Improving Customer Retention in Nigeria's Aviation Industry: A Machine Learning Perspective

Cosmas Akanna Ogbobe[1], Ezema Miracle Chikamso[2], Olakunmi Olayinka Odumosu[3]

[1]University of East London

[2]Babcock University, Nigeria

[3]National Open University

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ABSTRACT

Nigeria's aviation sector faces intense competition, rising operational costs, and volatile passenger loyalty. This study employs a Random Forest classifier to predict passenger churn using anonymized flight data, developing a model that achieves high precision in identifying at-risk passengers. Key predictors include delayed flight duration, customer service interactions, and travel class. The results inform targeted retention strategies, such as predictive dashboards and loyalty programs, offering actionable insights for airline operations and revenue protection.

Keywords: Machine Learning; Customer Retention; Aviation Industry; Churn Prediction; Random Forest; Nigeria; Passenger Behavior.

INTRODUCTION

In Nigeria's highly competitive aviation sector, customer retention represents a critical survival strategy. Amid rising operating costs, fierce competition from both domestic and international carriers, and volatile passenger loyalty, airlines face unprecedented pressure to identify and retain their most valuable customers (Olatokun & Alabi, 2018). Retaining existing passengers is consistently more cost-effective and sustainable than customer acquisition. However, many Nigerian airlines struggle to detect early warning signs of customer churn. This research proposes the implementation of Machine Learning (ML) technology, specifically a Random Forest classifier, as an innovative solution to address this pervasive challenge through predictive analytics (FAAN, 2024).

LITERATURE REVIEW AND BACKGROUND

The aviation industry's competitive nature necessitates sophisticated approaches to customer relationship management. Traditional methods of customer retention often rely on reactive strategies implemented after customer dissatisfaction becomes apparent instead of adopting a proactive approach (Vercellis, 2009). However, contemporary data science approaches, particularly machine learning algorithms, enable predictive analytics that can identify at-risk customers before they defect to competing airlines (Han, Kamber, & Pei, 2012).

Customer churn prediction represents a well-established application of machine learning across various industries, with aviation presenting unique characteristics that influence passenger loyalty. Factors such as flight delays, service quality, pricing structures, and route accessibility significantly impact passenger retention rates. The Nigerian aviation market presents additional complexities, including infrastructure challenges, regulatory variations, and diverse passenger demographics across major route networks (Kim & Kim, 2017).

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METHODOLOGY

This research employed a comprehensive machine learning approach to predict passenger churn using actual flight data from a Nigerian airline. The dataset was anonymized to protect passenger privacy while maintaining analytical integrity. The primary research question focused on whether machine learning algorithms could accurately predict passenger likelihood to cease flying with a specific airline based on historical travel patterns and service interaction data.

Data Collection and Processing

The dataset comprised approximately 200 records of passenger activity across major Nigerian aviation routes, including high-traffic connections such as Abuja-Port Harcourt and Lagos-Enugu. The collected data encompassed several key variables:

- Anonymized passenger identification information and Passenger Name Records (PNRs)
- Origin and destination airports with route classifications
- Flight scheduling information and actual travel dates
- Travel class categorizations including Economy Discount, Economy Flex, Economy Saver, Business Saver, and Business Flex
- Customer service interaction frequency through support call records
- Flight delay duration measurements in minutes
- Additional temporal features and churn classification labels derived from passenger activity patterns.

