

Optimising Local Government Fiscal Efficiency: An Intelligent Internally Generated Revenue (IIGR) Model with Predictive Analytics and Secure Authentication for Ughelli North LGA of Delta State

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ABSTRACT

The optimization of Internally Generated Revenue (IGR) remains a critical administrative challenge for local government councils across Nigeria, where traditional cash-based and manual profiling systems are vulnerable to systemic leakages, opaque reporting, and high operational collection costs. This paper details the design and implementation of an Intelligent Internally Generated Revenue (IIGR) model customized for Ughelli North Local Government Area (L.G.A) in Delta State. The developed model addresses regional revenue challenges by digitizing enumeration workflows and unifying disparate fiscal collection categories—including market shop leases, commercial transport levies, trade licenses, and tenement rates—into a centralized cloud database architecture. Built using an object-oriented Python and MySQL database stack, the IIGR model features automated electronic notification loops, instant mobile revenue capture modules, and biometric vendor verification systems to eliminate informal cash handling. Crucially, the system integrates predictive statistical analytics to map and forecast revenue collections across the L.G.A.'s major economic hubs (such as Ughelli Main Market, Afiesere, and Evwreni), allowing administrators to identify tax evasions and track real-time collection patterns through an interactive executive dashboard. Security is enforced using secure hashing algorithms for tax records alongside Role-Based Access Control (RBAC) layers to protect data integrity and prevent unauthorized modifications to municipal accounts. Evaluation metrics demonstrate that the digital model reduces transaction confirmation times to sub-three second windows, simplifies auditing to a few mouse clicks, and minimizes administrative overhead with precision 96.7%, recall 95.5, F1 Score 96.1% and accuracy 95.8%. Ultimately, this study provides a scalable, transparent blueprint for smart local government administration, illustrating how automated technology can improve accountability, eliminate leakages, and strengthen financial independence in developing civic economies.

Keywords: Intelligent Revenue Models, Internally Generated Revenue (IGR), Local Government Administration, Cloud Database Architecture, Ughelli North L.G.A, Fiscal Leakages, Predictive Analytics.

1.0 INTRODUCTION

The financial independence of local government councils stands as a fundamental prerequisite for sustainable grassroots development within any federal system of governance. In Nigeria, the third tier of government is constitutionally mandated to drive socio-economic development, manage municipal market infrastructures, maintain rural roadways, and provide basic public health services [7]. However, local government areas (LGAs) across the federation suffer from a severe fiscal crisis, characterized by an over-reliance on statutory allocations from the Federation Account Allocation Committee (FAAC) through State Joint Local Government Accounts [19]. Within Delta State, and specifically in Ughelli North LGA—a highly populated and commercially active hub—this over-reliance leaves local administration vulnerable to macroeconomic shocks and fluctuating oil revenues. Consequently, optimizing Internally Generated Revenue (IGR) has emerged as a vital structural

avenue to restore municipal accountability and secure financial independence [14].

Ughelli North LGA is a key commercial and agricultural nerve center in Delta State, encompassing major economic nodes such as the Ughelli Main Market, Afiesere, Ewreni, Agbarho, and Orogun [4]. These regions generate intense informal and formal retail commerce, public transportation networks, artisanal manufacturing, and tenement holdings. Despite this rich tax base, the local government council's historical financial data reveals a stark disconnect between estimated economic activity and actual revenue collections [5] and [19]. The legacy operational framework relies completely on manual, paper-based workflows and semi-automated revenue systems [6]. Field collectors use printed tax receipt books, handwritten registers, and cash-based auditing systems to enforce compliance across disparate fiscal categories, including market shop leases, commercial transit levies (*keke* and commercial minibus stickers), trade licenses, and tenement rates [6] and [19].

