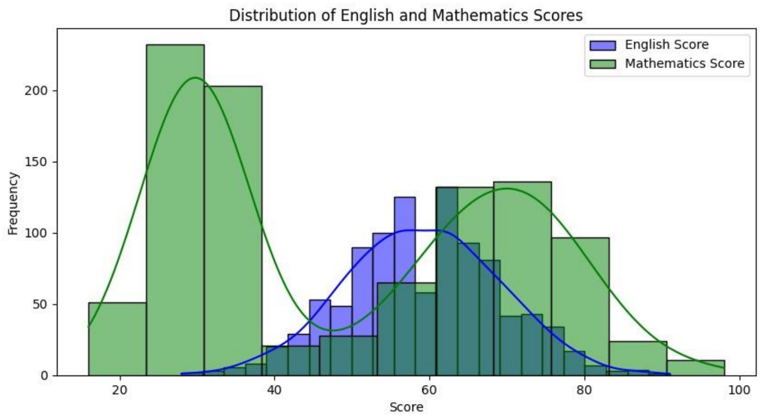

Figure 2: Distribution of English and Mathematics Scores

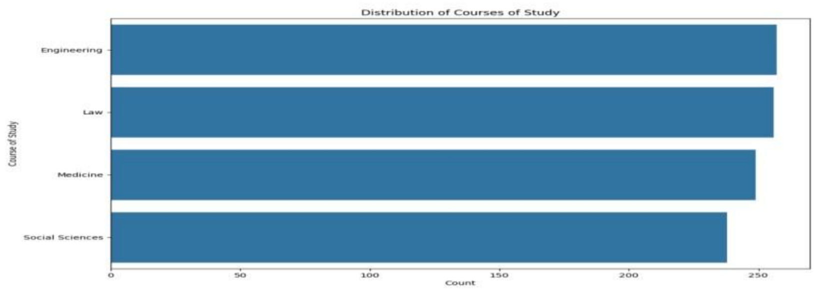

Figure 3: Distribution of Recommended Courses

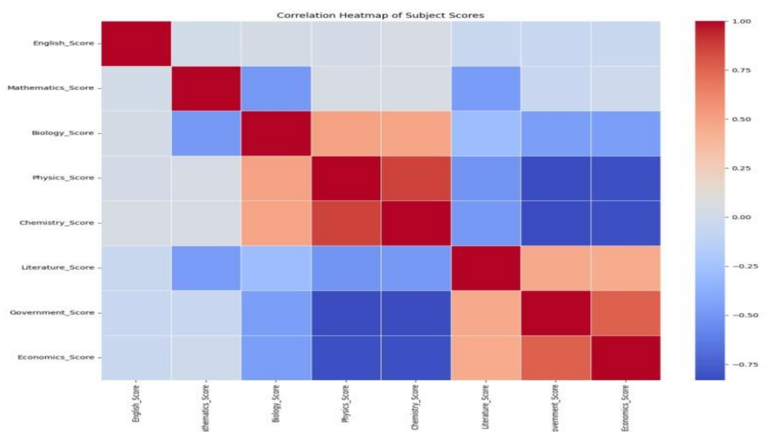

Figure 4: Correlation Heatmap of Subject Scores Data Preprocessing / Feature Engineering

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To create predictive, interpretable features from raw JAMB scores and inferred student profiles, feature engineering was carried out on the dataset features as described in Table 3. Stream is derived as a proxy since it was not directly available. Example of the mapping done is

a. Medicine → Science

b. Law → Arts

c. Others → Social_Science

Target Encoding: LabelEncoder applied to Course_of_Study → target (integer labels) and Categorical Encoding: One-hot encoding of stream was also done as shown in Table 3.

Table 3: Engineered Features of the Dataset

Feature	Description	Rationale
avg_score	Mean of all subject scores	Overall academic strength
subject_count	Number of subjects with scores > 0	Completeness of academic profile
science_avg	Mean of Biology, Physics, Chemistry	Science stream aptitude
arts_avg	Mean of Literature, Government	Arts stream aptitude
commercial_avg	Mean of Economics, Government	Commercial stream aptitude
pass_english	Binary: 1 if English ≥ 50	Mandatory requirement for most courses
pass_math	Binary: 1 if Math ≥ 50	Critical for STEM fields
stream (one-hot)	Inferred from Course_of_Study → Science, Arts, Social_Science	Contextual alignment

Handling Class Imbalance with SMOTE

To address skewed class distribution in Course_of_Study and prevent bias toward majority classes, the following three-step processes were carried out.