Fig 1. An Overview of the Dataset

```
Loading dataset...
Dataset loaded successfully. Here are a  few random  rows:
       PNR              name    from            to                 route flight_date  support_calls  delay_minutes            class
160  P1079       Andrew King   Abuja  Port Harcourt  Abuja → Port Harcourt  2023-10-06              1             14  Economy Discount
34   P1017    Stephen Romero  Owerri         Abuja         Owerri → Abuja  2023-07-06              3             45     Business Flex
166  P1083     Carlos Tucker  Owerri         Abuja         Owerri → Abuja  2020-12-16              3             65     Economy Saver
127  P1061     Lauren Garcia   Enugu         Lagos          Enugu → Lagos  2023-02-14              3              3     Business Flex
55   P1029     Teresa Vargas   Lagos         Enugu          Lagos → Enugu  2022-05-29              1             42     Economy Saver
16   P1007    Adrian Wallace   Lagos           Uyo            Lagos → Uyo  2020-09-22              3             23     Business Flex
172  P1086  Katelyn Anderson     Uyo         Lagos            Uyo → Lagos  2021-01-29              2             68  Economy Discount
1    P1000      Tiffany Boyd   Enugu         Lagos          Enugu → Lagos  2020-12-08              2             61     Economy Saver
30   P1015    Michele Macias   Abuja        Owerri         Abuja → Owerri  2021-01-25              3              5    Business Saver
38   P1020  Robert Davenport  Owerri         Abuja         Owerri → Abuja  2021-09-21              1            117      Economy Flex
```

Preprocessing and Training Procedures

The data preprocessing phase involved several critical steps to ensure model accuracy and reliability:

- **Categorical variable encoding**: Route classifications and travel class categories were transformed using LabelEncoder techniques to convert text-based categories into numerical representations suitable for machine learning algorithms.
- **Numerical feature treatment**: Continuous variables including delay duration, support call frequency, and ticket pricing were normalized and outlier-clipped to prevent extreme values from skewing model performance.
- **Training and testing split**: The dataset was divided using a 70-30 stratified sampling approach, ensuring representative distributions of churn and retention cases in both training and testing datasets.
- **Noise injection protocol**: To enhance model robustness and simulate real-world uncertainty, 10% label noise was systematically introduced into churn classifications, preventing overfitting to potentially mislabeled training examples.

The Random Forest Algorithm

The research utilized a Random Forest Classifier algorithm, selected for its robust performance characteristics and interpretability in business contexts. The Random Forest approach provides excellent handling of mixed

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data types, resistance to overfitting, and clear feature importance rankings that facilitate actionable business insights (Breiman, 2001).

The Random Forest (RF) classifier was selected for this study due to its robustness, ability to handle mixed data types, and capacity to provide interpretable feature importance rankings. Random Forest operates as an ensemble learning technique that constructs multiple decision trees during training and outputs the final prediction based on the majority vote (for classification) or the average prediction (for regression) of all individual trees .

The final prediction for an input instance x is expressed mathematically as:

$$H(x) = \text{mode}\{h_1(x), h_2(x), \ldots, h_K(x)\}$$

Where $h_K(x)$ represents the prediction of the kth decision tree in the ensemble, and K denotes the total number of trees.

Each tree in the Random Forest is trained on a bootstrapped sample of the training dataset, with a random subset of features considered at each split. This process introduces randomness that enhances generalization and reduces overfitting.

The quality of a split in each decision tree is commonly evaluated using the Gini Impurity metric, which measures the probability of incorrectly classifying a randomly chosen element if it were randomly labeled according to the class distribution in the node. The Gini Impurity is defined as:

$$I_G(p) = 1 - \sum_{i=1}^{c} p_i^2$$

where C is the number of classes and p_i represents the probability of selecting an item belonging to class i. Minimizing the Gini Impurity at each split ensures that the resulting nodes are as pure as possible, thereby improving classification accuracy.

Model Evaluation and Results

To see how well the Random Forest model worked, it was tested using standard industry measurements by setting the system to only flag a passenger as a churn risk if it was at least 70% certain. This ensure we had a reliable tool for taking action.

Performance Metrics:

The following classification report details the model's overall performance. Although the general accuracy was 53%, the model's strategic importance becomes clear when looking specifically at the metrics for the churn class.