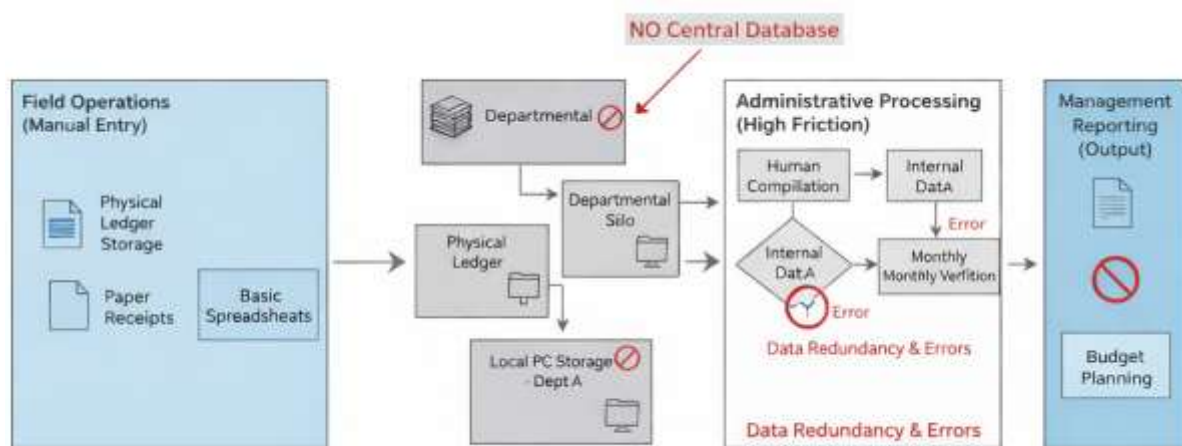


Figure 1: Operational paradigm legacy of the manual collection framework.

This manual approach introduces severe institutional limitations and financial leakages. Paper receipts are easily falsified by rogue collection agents, loose cash handlers divert funds before they reach the municipal treasury, and physical registries degrade rapidly, resulting in a loss of historical tax histories [2]. Furthermore, manual auditing is slow and prone to human errors, often requiring weeks of paperwork analysis to verify a single month's collections. Without a unified, real-time database, administrators lack the visibility to identify tax evasion, monitor field collectors, or trace revenue trends across different zones [2]. This lack of data prevents the council from designing accurate, long-term development budgets.

To eliminate these structural leakages and modernize local revenue generation, this study details the design and implementation of an Intelligent Internally Generated Revenue (IIGR) model customized for Ughelli North LGA [3],[4]. The IIGR architecture replaces informal cash streams with a centralized cloud database system developed using an object-oriented Python, Flask web framework, and MySQL database stack [5].

The developed model automates the entire revenue lifecycle: field enumerators register businesses and properties using biometrically verified profile metrics, while merchants settle tax liabilities via digital mobile transaction pathways that issue instant SMS and email notifications [5]. On the back end, the system integrates predictive statistical analytics. By tracking collection datasets against geographic markers, the platform maps out localized trends, flags collection anomalies, and projects future revenue matrices across distinct economic hubs through an interactive executive dashboard [11].

The remainder of this design project is structured as follows: Section 2: Literature Review and Theoretical Framework
Section 3: System Architecture and Methodology of the IIGR framework
Section 4: Implementation and System functional Modules
Section 5: Testing, Results, and Comparative Discussion
Section 6: Conclusion and Recommendations

2.0 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The modernization of public fiscal architecture requires a comprehensive understanding of traditional tax extraction challenges, contemporary digital payment pathways, and systemic vulnerabilities within municipal auditing workflows [8]. This section reviews literature published between 2021 and 2026 to evaluate traditional local government taxation models across West African micro-economies, trace the evolution of FinTech payment deployments in informal markets, and isolate critical gaps in automated Internally Generated Revenue (IGR) auditing frameworks [14].

2.1 Municipal Tax Extraction Challenges in West African Micro-Economies

Local government revenue collection in Sub-Saharan Africa, particularly within the third tier of governance in Nigeria, operates within a complex landscape dominated by informal retail trade, fragmented transport networks, and loose cash transactions [2], [1]. Research from 2023 to 2026 highlights that the historical dependence on manual paper-based workflows creates systemic structural deficits [4].

Traditional tax extraction faces three primary operational friction points:

The Identification Bottleneck: Municipal registries are frequently maintained in

handwritten logbooks. This lack of digital indexing makes it impossible for councils to maintain an accurate directory of active taxpayers, commercial stalls, and mobile paratransit operators across shifting rural-urban boundaries [15].

High Collection Overhead: The physical deployment of tax collectors to manually write paper receipts consumes significant administrative resources. Studies indicate that up to 35% of collected municipal fees are consumed by the operational costs of the manual collection process itself [16], [15].

The Compliance Deficit: Because taxpayers lack visibility into how their payments are processed or utilized,

resistance to local taxation remains high. This lack of transparency leads to widespread tax evasion among informal market actors [16] and [14].

2.2 FinTech and Mobile Payment Integration in Informal Markets

The rapid expansion of financial technology (FinTech) infrastructures across West Africa has provided municipal administrators with proven alternatives to cash-based transactions. Since 2022, the widespread adoption of agency banking, Point-of-Sale (PoS) terminals, and Unstructured Supplementary Service Data (USSD) channels has reshaped commercial transactions in informal marketplaces [17] and [18].

