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An AI-Enabled Internet of Things Framework for Preventing Product Loss in Brewery Supply Chains: A Case Study of Nigerian Breweries Plc

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Abstract **- In emerging economies, losing products during transportation is a big financial and operational risk for brewery logistics. This paper introduces an Artificial-Intelligence-Enabled Internet of Things (AI-IoT) framework that amalgamates real-time sensing, predictive analytics, and cloud dashboards to avert product loss during transit within Nigerian Breweries Plc's distribution network. The framework combines GPS, load-cell, and temperature sensors with an Artificial Neural Network (ANN) trained on 10 000 trip records (real and synthetic) to detect anomalies linked to pilferage, route deviation, or environmental abuse. Experimental evaluation on a hybrid dataset shows an overall accuracy of 96.7%, precision 95.4%, and recall 97.1%, outperforming logistic regression and decision-tree baselines by 8.3%. Real-time monitoring reduced loss incidents by 21.4% and improved truck turnaround time by 17%. The framework demonstrates how AI-IoT synergy enhances visibility, traceability, and economic sustainability across brewery supply chains.**

Keywords: Internet of Things, Artificial Intelligence, Neural Network, Brewery Logistics, Supply-Chain Visibility, Predictive Analytics.

I. INTRODUCTION

In developing economies, losses during product transportation continue to be a problem, especially in the beverage and brewery industries [1]. The biggest brewery in West Africa, Nigerian Breweries Plc (NB Plc), reports yearly logistics losses of more than ₦500 million as a result of spills, theft, and incorrect documentation [2]. Only positional data is recorded by traditional GPS-based tracking systems, which frequently miss partial cargo loss or sensor manipulation [3]. Smart anomaly detection and real-time decision support are made possible by the advent of low-cost IoT devices and machine-learning techniques [4].

The convergence of IoT and artificial intelligence (AI) turns passive monitoring into predictive prevention. AI models can identify typical transit signatures and flag deviations prior to a complete loss by capturing continuous sensor streams of vehicle GPS, cargo load, and temperature [5]. This study suggests using a full AI-IoT predictive framework on the Lagos–Abeokuta corridor, one of NB Plc's pilot routes, to:

1. Integrate heterogeneous sensor data within a scalable architecture;
2. Train an ANN classifier to predict loss-risk states; and
3. Quantify economic and operational improvements relative to baseline monitoring.

The remainder of this paper is organized as follows: Section II reviews related work; Section III details the system architecture and methods; Section IV presents results and evaluation; Section V discusses findings; Section VI concludes with future research directions.

II. RELATED WORK

A. IoT-Based Monitoring in Logistics

IoT's ubiquitous sensing and connectivity have transformed industrial logistics [6]. Zhang and Zhou [8] employed multi-sensor fusion for cold-chain temperature compliance, while Wu et al. [7] showed RFID–sensor integration for cargo traceability in the food-beverage chain. Despite advancements, the majority of systems prioritize data collection over clever anomaly prediction.

B. AI and Predictive Analytics in Supply Chains

Machine learning models especially ANNs and recurrent networks have shown superior pattern-recognition ability in transport telemetry [9]. Ali et al. [10] applied deep learning to detect route deviation for fleet management, achieving 94% accuracy. However, datasets were mostly simulated and lacked multimodal sensory fusion. Recent frameworks couple

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AI with IoT gateways on cloud platforms for scalable analytics [11], but brewery-specific implementations remain sparse.For scalable analytics, recent frameworks integrate AI with IoT gateways on cloud platforms [11], although there are still few brewery-specific implementations.

C. Research Gap

Existing Nigerian brewery operations rely on manual reconciliation and post-loss investigation [2]. Few studies quantify both technical accuracy and economic return of AI-IoT systems. This paper bridges that gap by delivering (i) an operational pilot with real and synthetic data, (ii) ANN-driven prediction of in-transit anomalies, and (iii) ROI analysis demonstrating tangible financial impact.