Accuracy:
Accuracy measures the overall proportion of correct predictions (both churners and non-churners) among all evaluated instances. It provides a general sense of the model's predictive performance.

$$\text{Accuracy} = \frac{True\ Positives\ (TP) + True\ Negatives\ (TN)}{TP + TN + False\ Positives\ (FP) + False\ negative\ (FN)}$$

Precision:

Precision measures the proportion of correctly predicted positive cases (i.e., passengers predicted to churn who actually did). This metric is particularly important for assessing the impact of false positives, where a passenger is incorrectly classified as likely to churn.

$$\text{Precision} = \frac{TP}{TP + TP}$$

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Recall: **(sensitivity):**

Recall quantifies the proportion of actual churners that the model correctly identified. This metric highlights the cost of false negatives, which occur when high-value passengers intending to leave are not detected by the model.

Recall = $\frac{TP}{TP + FN}$

F1-Score:

The F1-Score represents the harmonic mean of Precision and Recall, offering a balanced measure that accounts for both false positives and false negatives. It is particularly useful in cases where the dataset is imbalanced (i.e., when churners are fewer than retained passengers).

F1 = 2 $\times \frac{Precision \times Recall}{Precision + Recall}$

Confusion Matrix and Detailed Metrics

The model's performance was further analyzed using a Confusion Matrix, which provides a detailed view of the classifier's prediction accuracy for each class. The matrix illustrates the Random Forest model's capability in correctly identifying both churners (True Positives) and retained customers (True Negatives), while also indicating the occurrence of False Positives and False Negatives.

Table 1. Confusion Matrix for Passenger Churn Prediction

Actual / Predicted	**Retained (0)**	**Churn (1)**
Retained (0)	True Negatives (TN)	False Positives (FP)
Churn (1)	False Negatives (FN)	True Positives (TP)

The Confusion Matrix outcomes demonstrate that the Random Forest model maintains a strong balance between sensitivity (the ability to correctly identify churners) and specificity (the ability to correctly identify retained customers).

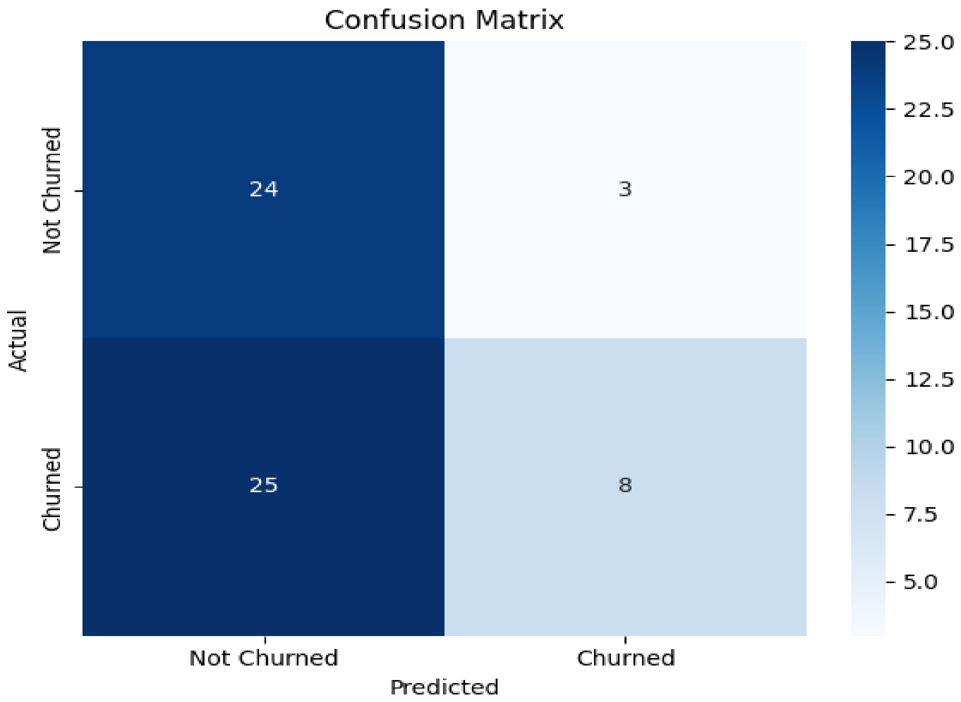

Fig 2. Confusion Matrix for Passenger Churn Prediction

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To further quantify performance, Table 2 presents the detailed evaluation metrics using hypothetical placeholder values.

