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Cargo Revenue Prediction in Nigeria Using Machine Learning: An Ensemble Regression Approach

OLORUNDA SEYI PHILEMON[1], IDOWU PETER ADEBAYO[2], AWOSOLA ADEOLUWA SAMUEL[3]

[1,3]*Dept. of Computer Science, Gateway ICT Polytechnic, Saapade, Ogun-State*

[2]*Dept. of Computer Science, Lead City University, Ibadan, Oyo state, Nigeria*

Abstract- ***The cargo business forms the backbone of global trade and national economies, yet revenue forecasting in emerging markets like Nigeria remains highly challenging due to infrastructural deficiencies, regulatory inconsistencies, fuel volatility, port congestion, and seasonal disruptions. The global freight transport market was valued at approximately $19.34 trillion in 2023 and is projected to reach $28.65 trillion by 2030 (International Transport Forum, 2024). In Nigeria, the freight and logistics market stood at USD 60.22 billion in 2022 and continues to grow rapidly (Verified Market Research, 2022; Mordor Intelligence, 2023). Traditional forecasting approaches, reliant on historical benchmarking and linear models, achieve only 65–75% accuracy under stable conditions and deteriorate sharply during volatility (Christopher, 2022; McKinsey & Company, 2023). This study develops and prototypes a localized machine learning framework for cargo revenue prediction tailored to Nigeria's unique operational realities. Drawing on transactional data from selected Nigerian logistics operators, the research (i) identifies context-specific predictors, (ii) designs a conceptual model integrating Nigerian-specific variables (road conditions, fuel scarcity, port dwell times, and regulatory factors), (iii) evaluates model performance, and (iv) implements a functional prototype decision-support system. By bridging the gap between imported global models and local conditions, the framework delivers significantly higher predictive accuracy than conventional methods. The findings offer practical tools for revenue optimization, resource allocation, and risk reduction, while contributing to the literature on data-driven logistics in developing economies. Limitations include regional data scope and handling of missing values. Future extensions will incorporate macroeconomic indicators and multi-firm datasets.***

Index Terms- ***Cargo Revenue Prediction, Machine Learning, Nigerian Logistics, Emerging-Market Forecasting, Predictive Analytics, Ensemble Regression, Supply-Chain Resilience***

I. INTRODUCTION

1.1 Background to the Study

The dynamic landscape of global commerce relies heavily on cargo businesses, which serve as one of the principal backbones of international trade by enabling the seamless movement of goods across national borders and connecting markets worldwide. These businesses spanning maritime shipping, road transportation, air freight, and rail networks form a complex, interdependent ecosystem that underpins global supply chains. The economic significance of the cargo industry cannot be overstated: the global freight transport market was valued at approximately $19.34 trillion in 2023 and is projected to reach $28.65 trillion by 2030 (International Transport Forum, 2024). According to the World Bank's Logistics Performance Index, improvements in cargo efficiency are closely linked to national economic growth, with a 10% increase in logistics performance correlating with a 0.5% rise in GDP across developing economies (World Bank, 2023).

Within this expansive industry, revenue prediction plays a pivotal role in strategic planning, resource allocation, and business sustainability. Over the past few decades, the cargo and logistics sector has undergone substantial transformation driven by globalization, technological innovation, evolving consumer expectations, and regulatory evolution (Kumar & Singh, 2021). Traditionally, cargo businesses approached revenue forecasting through historical benchmarking, seasonal adjustments, and market intelligence. While structured, these methods were largely dependent on human judgment and lacked the analytical precision required to consider multiple dynamic factors concurrently, typically achieving accuracy rates of only 65–75% under stable conditions (Christopher, 2022).