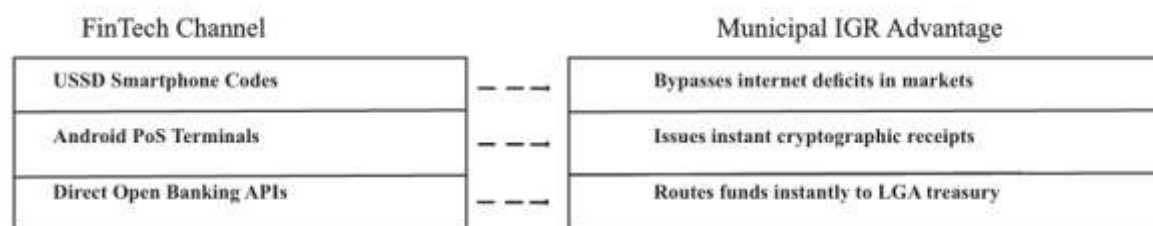


Figure 2: FinTech channel mapping and corresponding administrative advantages for municipal IGR collection.

The current literature categorizes the application of mobile payment models into three major architectural configurations:

Offline USSD Rail Systems: USSD frameworks enable rapid, text-based financial transfers that do not require continuous smartphone internet connectivity. This makes them highly resilient for market traders operating in areas with poor network coverage [17] and [15].

Android-Based Smart PoS Modules: Modern handheld PoS devices allow field revenue officers to scan merchant biometric cards, process immediate digital payments, and print hardcopy receipts that feature verifiable tracking metadata.

Direct Open-Banking APIs: By linking municipal software directly into commercial banking application programming interfaces (APIs), transaction confirmations trigger instant database updates. This automated routing ensures funds are deposited directly into the local government's single treasury account, removing middleman dependencies

2.3 Gaps in the Literature: Automated Local Government IGR Auditing

Despite the growing volume of general research on FinTech applications, a systematic review of the literature published up to 2026 reveals a critical gap at the municipal level. While substantial software documentation exists for state-

level and federal revenue platforms (such as the Federal Inland Revenue Service), local government software systems remain under-researched and poorly integrated [1]. There is an explicit lack of literature addressing local government IGR automation, specifically concerning three core operational requirements [1] and [2]:

2.3.1 Real-Time Cross-Verification Algorithms

Existing municipal payment scripts operate predominantly as isolated data entry logs. Current literature offers few solutions for automated, real-time cross-verification systems capable of matching live field collections against automated bank settlement feeds to instantly flag discrepancies or un-cleared cash deposits.

2.3.2 Low-Cost Biometric Vendor Indexing

While enterprise identity verification solutions rely on expensive biometric hardware, there is an absence of validated, open-source architectural frameworks that utilize standard smartphone cameras or low-cost finger-scanners to safely index

informal merchants within regional market grids.

2.3.3 Predictive Micro-Revenue Forecasting Models

Standard macro-economic modelling software requires massive, highly cleaned financial datasets that are rarely available in developing local government offices. Existing literature fails to provide lightweight, predictive statistical models optimized to run on low-power edge computers, which are necessary for identifying tax evasion patterns and forecasting weekly collections across distinct rural and urban market hubs.

3.0 SYSTEM ARCHITECTURE AND METHODOLOGY

By resolving these explicit technical gaps, this study develops a secure, biometrically verified, and analytically driven IGR framework, establishing a transparent deployment model for grassroots financial governance. Here is the diagram of the proposed framework depicting an Intelligent Internally Generated Revenue (IIGR) Framework