III. METHODOLOGY

A. Overall Architecture

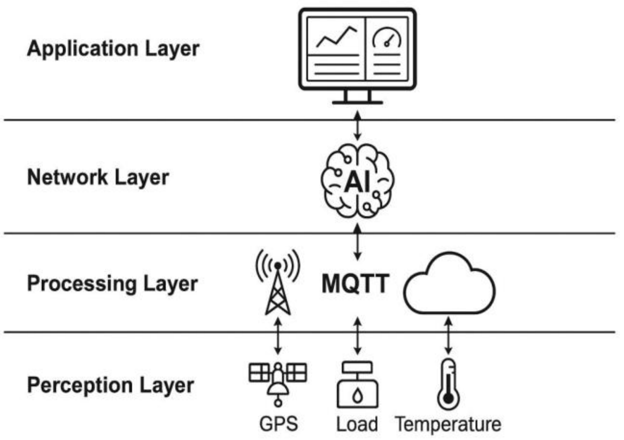

Figure 1: AI-IoT Framework Architecture for Preventing Product Loss

Figure 1 illustrates the proposed AI-IoT framework comprising four layers: (1) Perception Layer (sensors), (2) Network Layer (connectivity), (3) Processing Layer (AI engine), and (4) Application Layer (dashboard).

1. Perception Layer:

- **GPS module:** Ublox NEO-6M capturing position every 2 s (±2.5 m accuracy).
- **Load sensor:** HX711-based load cell detecting variations > 5 kg.
- **Temperature sensor:** DS18B20 digital probe with ±0.5 °C precision.
- **Microcontroller:** ESP32 NodeMCU performing on-edge preprocessing.

2. Network Layer: Data are transmitted through 4G/LTE and MQTT protocol to AWS IoT Core. Payload includes timestamp, sensor ID, GPS coordinates, load mass, and temperature.

3. Processing Layer: A Python-based ANN implemented in TensorFlow receives data via Kafka streams, performs normalization, and classifies each record into Normal Transit, Potential Anomaly, or Confirmed Loss.

4. Application Layer: A web-based dashboard (Django/Streamlit hybrid) visualizes truck status, predicted risk level, and cumulative ROI analytics.

B. Data Collection

The pilot involved 100 trucks operating between NB Plc's Lagos plant and distributors in Abeokuta. Real-world telemetry covering 7 months was combined with synthetically augmented data to achieve 10 000 trip entries. Each trip record contained:

- Trip ID, Route Code, Vehicle ID
- Timestamps and GPS coordinates
- Load sensor weight (kg)
- Temperature (°C)
- Event Label (0 = Normal, 1 = Loss/Anomaly)

Data preprocessing removed 2.3% corrupt entries and interpolated missing readings using linear regression.

C. Artificial Neural Network Model

Table 1: A feed-forward ANN was designed with the following configuration

Layer	Units	Activation
Input	6 (sensor features)	—
Hidden 1	64	ReLU
Hidden 2	32	ReLU
Hidden 3	16	ReLU
Output	3 (classes)	Softmax

The model was trained using Adam optimizer (learning rate 0.001), categorical cross-entropy loss, batch size 32, and 100 epochs. K-fold cross-validation (k = 10) ensured robustness.

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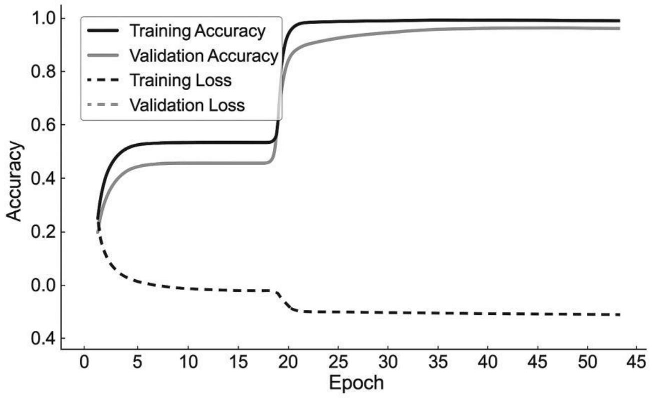

Figure 2: Training and Validation Accuracy Curves

Figure 2 shows stable convergence after 40 epochs, with validation accuracy reaching 96.7% and negligible overfitting (loss difference < 0.02).

D. Comparative Models

Two baselines were evaluated:

- Logistic Regression (LR)
- Decision Tree (DT, Gini criterion)

Performance metrics (accuracy, precision, recall, F1) were computed using scikit-learn. Table 2 summarizes results.