The limitations of traditional forecasting have become increasingly apparent amid mounting volatility. Global events such as the 2008 financial crisis, the 2020 COVID-19 pandemic, and the 2021 Suez Canal blockage exposed the fragility of linear models, with forecast errors reaching 30–40% during disruptions (McKinsey & Company, 2023; Wang et al., 2022). The early 2000s marked a paradigm shift toward data-driven decision-making, accelerated by Enterprise Resource Planning systems and the emergence of machine learning (ML) technologies. ML algorithms now enable detection of complex, nonlinear relationships across vast datasets, delivering up to 22% higher forecast accuracy than traditional statistical methods and 3–5% gains in overall profitability (Zhang & Johnson, 2023; PwC, 2024). Today, approximately 65% of large logistics firms deploy ML in financial forecasting (Deloitte, 2024).

This research explores the application of machine learning techniques to cargo revenue prediction in Nigeria, integrating domain-specific knowledge to enhance decision-making in an increasingly data-rich but contextually volatile environment.

1.2 Statement of the Problem

The freight and logistics sector in Nigeria represents a pivotal engine of economic development, trade facilitation, and national mobility. The Nigerian freight and logistics market was valued at approximately USD 60.22 billion in 2022 and is projected to experience substantial growth by 2028, driven by rapid urbanization, population expansion, and e-commerce (Verified Market Research, 2022; Mordor Intelligence, 2023). Despite this outlook, logistics firms continue to face significant revenue instability resulting from infrastructural deficiencies, bureaucratic customs processes, unpredictable cost structures, port congestion, erratic fuel pricing, informal cargo handling, and regulatory inconsistencies.

While machine learning models have been successfully deployed for cargo revenue prediction in advanced economies, their direct application in Nigeria remains limited and largely ineffective (Martin et al., 2020; Samuel, 2020). Imported models, trained on highly structured, data-rich environments in Europe, North America, and Asia, fail to generalize because they omit critical Nigerian-specific variables such as inadequate road networks, seasonal fuel scarcity, traffic gridlock, and informal practices. Consequently, existing frameworks produce unreliable results and limit practical adoption among Nigerian freight operators. There is thus a pressing need for a localized, context-aware machine learning model capable of capturing the complex interplay of infrastructural, socio-economic, and behavioral factors unique to Nigeria's freight environment.

1.3 Aim and Objectives of the Study

The aim of this study is to develop and prototype a predictive machine learning model for cargo revenue forecasting in Nigeria based on locally relevant operational and environmental factors. The specific objectives are to: i. elicit knowledge about the factors associated with cargo business revenue prediction and collect relevant data; ii. design a conceptual model for cargo revenue prediction; iii. evaluate the performance of the model; and iv. prototype the model as a decision-support system for Nigerian cargo operators.

1.4 Significance of the Study

Accurate revenue prediction can facilitate timely business interventions, improve profit margins, reduce financial risks, and support data-driven strategies for financial planning and operational efficiency. The developed framework offers valuable decision support for business managers, logistics planners, and policymakers in Nigeria's critical cargo sector.

1.5 Scope of the Study This study focuses exclusively on revenue prediction in the cargo business sector and does not cover expenditure forecasting or detailed revenue streams by cargo category or transport route.

1.6 Limitations of the Study Limitations include: (i) the dataset was drawn from selected cargo logistics companies operating within specific regions of Nigeria and may not fully represent the entire industry; and (ii) missing values were addressed through median imputation for numeric variables and placeholder labels for string variables.

1.7 Structure of the Paper The remainder of the paper is organized as follows: Section 2 reviews relevant literature and theoretical foundations; Section 3 details the research methodology; Section 4 presents results and discussion; and Section 5 concludes with recommendations and future research directions.

II. LITERATURE REVIEW

2.0 Introduction This chapter presents a comprehensive review of literature on revenue prediction in the cargo business sector, with particular emphasis on machine learning applications. It clarifies key concepts, examines theoretical frameworks, reviews empirical studies (global and Nigerian), and identifies research gaps that the present study addresses.

2.1 Conceptual Review The conceptual foundation rests on three interrelated pillars: Cargo Business Definition and Scope (CBDS), Freight Classification Framework (FCF), and Strategic Economic Positioning (SEP).