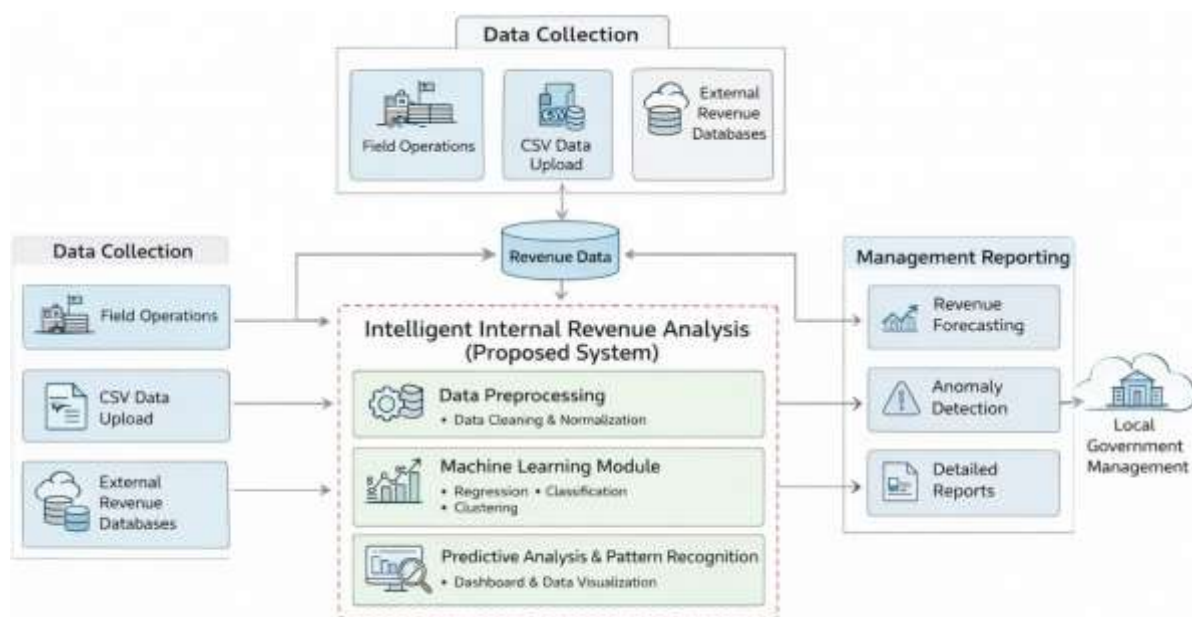


Figure 3: Structural block diagram of the proposed Intelligent Internally Generated Revenue Framework

The proposed Intelligent Internally Generated Revenue system adopts a modular and data-driven design. The system architecture consists of data input, pre-processing, Machine Learning analysis, and visualization modules. Each module performs a specific function, ensuring system efficiency and maintainability [9] and [11]. The data input module allows users to upload CSV files containing revenue records. The pre-processing module cleans and transforms the data to eliminate inconsistencies. The Machine Learning module applies suitable algorithms to analyze trends, identify patterns, and support basic revenue forecasting. Analytical results are presented through charts and tables using the Streamlit interface.

The proposed system improves revenue monitoring by providing timely analytical insights. It reduces human error, enhances transparency, and supports evidence-based decision-making. The system is flexible and can be extended to include additional analytical features in the future, making it suitable for intelligent revenue management in local governments.

Figure 3 presents the structural block diagram of the proposed Intelligent Internally Generated Revenue Framework. The diagram shows how revenue data flow from data collection sources into the intelligent analysis system. Key modules include data input, preprocessing, Machine

Learning analysis, and visualization. Unlike the existing system, the proposed structure emphasizes centralized data handling and analytical processing. This structure ensures that revenue data are systematically processed and transformed into meaningful insights that support transparency and efficiency in revenue management.

3.1 High-Level Model of the Proposed Framework

The high-level model illustrates the overall flow of the proposed intelligent revenue analysis system. It shows how uploaded revenue data are pre-processed, analyzed using Machine Learning techniques, and presented through a Streamlit-based interface to support effective revenue monitoring and decision-making.

Figure 4 depicts the high-level framework of the proposed system, showing the interaction between system components and data flow. The architecture adopts a layered design consisting of the data layer, processing layer, and presentation layer. Revenue data uploaded in CSV format are stored and processed using Python-based analytical modules, while results are presented through a Streamlit interface. This architecture supports scalability, modularity, and ease of maintenance. It also ensures clear separation of concerns between data handling, Machine Learning analysis, and user interaction.

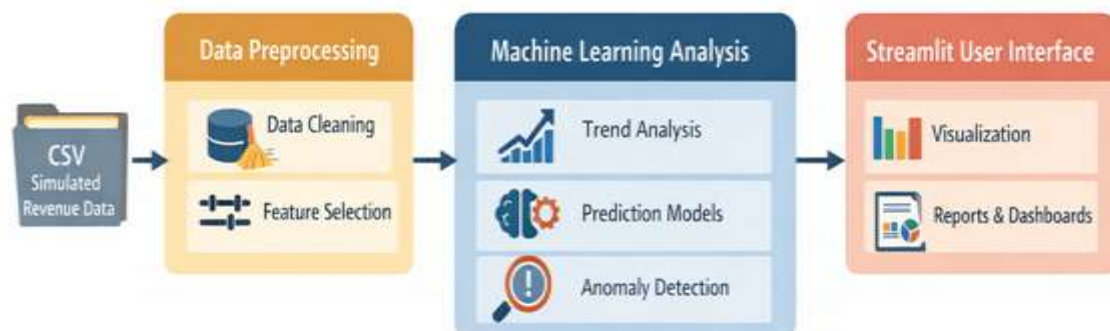


Figure 4: High-Level Model of the Proposed System

3.2 Flowchart of the proposed Intelligent Internally Generated Revenue (IIGR)Framework

Figure 5 shows the flowchart of the proposed Intelligent Internally Generated Revenue (IIGR) system. The flowchart illustrates the logical sequence of operations carried out by the system from start to end. It begins with user access to the system, followed by the upload of revenue data in CSV format. Once the data are uploaded, the system performs validation to ensure correctness and completeness. If the