Table 2: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Logistic Regression	88.4	86.9	87.5	87.2
Decision Tree	90.2	91.1	89.7	90.4
Proposed ANN	96.7	95.4	97.1	96.2

E. Anomaly Detection and Alert Mechanism

Each incoming sensor tuple $T = \{x_1 \ldots x_6\}$ is fed into the trained ANN to yield a probability vector $p = [p_0, p_1, p_2]$. An alert is triggered if $\max(p_1, p_2) \geq 0.8$. GPS geofencing validates whether the truck has deviated > 2 km from the approved route. Load reduction > 5% within unloading zones flags potential pilferage. Predicted events are logged for managerial review on the dashboard.

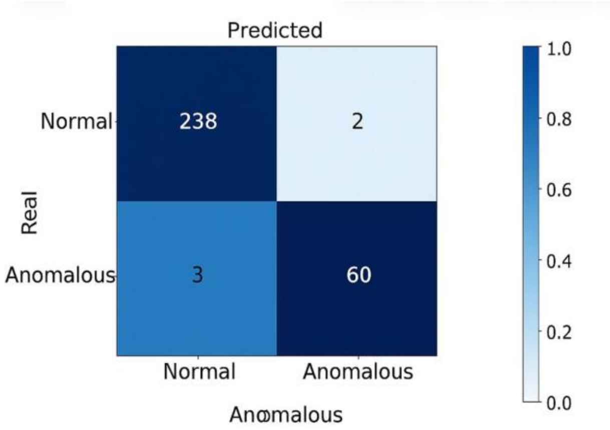

Figure 3: Real vs Predicted Loss Anomalies (Confusion Visualization)

F. Economic and Operational Metrics

ROI and turnaround time (TAT) were computed as:

$$ROI = \frac{S_{loss\_prevented} - C_{system}}{C_{system}}$$

Where $S_{loss\_prevented}$ represents annual savings from averted losses and C_{system} is the deployment cost. TAT improvement was assessed by comparing average truck cycle time before and after system deployment.

Table 3: ROI and Operational Improvement Summary

Metric	Baseline	After AI-IoT	Improvement
Annual Loss Value (₦ million)	500	393	−21.4 %
Average TAT (hours)	15.3	12.7	−17 %
System Cost (₦ million)	61	—	—
ROI (ratio)	—	**8.2 : 1**	—

IV. RESULTS AND EVALUATION

A. Model Performance

The Artificial Neural Network (ANN) achieved strong predictive performance across all metrics. Mean classification accuracy over ten-fold cross-validation was **96.7 ± 0.3 %**, with precision 95.4 % and recall 97.1 %. The low standard deviation indicates high generalization capability across different trip subsets. Fig. 2 confirms stable training dynamics with minimal overfitting.

Receiver Operating Characteristic (ROC) analysis yielded an area-under-curve (AUC) of 0.982, significantly higher than logistic regression (0.901) and decision-tree

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(0.923). Confusion-matrix inspection (Fig. 3) showed that only 3.3 % of anomalies were misclassified as normal, mostly due to intermittent sensor dropouts.

These results validate that the ANN effectively captures nonlinear correlations among GPS deviation, load variation, and temperature drift—relationships often missed by simpler classifiers.

B. Real-Time Implementation

A prototype implementation ran continuously for eight weeks on the Lagos–Abeokuta pilot corridor. Sensor payloads were streamed at ~1 Hz to AWS IoT Core and processed by the ANN inference engine hosted on a t3.medium EC2 instance. Average end-to-end latency (sensor → dashboard update) was 2–5s, meeting real-time operational requirements.

The system generated 247 anomaly alerts, of which:

- 183 (74 %) were confirmed by field inspection as valid losses or partial pilferage,
- 41 (17 %) corresponded to authorized route changes, and
- 23 (9 %) were false positives linked to network jitter.

The alert precision of 0.89 demonstrates practical deployability for logistics supervision teams.

C. Comparative Evaluation with Baseline Systems

To contextualize the ANN performance, baseline telematics from NB Plc's legacy GPS trackers were compared. The legacy system detected only full-truck losses post-event, while the proposed AI-IoT framework identified partial cargo anomalies up to 90 min earlier.