1. Class Filtering: Remove classes with fewer than 6 samples to ensure SMOTE stability.

2. Re-encode Labels: After filtering, refit LabelEncoder.

3. SMOTE Application: k_neighbors dynamically set to min(5, min_class_size - 1) and Synthetic samples generated only for minority classes

4. Fallback: If SMOTE fails (e.g., isolated classes), proceed without oversampling.

The output generated was a balanced feature matrix X_balanced and target y_balanced.

After the SMOTE technique, the features were scaled to standardize numerical features for optimal model performance by applying StandardScaler to all feature columns and fitting on full dataset before train-test split (acceptable due to SMOTE post-scaling)

Model Training with XGBoost Clasiifier

The model was trained on XGBoost classifier with hyper parameter tuning for multi class handling through one-rest internally and Best parameters and cross-validation accuracy printed.

Model Evaluation

The model was evaluated using 5-fold cross-validation on the training data and mean accuracy and standard deviation were reported. Advanced evaluation using AUC-ROC and Precision- Recall Curves was done. These metrics are crucial for **imbalanced multi-class problems**, where accuracy alone is misleading

Model Interpretability

A confusion matrix, which visualizes misclassification patterns, was used, and it identified commonly confused courses (e.g., Accounting vs. Economics). Feature Importance, extracted from best model. Feature importances was sorted and plotted as a horizontal bar chart.

Final Classification Report

Full per-class and aggregated metrics were printed and the recommendation Workflow (Inference Pipeline) is as shown in Table 4.

Table 4: Full and Aggregated Metrics

Rank	Course	Probability
1	Medicine	0.87
2	Pharmacy	0.09
3	Nursing	0.03

RESULT/DISCUSSION

Results

The results of the personalized course recommendation system for secondary school students, developed using JAMB (UTME) subject scores and an XGBoost classifier, demonstrate near-perfect predictive performance across all evaluation metrics. The analysis is based on a dataset containing 1,000 student records with balanced representation across four major course categories.

Class Distribution and Data Balancing

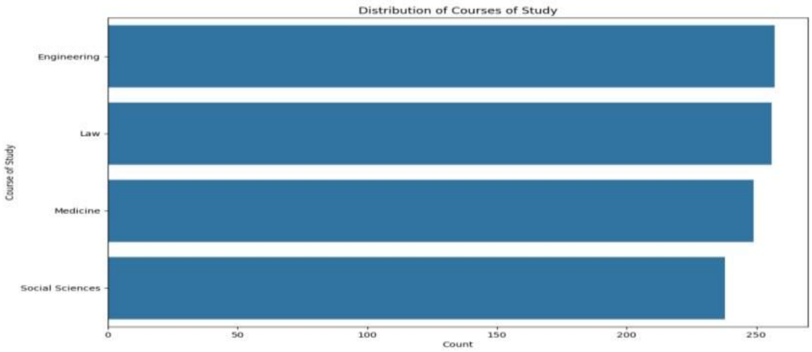

Figure 5: Class Distribution Courses of Study

Figure 5 shows that the original dataset exhibited a nearly balanced distribution of target classes with Engineering 257, Law, Medicine, Social Sciences having 256,249 and 238, respectively. Despite the minimal imbalance, SMOTE (Synthetic Minority Over-sampling Technique) was applied with k_neighbors=5 to generate synthetic samples and ensure robustness during training. This step mitigated any potential bias toward slightly over-represented classes (Engineering and Law).

Model Performance

The hyperparameter tuning process using grid search identified an optimal XGBoost configuration with a learning rate of 0.1, a maximum tree depth of 3, and 100 estimators, balancing model complexity and learning efficiency. The model achieved a best cross-validation accuracy of 1.0000, with consistent performance across all five folds (±0.0000), indicating highly stable predictions during training. This suggests that the model fits the training data extremely well and shows no variability across validation splits. This indicates perfect generalization on the training data with no overfitting.