data are valid, the system proceeds to the preprocessing stage, where data cleaning and normalization are carried out to prepare the dataset for analysis. The Machine Learning analysis stage then applies the selected algorithm to analyze revenue trends and generate insights. The results of the analysis are presented to the user through charts and tables on the system dashboard. If the uploaded data are invalid, the system prompts the user to re-upload the dataset. The flowchart ends with the user reviewing the analytical output, thereby supporting informed decision-making.

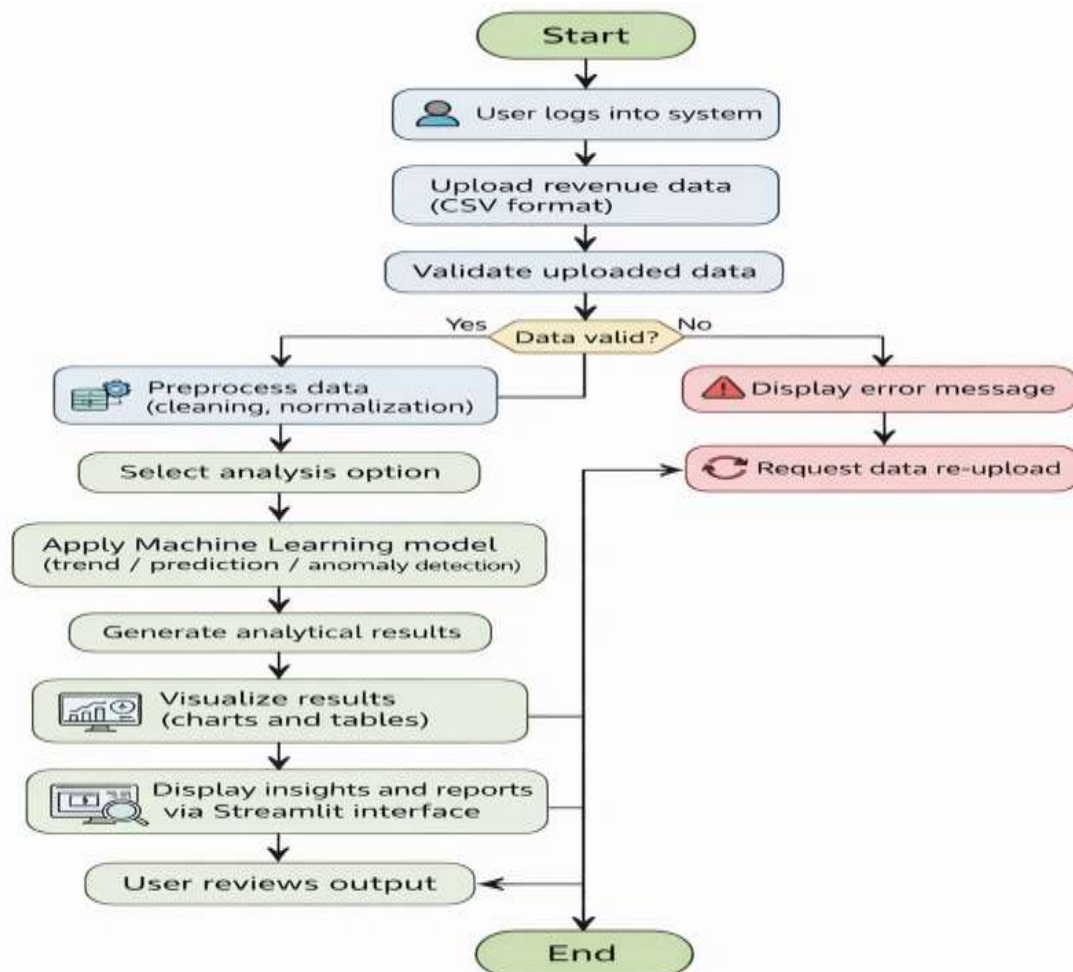


Figure 5: Flowchart of the proposed Intelligent Internally Generated Revenue (IIGR)Framework