Cargo business is conceptualized as a comprehensive commercial ecosystem responsible for the multimodal movement of goods, extending beyond transportation to include freight forwarding, cargo handling, and warehousing (Adenigbo et al., n.d.). The Freight Classification Framework employs dual categorization—by mode of transport (air, ocean, ground, multimodal) and by nature (containerized, bulk, break-bulk, Ro-Ro, specialized project cargo)—to reflect diverse cost structures and logistical demands (Meiwell et al., n.d.; Notteboom et al., n.d.). Strategic Economic Positioning recognizes cargo as an economic multiplier contributing to GDP growth, employment, and trade facilitation in Nigeria (Ndalu&Umennaihe, n.d.).

2.1.1 Cargo Business: Definition and Operational Dimensions Cargo business in Nigeria operates as a multi-layered network linking producers, distributors, and consumers. Modal classification distinguishes air freight (speed for high-value goods), ocean freight (backbone of international trade), ground freight (dominant for domestic logistics despite constraints), and multimodal operations. Cargo nature classification further differentiates handling requirements (Ayemenre, n.d.).

2.1.2 Advantages and Common Challenges Advantages include economic growth, employment generation, growing market potential (3.67% annual air freight growth), profitability of air cargo, reduced warehousing needs, technological advancements, export diversification, and Nigeria's strategic location as a West African hub (Ndalu&Umennaihe, n.d.).

Common challenges constraining performance and forecasting accuracy are poor infrastructure, high transportation costs, delays and inefficiencies, lack of transparency, security risks, limited reliable operators, and complex government regulations (various sources cited in thesis).

2.1.3 How Cargo Business Works The operational workflow—client booking, packaging/documentation, customs clearance, transportation, tracking, delivery, and payment—introduces cost and time variables that must be captured in predictive models.

2.2 Conceptual Framework The study's conceptual framework comprises four interlinked pillars: Revenue Generation, Economic Positioning, Predictive Modeling, and Framework Integration/Application. Revenue streams (core freight, operational, documentation, value-added, ancillary) are influenced by demand-side, supply-side, and market-structure determinants. Economic positioning views cargo as a direct, indirect, and strategic value creator. The predictive modeling pillar integrates historical performance, operational variables, and external factors within a hybrid statistical-ML approach. Integration principles emphasize variable selection, feature engineering, interpretability, and business application. Limitations of the framework (abstraction of institutional frictions, omitted variables, bounded rationality, extreme disruptions) are acknowledged.

2.3 Theoretical and Empirical Foundation of Machine Learning in Revenue Prediction The study is anchored on three complementary theories: • Demand–Supply Theory in Transportation (Rodrigue & Zakaria, n.d.): Freight demand is derived from economic activity and sensitive to generalized transport costs; supply elasticity in Nigeria is constrained by infrastructure under-investment, leading to revenue volatility. Equilibrium shifts directly affect pricing and throughput. • Revenue-Management Theory: Supports dynamic pricing and yield optimization under capacity constraints. • Statistical-Learning Theory: Provides the mathematical basis (empirical risk minimization, bias–variance trade-off) for algorithm selection and validation.

Empirical evidence shows ML ensembles outperform traditional methods globally, yet Nigerian studies remain scarce and largely reliant on non-localized models (Martin et al., 2020; Samuel, 2020; Accenture, 2023). This research bridges the gap by developing a context-aware ML framework that incorporates Nigeria-specific variables omitted in prior work.

III. RESEARCH METHODOLOGY

3.1 Research Design This study adopted a quantitative predictive modelling design within the positivist paradigm. The research followed a structured machine learning pipeline to develop, train, evaluate, and prototype a context-aware revenue prediction system tailored to Nigerian cargo operations.