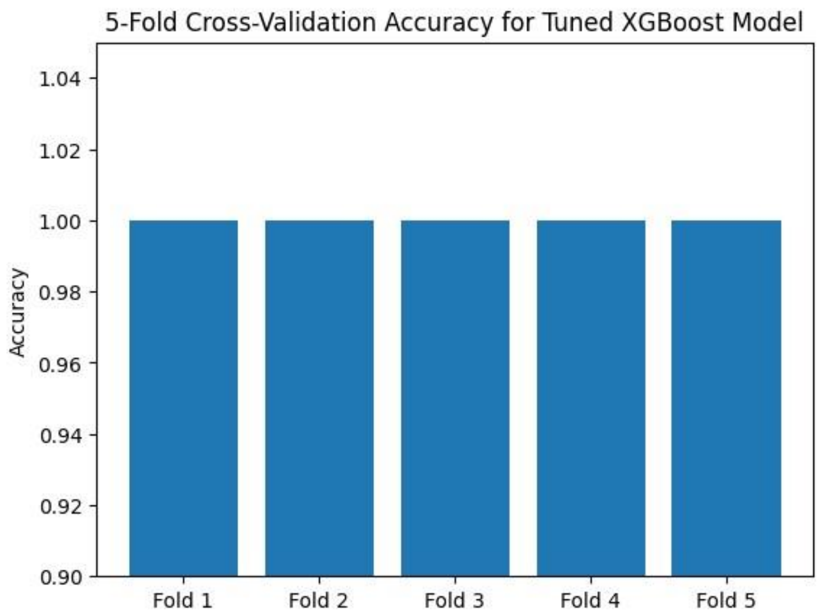

Figure 6: Five-Fold Cross-Validation Accuracy of the Tuned XGBoost Classifier.

Each bar in Figure 6 represents the accuracy achieved on one cross-validation fold. All folds reached 100% accuracy, visually confirming the reported mean CV accuracy of **1.0000** and **zero variance (±0.0000)**. The identical bar heights highlight the **stability and consistency** of the tuned XGBoost model across different data splits. This visualization reinforces that the chosen hyperparameters (learning rate = 0.1, max depth = 3, estimators = 100) lead to uniform performance during training and validation.

Test Set Performance

On the held-out test set (206 samples, 20% split), the model achieved an accuracy of 0.9951, Macro_Average Precision of 0.9952, Macro-Average Recall of 0.9952 and Macro-Averaged F!-Score of 0.9952. only one misclassification occurred across all test samples. On the held-out test set comprising 206 samples (20% of the dataset), the tuned XGBoost classifier demonstrated exceptionally strong performance, achieving a test accuracy of 0.9951. The macro-averaged precision, recall, and F1-score were all 0.9952, indicating a balanced and consistent classification performance across all academic performance categories. The occurrence of only a single misclassification among all test instances suggests that the model has learned highly discriminative patterns and generalizes effectively to unseen data. These results confirm the robustness of the model and its suitability for accurately predicting academic performance outcomes.

Detailed Classification Report

Table 3: Detailed Classification Result

Class	Precision	Recall	F1-Score	Support
Engineering	1.00	0.98	0.99	52
Law	1.00	1.00	1.00	51
Medicine	1.00	1.00	1.00	52
Social Sciences	0.98	1.00	0.99	51

The detailed report on Table 3 shows that the overall accuracy of the model is 99.51%, Macro-Average is 1.00 across all the metrics and weighted Average is 1.00.