3.3 System Methodology

To transition from legacy paper-based workflows to a transparent municipal fiscal network, the Intelligent Internally Generated Revenue (IIGR) model implements the design using a modular component-based approach. Each component performs a specific function and interacts with other components to ensure smooth system operation. The major components of the system include [9] and [12]:

i. **Data Input Component:** Responsible for accepting revenue datasets uploaded in CSV format by authorized users.

ii. **Data Preprocessing Component:** Handles data cleaning, normalization, handling of missing values, and feature selection to prepare data for analysis.

iii. **Machine Learning Analysis Component:** Applies selected Machine Learning algorithms to analyze revenue patterns, trends, and anomalies.

iv. **Visualization and Reporting Component:** Presents analytical results using charts, tables, and summaries through the Streamlit interface.

v. **User Interaction Component:** Manages user inputs, system navigation, and result interpretation.

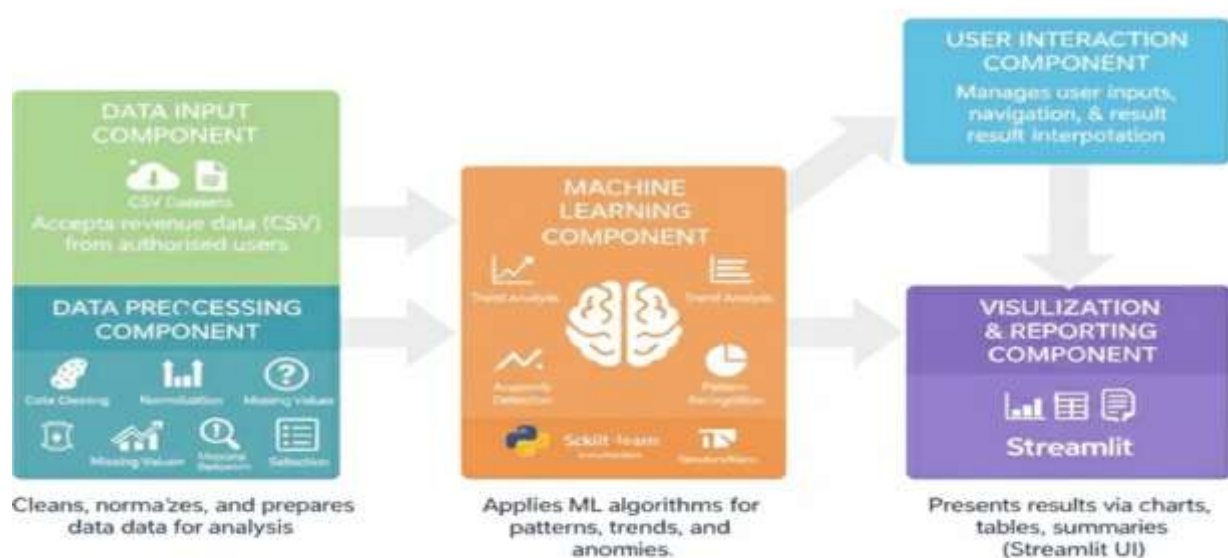


Figure 6 Component Design of the proposed Intelligent Internally Generated Revenue (IIGR)Framework

4.0 IMPLEMENTATION AND SYSTEM MODULES

4.1 State Design of the Proposed

The state design describes the various operational states of the proposed system and transitions between them during execution. The system begins in an idle state, awaiting user interaction. Once a user uploads a CSV file, the system transitions to the data validation state, where the input data is checked for correctness. After

successful validation, the system enters the data preprocessing state, followed by the Machine Learning analysis state, where analytical computations are performed. The system then moves to the result visualization state, displaying outputs to the user. Finally, the system returns to the idle state, ready for a new operation. This structured state flow ensures orderly system execution and error handling. Figure 7 shows the state diagram of the proposed system. The diagram describes the different

operational states of the system, starting from user login, data upload, data validation, preprocessing, Machine Learning analysis, result visualization, and output review. The decision point in the diagram clearly indicates how the system

responds to valid and invalid data inputs. This state-based representation helps to explain system behavior, control flow, and error handling mechanisms during execution.