3.2 Data Collection and Description Transactional data comprising 1,133 complete shipment records were obtained from a major Nigerian logistics operator (Evergreen Logistics) operating primarily in Lagos and surrounding corridors (2021–2023). The dataset included the target variable Total Revenue (₦) and the following features:

- Kilo (KG) – shipment weight
- Rate (₦/kg) – charged rate per kilogram
- Load – sequential load identifier
- Name – client category (corporate, individual, government)
- Destination – major route (Lagos–Abuja, Lagos–Port Harcourt, etc.)
- Payment Method – cash, bank transfer, POS
- Month and Year (derived from shipment date)

These variables directly reflect the operational realities highlighted in the literature (port congestion, fuel volatility, route-specific constraints, and client behaviour).

3.3 Data Preprocessing

- Missing numeric values were imputed using median (robust to outliers).
- String-type missing values received appropriate placeholder labels.
- Categorical features were encoded using a combination of label encoding and one-hot encoding.
- Numerical features were standardized using StandardScaler.
- The dataset was randomly split into 80% training and 20% testing sets. No class imbalance existed as this is a regression task.

3.4 Machine Learning Models Four supervised regression algorithms were implemented in Google Colab using scikit-learn:

1. Gradient Boosting Regressor (GBR) – iterative residual correction for capturing complex non-linear interactions.
2. Random Forest Regressor (RFR) – bagging ensemble of decision trees to reduce variance.
3. Decision Tree Regressor (DTR) – baseline single-tree model.
4. SAMIRA – custom Stacked Adaptive Multi-Input Regression Algorithm (hybrid stacking + boosting ensemble developed for this study).

Hyperparameters were tuned via GridSearchCV with 10-fold cross-validation.

3.5 Model Training and Validation Models were trained on the scaled training set. Robustness was assessed through 10-fold cross-validation and a strict temporal validation check (training on 2021–2022 data, testing on 2023).

3.6 Performance Evaluation Metrics The following metrics were used:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |yi - yi|$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} (yi - yi)\,2, RMSE = \sqrt{MSE}$$

3.7 Prototype Development A functional mobile/web decision-support prototype named CargoRevAPP was developed. The backend (Flask + Python) hosts the best-performing model. The Android frontend (Kotlin + Retrofit) allows field operators to input shipment details and receive instant revenue forecasts. The system includes a dashboard for seasonal trend visualisation and “what-if” scenario analysis.

IV. RESULTS AND DISCUSSION

4.1 Exploratory Data Analysis The dataset comprises 1,133 transactional shipment records from a major Nigerian cargo logistics operator (primarily operating in Lagos and key corridors, spanning 2021–2023). The target variable, Total Revenue (₦), exhibits a right-skewed distribution typical of revenue data in emerging-market logistics: mean ≈ ₦580,629, median ≈ ₦130,000, with notable high-value outliers reflecting large corporate or bulk shipments.

Key insights from exploratory analysis include:

- A very strong positive linear correlation between Kilo (KG) (shipment weight) and Total Revenue (Pearson r ≈ 0.92), confirming weight as the primary revenue driver.
- Rate (₦/kg) shows clustering around common tariff levels (e.g., ₦2,000/kg for standard loads), with variability tied to route, client type, and seasonality.
- Clear seasonal patterns emerge: revenue peaks in January (post-holiday recovery and new-year contracts), August, and September (end-of-rainy-season surge in agricultural and construction cargo). These align with Nigeria's economic calendar, festive periods, and harvest cycles.
- Corporate clients and high-demand routes (e.g., Lagos–Abuja, Lagos–Port Harcourt) consistently generate higher average revenues compared to individual or shorter-haul shipments.
- Payment method and load identifier reveal behavioral patterns: bank transfers correlate with larger, more predictable revenues, while cash payments show higher variance.

These findings underscore the need for models that capture nonlinear interactions, seasonality, and Nigeria-specific operational factors (e.g., route congestion, client segmentation) absent in global standardized datasets.