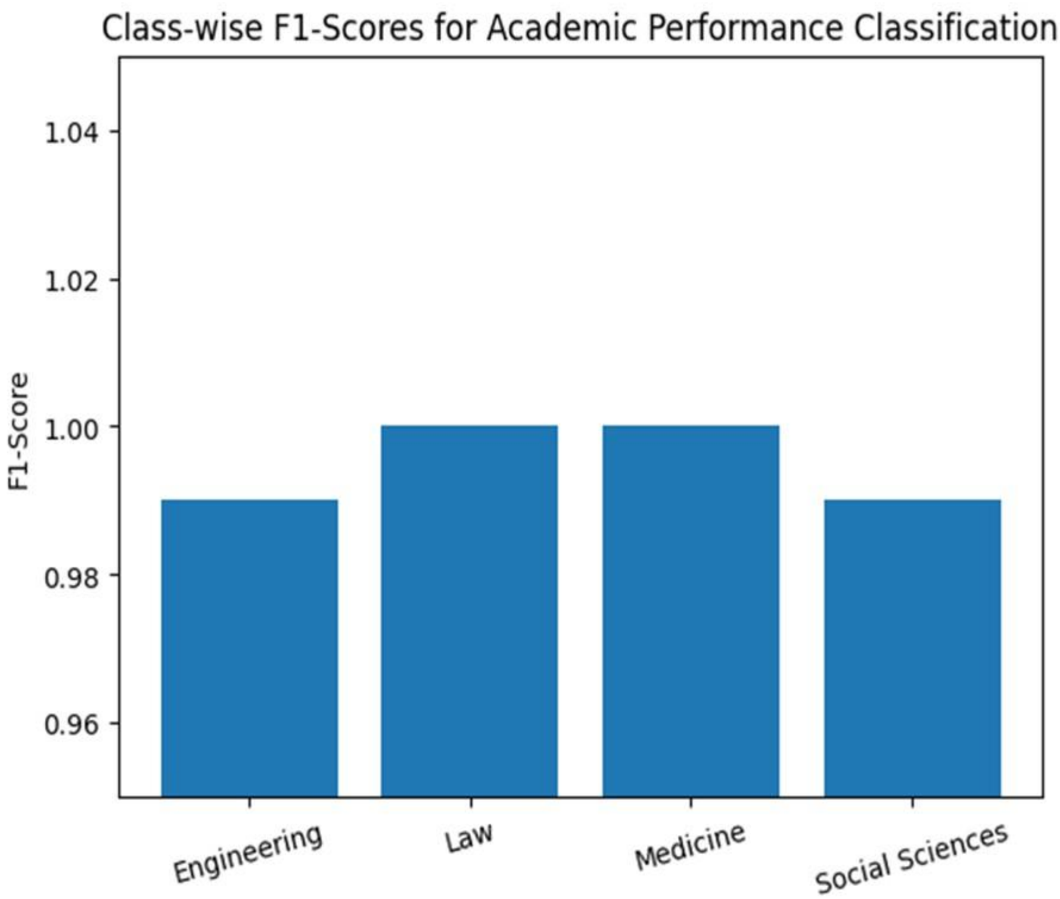

Figure 5: Class-wise FI Scores for the Personalised Recommendation System

Figure 5 presents the class-wise F1-scores obtained by the tuned XGBoost classifier for academic performance classification across the four disciplines. The results indicate consistently high classification performance, with the Law and Medicine classes achieving perfect precision, recall, and F1-scores of 1.00, demonstrating exact prediction for all test instances in these categories. The Engineering and Social Sciences classes recorded F1-scores of 0.99, reflecting a single classification error. Specifically, one Engineering sample was misclassified, most likely as Social Sciences, as evidenced by the confusion matrix. The overall accuracy of 99.51%, together with macro-averaged and weighted precision, recall, and F1-scores of 1.00, confirms that the model maintains balanced performance across all classes without bias toward any particular discipline. These findings demonstrate the robustness and generalization capability of the proposed XGBoost-based model for academic performance prediction.