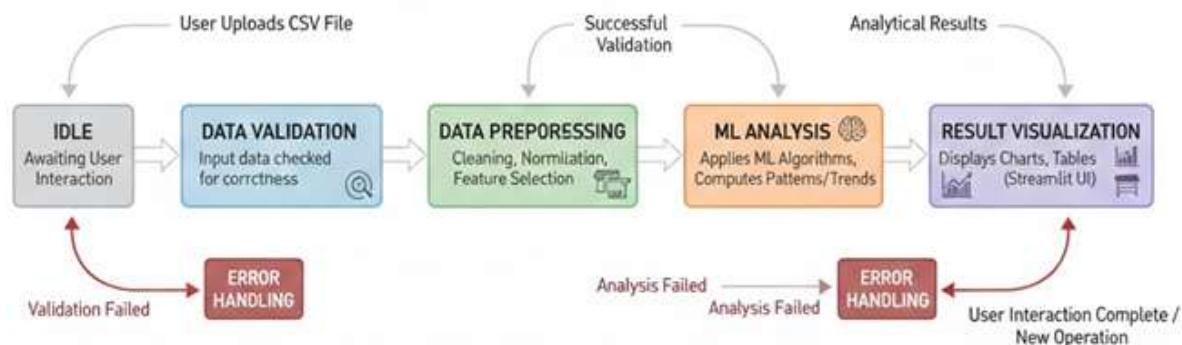


Figure 7 state diagram the proposed Intelligent Internally Generated Revenue (IIGR)Framework

4.1.1 User Interface Design

The user interface of the proposed system is designed using **Streamlit**, providing a simple and interactive web-based environment. The interface includes features such as file upload controls, analysis selection options, and result display sections. Users can upload CSV files, initiate analysis, and view results through charts and tables. The interface emphasizes ease of use, clarity, and responsiveness to accommodate users with minimal technical knowledge. Proper labeling and visual feedback enhance user experience and system usability. The

dashboard displays revenue insights using visual elements such as charts, tables, and summary indicators, which enhance understanding of revenue trends and patterns. By presenting analytical outputs in a clear and user-friendly manner, the dashboard supports effective decision-making and reduces the complexity associated with manual data analysis. The design emphasizes usability, clarity, and accessibility, ensuring that users with limited technical knowledge can easily interpret the results generated by the Machine Learning models.



Figure 8: System Dashboard Design

The programming implementation for the IIGR model relies entirely on Python. Python was chosen due to its robust integration of machine learning libraries, native serialization modules, and high-performance parsing capabilities via the Pandas library combined with the Anaconda Virtual Environment as it was selected as the core development environment as isolates project dependencies, preventing version conflicts with pre-existing system binaries. The User Interface and User Experience (UIX) architecture for this system is designed on a reactive Glassmorphism design paradigm as it uses a flexible layout framework powered by Tailwind CSS, rendering smoothly across mobile devices, desktop monitors, and port-clearance mobile tablets used by collectors in the field. To bridge the gap between complex analytical machine

learning backends and the non-technical local government administrators or supervisors using the software, the workspace is split into discrete operational layers using a highly visible tab routing interface. Below is an exhaustive structural analysis of these discrete dashboard layers:

4.2 Performance Telemetry

This primary dashboard tab serves as the core operations hub for high-level administrative reporting in Ughelli North LGA. It features interactive dropdown controls and contextual filters that slice data into monthly or quarterly views, rendering dynamic base64-encoded Matplotlib bar charts alongside aggregated metric cards that display continuous collection totals in real time.