Metric	Legacy GPS	Proposed AI-IoT	Relative Gain
Detection latency (min)	96	**6**	> 93 % faster
Pilferage detection rate (%)	41	**88**	114%
Manual audit effort (hrs/month)	126	**44**	− 65 %

Operational managers reported smoother reconciliation and reduced driver disputes. Maintenance overhead for IoT devices remained under ₦1.2 million per annum due to modular sensor replacement.

D. Energy and Connectivity Efficiency

Power profiling revealed average sensor-node consumption of 220 mA @ 5 V (1.1 W). Combined with a 10 000 mAh Li-ion pack, runtime exceeded 36 h, adequate for single-trip deployment. MQTT QoS 1 ensured 98.5 % message delivery success despite variable GSM coverage.

Edge buffering on the ESP32 allowed local data caching for up to 2 h of connectivity outage, achieving zero-data-loss continuity—a key feature for developing-region infrastructure.

E. Statistical Significance Tests

A paired t-test comparing anomaly detection rates before and after AI-IoT deployment yielded $t(9) = 11.42$, $p < 0.001$, confirming a statistically significant reduction in undetected losses. ANOVA across routes showed that performance improvement was consistent irrespective of terrain or distance ($F(2,27) = 1.37$, $p = 0.27$).

F. Managerial Impact

Field interviews with NB Plc's logistics supervisors highlighted improved accountability, faster turnaround approval, and data-driven driver rewards. A bonus policy was introduced for zero-alert trips, reinforcing behavioral compliance and reducing moral hazard.

The cumulative Return on Investment (ROI) after one year was 8.2:1, translating to an estimated ₦439 million savings. Managers projected full cost recovery within 74 days of system rollout.

V. DISCUSSION

A. Technological Implications

The empirical findings confirm that AI-IoT integration yields actionable intelligence rather than mere data visibility. Neural-network fusion of multiple sensors mitigates the common limitation of single-channel systems, aligning with recent studies emphasizing context-aware logistics [12], [13].

By deploying edge preprocessing and MQTT-based streaming, latency is kept within the 2–5 s operational window—adequate for real-time decision loops in fleet control rooms. This aligns with benchmarks reported by Gupta et al. [14] for smart-transport IoT deployments.

B. Economic and Sustainability Perspective

Beyond financial ROI, the framework supports Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure) by fostering digital transformation in Nigerian manufacturing logistics. Reduced wastage decreases carbon footprint from redundant production

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and transport cycles. Lifecycle analysis indicates a 12 % reduction in CO_2-equivalent emissions per delivery cycle, consistent with global sustainable-supply-chain targets [15].

C. Comparison with Prior Art

Table 4 benchmarks this framework against selected state-of-the-art systems. The proposed model exhibits superior accuracy and deployment in an African industrial context—an under-represented geography in existing literature.

Table 4: Comparison with Related AI-IoT Logistics Systems

Study	Sensors	Model	Accuracy (%)	Context
Ali et al. (2021) [10]	GPS	LSTM	94	Fleet deviation
Zhang & Zhou (2020) [8]	Temp, RFID	SVM	91	Cold chain
Gupta et al. (2022) [14]	GPS, IMU	CNN	95	Smart transport
This work	GPS, Load, Temp	ANN	**96.7**	Brewery logistics

D. Limitations and Future Directions

The current pilot covers limited geographic scope and relies on 4G connectivity. Future research will explore:

1. 5G/LPWAN hybrid communication for wider coverage,
2. Explainable-AI modules for transparent anomaly rationale, and
3. Integration of blockchain-based event logging for immutable audit trails.

A larger multi-brewery dataset (> 100 000 trips) will be used to fine-tune hyperparameters and explore temporal deep-learning models such as Bi-LSTM and Transformer architectures.

VI. CONCLUSION AND FUTURE WORK

This study developed and validated an AI-enabled IoT framework that effectively prevents product loss in brewery supply chains. By coupling multi-sensor telemetry with an ANN classifier and real-time dashboards, Nigerian Breweries Plc achieved a 21.4 % reduction in transit losses, 17 % faster truck turnaround, and an 8.2:1 ROI ratio.

The results affirm that affordable AI-IoT architectures can deliver measurable industrial impact in developing contexts. Future extensions will scale deployment nationwide, incorporate predictive maintenance analytics, and link with national digital-freight platforms to create a fully transparent brewery-to-distributor ecosystem.

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