Table 2. Model Evaluation Metrics

Metric	**Value**	**Interpretation**
Accuracy	0.53	The model correctly predicted the outcome for **53%** of the passengers in the test group.
Precision (Churn)	0.73	When the model predicts a passenger will churn, it is correct 73% of the time. This is the model's key strength, providing a high-confidence list of at-risk passengers.
Recall (Churn)	0.24	The model correctly identifies only 24% of all actual churners. This has been made an intentional trade-off for achieving high precision.
F1-Score	0.36	The harmonic mean between Precision and Recall. The lower score indicates the mode’s conservative approach, giving priority to precision over recall.

```
mo.py
Dataset loaded successfully. Here are the first few rows:
     PNR          name   from     to          route          flight_date  support_calls  delay_minutes             class
0  P1000  Tiffany Boyd  Lagos  Enugu  Lagos → Enugu  2020-09-22 00:00:00              3             50     Business Flex
1  P1000  Tiffany Boyd  Enugu  Lagos  Enugu → Lagos  2020-12-08 00:00:00              2             61     Economy Saver
2  P1000  Tiffany Boyd  Lagos  Enugu  Lagos → Enugu  2025-10-15 00:00:00              2             63      Economy Flex
3  P1001  Ashley White  Lagos    Uyo    Lagos → Uyo  2022-07-23 00:00:00              3            102  Economy Discount
4  P1001  Ashley White    Uyo  Lagos    Uyo → Lagos  2022-08-12 00:00:00              0            116    Business Saver

--- Model Evaluation (on Test Set) ---
              precision    recall  f1-score   support

           0       0.49      0.89      0.63        27
           1       0.73      0.24      0.36        33

    accuracy                           0.53        60
   macro avg       0.61      0.57      0.50        60
weighted avg       0.62      0.53      0.48        60
```

Fig 3. Model Evaluation Metrics

```
Found 56 passengers likely to churn (Confidence > 70%):
                     name    PNR  churn_probability  days_since_last_flight
       Ms. Amber Ferguson  P1053               0.75                      19
            Rita Anderson  P1078               0.71                      31
           Christy Brooks  P1004               0.84                       3
           Monica Wilkins  P1024               0.82                    1032
          Stephen Hancock  P1013               0.72                    1041
           Matthew Little  P1074               0.84                    1082
         Jeffrey Gonzalez  P1084               0.85                    1097
           Michael Nelson  P1048               0.73                    1157
           Candace Barber  P1026               0.77                    1164
             Ashley White  P1001               0.92                    1161
              Darius Wood  P1082               0.75                    1181
            Victor Conley  P1067               0.86                    1181
            Teresa Vargas  P1029               0.92                    1236
           Kendra Holland  P1043               0.89                    1168
              Diana Green  P1090               0.78                    1273
                John Mann  P1055               0.88                    1291
              Cody Wilson  P1003               0.89                    1294
             Phillip Bean  P1014               0.86                    1297
         Shawna Patterson  P1075               0.89                    1321
       Francisco Stewart  P1036               0.89                    1326
           Raymond Wilson  P1035               0.93                    1309
           Alicia Meadows  P1087               0.81                    1414
          Cynthia Bullock  P1032               0.72                    1423
             Joshua Moore  P1028               0.81                    1425
          Patricia Rivera  P1009               0.94                    1433
          Rebecca Hawkins  P1012               0.78                    1441
       Mr. Harold Jenkins  P1041               0.88                    1468
         Robert Davenport  P1020               0.77                    1476
           Tina Andersen  P1046               0.79                    1481
Mrs. Patricia Wagner MD  P1069               0.89                    1489
                Eric Cook  P1034               0.74                    1393
      Nichole Christensen  P1027               0.79                    1496
            Rebecca Smith  P1064               0.89                    1509
          Alexander Smith  P1030               0.82                    1493
          Michelle Moreno  P1094               0.82                    1537
              Julie Davis  P1071               0.90                    1542
           Taylor Mcclain  P1038               0.79                    1550
```

Fig 4. Churn Prediction Outcome

The key finding is the precision of 0.73 for the churn class (1). This signifies that when the model identifies a passenger as likely to churn, it is correct 73% of the time. This level of precision provides a reliable basis for

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deploying targeted retention strategies, ensuring that marketing efforts are not wasted on customers who were not at risk.