4.2 Model Performance Comparison Four regression models were evaluated on the 20% hold-out test set after 80/20 stratified split, preprocessing (median imputation, categorical encoding, standardization), and 10-fold cross-validation for robustness. Performance metrics are summarized in the table below:

Model	MSE (₦²)	RMSE (₦)	MAE (₦)	R²
Gradient Boosting Regressor (GBR)	2,740,552,680	52,350	11,213	0.9989
SAMIRA (Custom Hybrid Ensemble)	3,922,296,282	62,628	22,737	0.9984
Random Forest Regressor (RFR)	7,161,241,078	84,624	16,433	0.9970
Decision Tree Regressor (DTR)	152,187,519,901	390,112	26,536	0.9937

Gradient Boosting Regressor (GBR) delivered the superior performance, with near-perfect explanatory power (R^2 = 0.9989) and very low absolute errors relative to mean revenue (~2% MAE). Cross-validation confirmed stability (mean $R^2 \approx 0.9969$ across folds), with minimal overfitting. Actual-vs-predicted scatter plots showed tight clustering along the identity line, even for outlier high-revenue shipments. SAMIRA (the custom hybrid) performed competitively but was outperformed by standard GBR in generalization. Random Forest and single Decision Tree showed higher errors, particularly on seasonal peaks and extreme values, highlighting the advantage of sequential error correction in boosting methods.

4.3 Interpretation of the Best Model Feature importance analysis (via built-in GBR importance scores and SHAP values) ranked predictors as follows:

1. Kilo (KG) — dominant driver (~45–50% contribution), capturing volume-based pricing.
2. Rate (₦/kg) — strong influence on per-unit value.
3. Month (seasonal component) — explains cyclical fluctuations.
4. Destination and Client Category — reflect route-specific costs/congestion and bargaining power.
5. Payment Method and Load — secondary but meaningful for behavioral and operational nuance.

SHAP summary plots revealed that high kilo values consistently push predictions upward, while off-peak months and shorter/less congested routes pull them downward—patterns that align closely with Nigeria's logistics realities (e.g., rainy-season delays, fuel-price spikes affecting rates).

4.4 Discussion The exceptional performance of Gradient Boosting ($R^2 > 0.998$) substantiates the core hypothesis: localized ensemble machine learning, trained on real Nigerian transactional data, substantially outperforms traditional linear/statistical methods (typically 65–75% accuracy under stable conditions) and imported global models that ignore context-specific variables like port dwell times, informal practices, regulatory delays, and seasonal fuel scarcity.

This aligns with broader literature trends: AI/ML-driven forecasting in logistics reduces errors by 20–50% compared to traditional approaches, with achievable accuracies of 85–95% in optimized settings. The present results exceed these benchmarks due to the incorporation of domain-relevant features, yielding errors far below the 30–40% reported during volatile periods in global studies.

Practically, the model enables Nigerian operators to:

- Forecast monthly/quarterly revenues with high confidence for budgeting and cash-flow management.
- Simulate "what-if" scenarios (e.g., rate adjustments during peak seasons or route changes).
- Support dynamic pricing and capacity planning amid infrastructure constraints.

The CargoRevAPP prototype further bridges theory and practice: real-time predictions via mobile interface empower field managers to make data-informed decisions, addressing adoption barriers in resource-constrained emerging markets.

Compared to prior African/Nigerian studies (often limited to macroeconomic aggregates or non-localized ML), this work provides the first demonstrated high-accuracy, prototype-ready framework tailored to transactional cargo data. Limitations remain (single-operator dataset, regional focus, potential unmodeled external shocks like policy changes), but results offer a scalable foundation for multi-firm extensions.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Key Findings This study successfully developed and evaluated a localized machine learning framework for cargo revenue prediction in Nigeria, addressing the critical gaps in traditional forecasting methods and imported global models. Using real transactional data from a major Nigerian logistics operator (1,133 shipment records, 2021–2023), the research identified key predictors including shipment weight (Kilo), rate per kg (Rate), seasonal factors (Month), route (Destination), client category, and payment method.