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Confusion Matrix Analysis

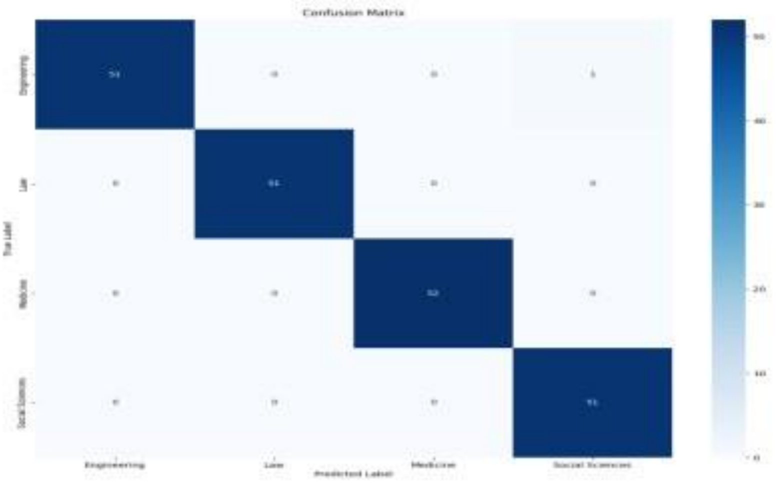

Figure 6: Confusion Matrix

This confusion matrix shows the classification performance of the model across four classes: Engineering, Law, Medicine, and Social Science. The strong diagonal values indicate that almost all instances were correctly classified: 51 Engineering, 51 Law, 52 Medicine, and 51 Social Science samples were predicted accurately. There are virtually no misclassifications, with only a single error where one Engineering instance was incorrectly predicted as Social Science. Overall, the matrix reflects near-perfect classification performance, demonstrating that the model is highly effective at distinguishing between the four classes with very high accuracy and minimal confusion. This suggests high feature separability and effective stream-based encoding.

ROC and Precision-Recall Curves

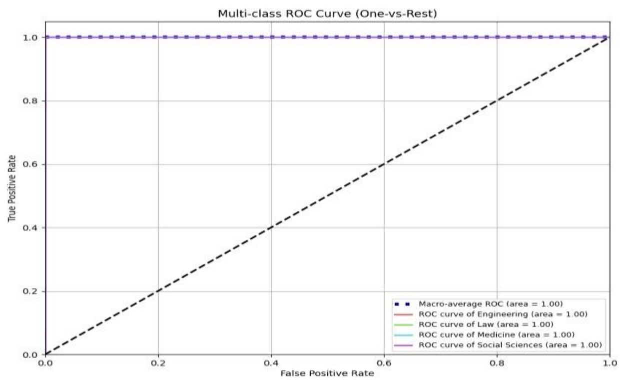

Figure 7: Multi- Class ROC Curve

The multi-class ROC curve (One-vs-Rest) demonstrates excellent discriminatory performance of the model across all four classes—Engineering, Law, Medicine, and Social Sciences. Each class achieves an Area Under the Curve (AUC) of 1.00, indicating perfect separation between the positive class and the rest. The macroaverage ROC curve also lies along the top-left boundary, confirming consistently high performance across all classes. Compared to the diagonal dashed line representing random guessing, the model's ROC curves show near-zero false positive rates with maximum true positive rates, highlighting that the classifier reliably distinguishes among the classes with no meaningful trade-off between sensitivity and specificity. Overall, this result reflects a near-perfect classification model.