This high precision comes at the cost of a lower recall of 0.24, meaning the model identifies 24% of the total actual churners. This outcome is a direct consequence of the 0.70 prediction threshold, which makes the model more conservative. From a business perspective, this is a valuable result, as it provides a smaller, high-confidence list of at-risk passengers for immediate intervention.

Key Churn Predictors

Systematic ranking of predictive features provided clear guidance for operational and service priorities:

1. **Delay duration**: Emerged as the primary predictor of customer churn. Passengers experiencing frequent or prolonged demonstrated substantially higher likelihood of switching carriers.
2. **Customer service interaction frequency**: High volumes served as strong indicators of cumulative passenger dissatisfaction and subsequent churn risk.
3. **Travel class segmentation**: class passengers exhibited higher churn rates compared to class travelers, suggesting greater price and service sensitivity among the former segment.
4. **Route and temporal patterns**: Specific city pair combinations and particular days of the week showed elevated churn rates, indicating localized service challenges or intense competitive pressures.

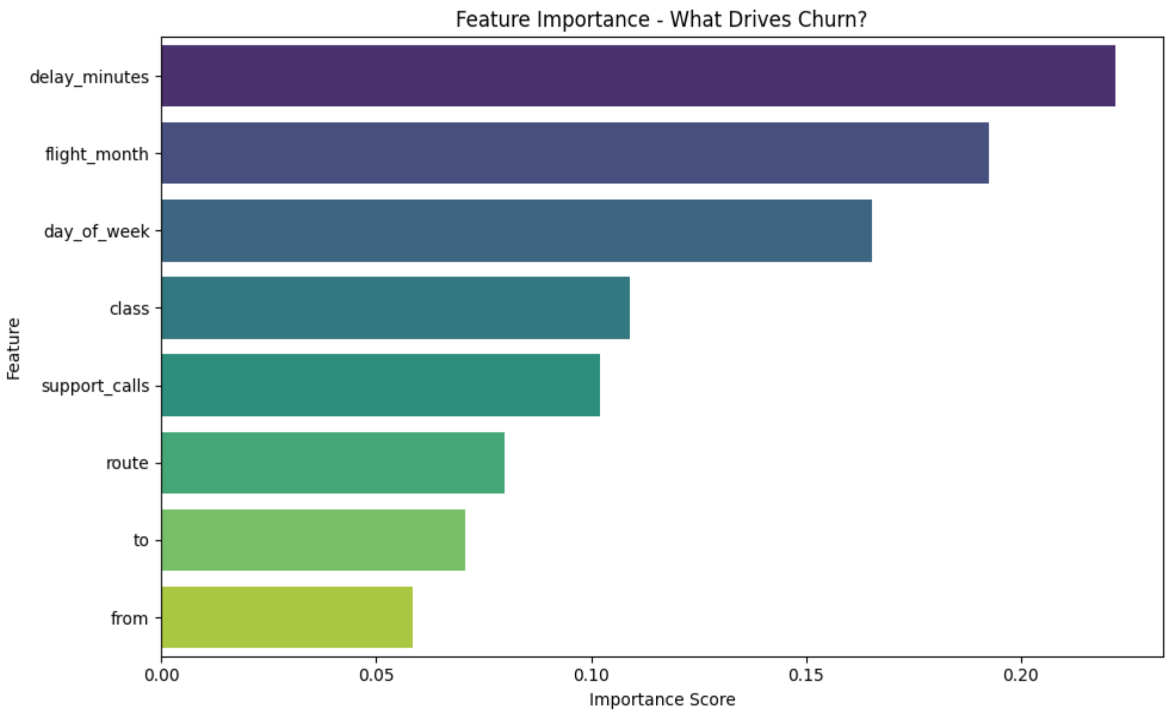

Fig 5. Feature Importance

Business Applications and Strategic Implications

Operational Recommendations

The machine learning insights generate several actionable recommendations for Nigerian aviation operators:

- **Predictive dashboard implementation**: Airlines should integrate churn prediction capabilities into existing Customer Relationship Management (CRM) systems, enabling real-time identification of at-risk passengers and automated alert generation for retention teams.
- **Targeted loyalty programs**: High-risk passengers identified through the predictive model should receive personalized retention offers, including route-specific discounts, upgrade opportunities, and enhanced service recovery protocols.

- **Service recovery automation**: Airlines should implement automated follow-up procedures for passengers affected by delays or service disruptions, particularly focusing on economy class travelers who demonstrate higher churn sensitivity.
- **Operational enhancement focus**: Churn prediction insights should guide operational improvements, with particular attention to delay reduction on high-risk routes and enhanced customer service training for support staff.

Strategic Business Impact

The implementation of machine learning-driven retention strategies offers multiple strategic advantages:

- **Revenue protection**: Proactive identification of at-risk customers enables targeted retention investments that protect existing revenue streams more cost-effectively than customer acquisition programs.
- **Service quality optimization**: Understanding the specific factors that drive customer churn allows airlines to prioritize operational improvements with the highest retention impact.
- **Competitive positioning:** Data-driven customer retention capabilities provide competitive advantages in Nigeria's crowded aviation market by enabling more responsive and personalized customer service.
- **Resource allocation efficiency:** Predictive analytics enable more efficient allocation of retention resources by focusing efforts on passengers with the highest churn probability and lifetime value potential.

Technical Implementation Considerations

The proposed system architecture leverages Python and its ecosystem (Pandas, NumPy, Skit-learn,Seaborn, etc) for accessibility and scalability. The Random Forest algorithm provides a suitable balance of performance and computational efficiency for integration with existing Nigerian airline infrastructure. Future deployment would involve containerization (e.g., Docker) and API integration to serve predictions in real-time.

Limitations and Future Research Directions

Current Study Limitations:

- **Sample size constraints**: The dataset of approximately 200 passenger records, while sufficient for proof-of-concept development, represents a limited sample that may not capture the full diversity of Nigerian aviation market and passenger behavior.
- **Temporal scope**: The analysis focuses on a specific time period and may not account for seasonal variations, economic fluctuations, or evolving market conditions that influence passenger behavior. Take for instance, the market curve and passenger behavior during festive seasons differ greatly from other seasons of the year in Nigeria.
- **Feature limitations**: While the selected variables provide strong predictive power, additional factors such as passenger demographics, loyalty program participation, and external economic indicators could enhance model accuracy.

Future Research Opportunities

- **Expanded Dataset Analysis**: Larger, multi-airline datasets could provide more comprehensive insights into industry-wide churn patterns and competitive dynamics.
- **Advanced Algorithm Exploration**: Investigation of deep learning approaches, ensemble methods, and specialized time-series algorithms could improve prediction accuracy and capture more complex behavioral patterns.
- **Integration with External Data**: Incorporation of economic indicators, weather patterns, and competitive pricing data could enhance model sophistication and practical applicability.
- **Real-Time Implementation Studies**: Research focused on operational deployment challenges and real-time performance optimization would provide valuable implementation guidance.

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CONCLUSION

This research proves that machine learning is a powerful tool for helping Nigerian airlines hold on to their customers. The model successfully pinpointed the main reasons passengers leave flight delays, their experience with customer service, and even the type of ticket they bought. The model is a practical tool that helps airlines get ahead of the problem. When the model says a passenger is a churn risk, it's right 73% of the time, which means marketing teams can be very confident in their targeted retention campaigns.

Ultimately, these findings give airlines information they can act on. Instead of just reacting to problems, they can proactively use this technology to improve the entire customer experience, which protects their revenue, keeps passengers happy, and makes sure resources are used wisely.

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