Four regression models were implemented and rigorously evaluated: Gradient Boosting Regressor (GBR), Random Forest Regressor (RFR), Decision Tree Regressor (DTR), and the custom hybrid SAMIRA ensemble. Gradient Boosting Regressor emerged as the superior model, achieving exceptional performance on the test set (R^2 = 0.9989, RMSE = ₦52,350, MAE = ₦11,213, MSE = ₦2.74 billion). This represents near-perfect explanatory power and low absolute errors (~2% of mean revenue), far surpassing the 65–75% accuracy of conventional methods under stable conditions and the 30–40% errors during volatility reported in global studies.

Exploratory analysis revealed strong kilo-revenue correlation ($r \approx 0.92$), seasonal peaks in January, August, and September (aligned with economic cycles, festive demand, and post-rainy-season recovery), and route/client-specific patterns reflecting Nigeria's infrastructural and behavioral realities. SHAP interpretability confirmed the model's ability to capture nonlinear, context-specific interactions omitted in non-localized frameworks.

The developed CargoRevAPP prototype (Flask backend + Android frontend) translates these results into a practical, real-time decision-support tool, enabling operators to forecast revenues, simulate scenarios, and optimize pricing/capacity in under five seconds.

5.2 Theoretical and Practical Contributions Theoretically, this work extends statistical learning theory and revenue-management principles to emerging-market logistics by demonstrating the superiority of ensemble boosting in volatile, data-constrained environments. It bridges demand–supply theory with ML by incorporating Nigeria-specific frictions (e.g., fuel scarcity, port congestion, informal practices), advancing the discourse on context-aware predictive analytics in developing economies.

Practically, the framework delivers measurable value: enhanced forecast accuracy supports better budgeting, cash-flow management, dynamic pricing during peaks, and risk mitigation amid infrastructure challenges. For Nigerian cargo operators, adoption could improve profitability (potentially 3–5% as per global benchmarks) and operational resilience. The prototype lowers barriers to ML adoption for SMEs, providing a scalable blueprint replicable across West African logistics ecosystems.

5.3 Policy and Managerial Recommendations

- For Logistics Operators and Managers: Integrate GBR-based forecasting into ERP systems; prioritize seasonal planning around identified peaks; use route/client segmentation for targeted pricing; pilot CargoRevAPP for field-level decisions to reduce revenue volatility.
- For Policymakers and Regulators: Promote standardized digital data collection in the sector to enable broader ML applications; incentivize ML/AI adoption via tax credits or training programs for SMEs; invest in infrastructure (roads, ports, rail) to reduce unmodeled volatility and enhance model generalizability.
- Industry Stakeholders: Collaborate on multi-firm datasets to build national benchmarks; explore integrations with macroeconomic indicators (e.g., fuel prices, inflation) for hybrid forecasting.

5.4 Limitations The study relied on data from one major operator in specific Nigerian regions (primarily Lagos corridors), limiting full national representation. Missing values were handled via median imputation and placeholders, which may introduce minor bias. External shocks (e.g., policy changes, global oil fluctuations) were not explicitly modeled, though seasonality partially captured some dynamics. The prototype focuses on revenue prediction only, excluding expenditure or multi-modal breakdowns.

5.5 Directions for Future Research Future extensions should:

- Expand to multi-operator, nationwide datasets for improved generalizability.
- Incorporate real-time external variables (fuel prices, GDP, exchange rates, weather) via API integrations.

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- Explore deep learning (e.g., LSTM for time-series) or hybrid AI models for longer horizons.
- Validate the prototype in live operations across SMEs and assess ROI.
- Investigate explainable AI enhancements (e.g., advanced SHAP) for regulatory compliance and trust-building.

In conclusion, this research demonstrates that context-tailored machine learning—particularly gradient boosting—offers a transformative, high-accuracy solution for cargo revenue prediction in Nigeria's challenging logistics landscape. By bridging empirical gaps and delivering a deployable prototype, the study paves the way for data-driven resilience, efficiency, and growth in an emerging-market sector vital to national development.

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