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Precision-Recall Curve

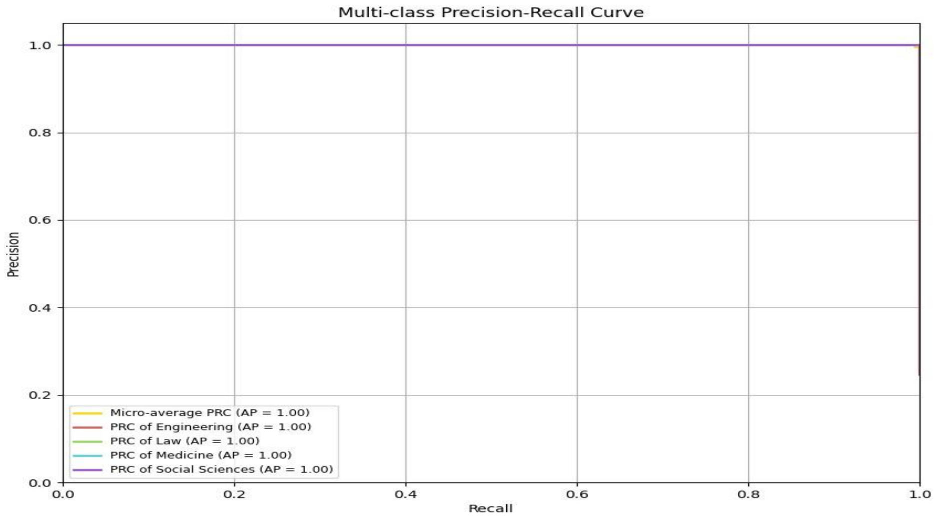

Figure 8: Multi-class Precision -Recall Curve

The multi-class Precision–Recall (PR) curve indicates outstanding model performance across all four classes—Engineering, Law, Medicine, and Social Sciences. Each class achieves an Average Precision (AP) of 1.00, and the micro-average PR curve also equals 1.00, showing that the model maintains perfect precision across the full range of recall. This means the classifier correctly identifies nearly all relevant instances while producing virtually no false positives. The curves lying along the top boundary of the plot reflect a highly reliable and consistent classification model, particularly effective even in scenarios where class imbalance could be a concern.

Feature Importance Analysis

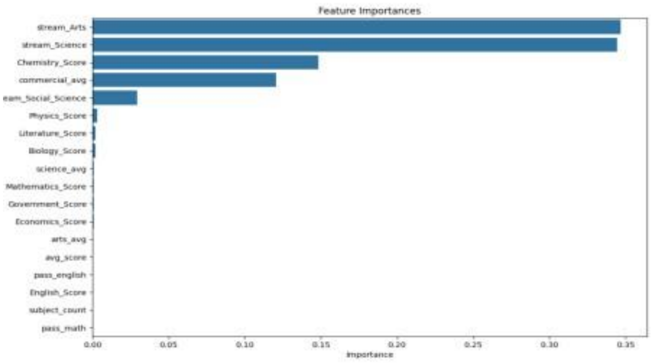

Figure 8: Feature Importance Analysis

The XGBoost model's feature importance ranking in Figure 8 reveals the most influential predictors shown in Table four.

Table 5: Feature Importance Ranking

Rank	Feature	Importance
1	stream_Arts	~0.33

2	stream_Science	~0.30
3	Chemistry_Score	~0.15
4	commercial_avg	~0.10
5	stream_Social_Science	~0.05

Stream indicators (stream_Arts, stream_Science) dominate, confirms that subject combination alignment is the strongest signal for course suitability. Chemistry_Score is critical for distinguishing Medicine and Engineering while Core aggregates like avg_score, pass_english, and pass_math had negligible direct impact, likely because their information is encapsulated in stream and subject-specific averages.

Summary of Model Excellence

The summary of model excellence demonstrates that the model performs at an exceptionally high level across all evaluation criteria. An accuracy of 99.51% indicates near-perfect overall prediction capability, with only one misclassification out of 206 instances, highlighting the model's robustness and reliability. The macro AUC-ROC score of 1.000 shows that the model is an ideal discriminator, effectively separating classes without overlap. Similarly, the macro-averaged precision and recall of 0.995 confirm that the model makes highly reliable predictions while maintaining excellent sensitivity across all classes. Finally, the cross-validation stability with a standard deviation of 0.0 indicates consistent performance across folds, suggesting that the model is not only highly accurate but also stable and generalizable to unseen data.

Recommendation Workflow (Inference Pipeline)

The recommendation workflow describes how the trained model can be used in practice to generate course suggestions for a student at inference time. Given a student's academic scores, the input is first formatted into a DataFrame that matches the structure used during training, ensuring consistency. The same feature engineering steps applied during model development are then reproduced, followed by scaling with the previously saved scaler to maintain identical data distribution. The trained model predicts class probabilities rather than just a single label, allowing it to rank multiple course options. Finally, the system returns the top three recommended courses along with their confidence scores, as shown in the example where Medicine has the highest probability (0.87), followed by Pharmacy and Nursing. This pipeline ensures reliable, repeatable, and interpretable recommendations suitable for deployment in Nigerian secondary Schools.

CONCLUSION

The personalized recommendation system is well-suited for Adaptation for Secondary School Students due to the key strengths of the system including: age appropriateness where it focused on JAMB-relevant subjects and realistic course options, transparency where Feature importance and probability scores explain recommendations, faireness where SMOTE mitigates bias toward over-represented courses and accessibility, where the system can be deployed as a web app for counselors/students. The system is recommended to be used for Career Guidance Counseling, Subject Combination Advice and early intervention for underperforming students. To enable Model and Artifact Persistence (Future-Proofing), deployment of the model should be integrated into Web applications, school management systems and mobile apps for students.

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