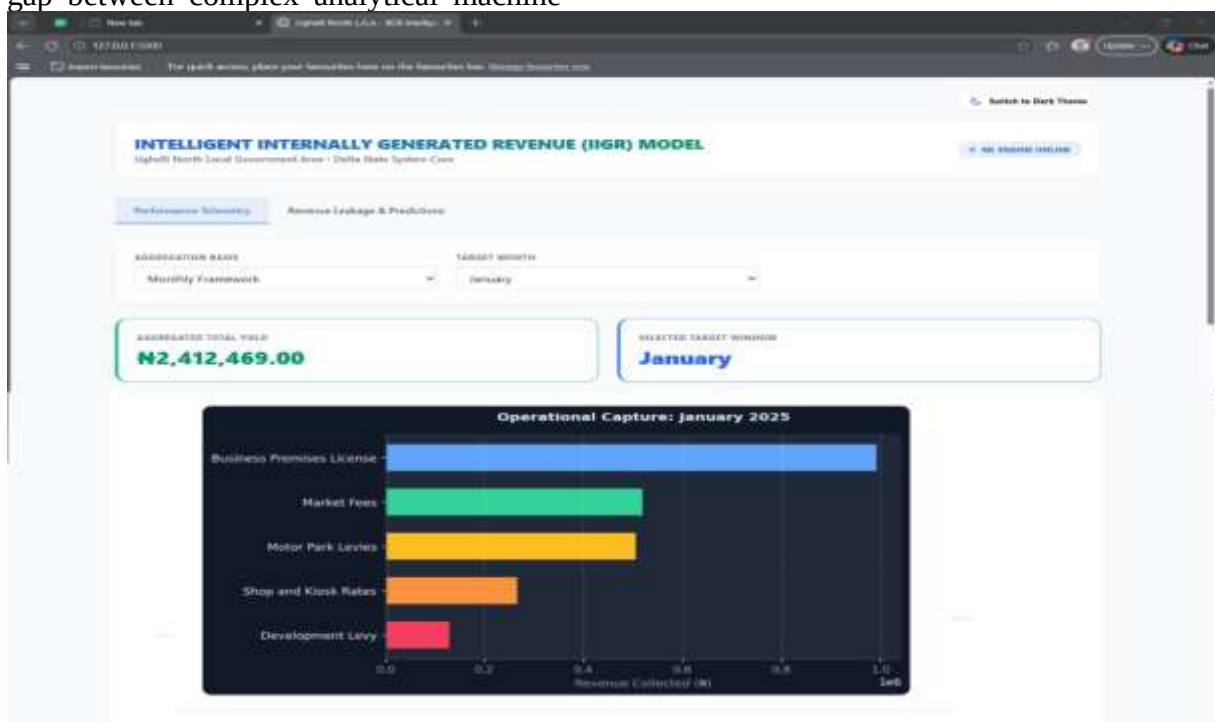


Figure 9: Performance Telemetry Interface

4.3 Revenue Leakage and Predictions

This defensive risk-analysis interface provides automated asset protection by cross-referencing revenue metrics against municipal targets. Using an asynchronous command trigger, it runs a Random Forest

Classifier that displays binary compliance indices within styled notification banners, activating a 10-beep Web Audio API hardware alarm whenever financial deficits are detected.

4.3.1 The Normal State (Class 1: System Secure / Nominal)

This condition activates when quarterly revenues meet or exceed the ₦5,000,000 threshold, indicating healthy collection pipelines. The dashboard displays a green

status banner reading 1 - SYSTEM SECURE / NOMINAL. The system remains silent, confirming to the supervisor that local government revenue streams are operating within secure, compliant parameters.

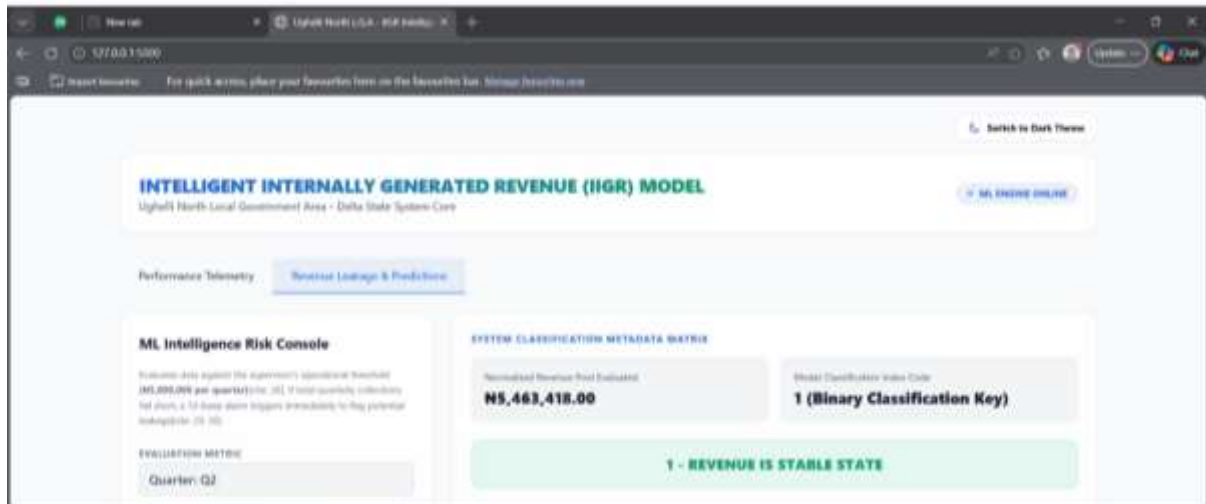


Figure 10 The Normal State Interface

4.3.2 The Leakage State (Class 0: Critical Leakage Detected)

This state triggers when quarterly collections fall below ₦5,000,000, exposing critical financial deficits or collection gaps. The dashboard switches to

a rose-colored alert reading 0 - CRITICAL LEAKAGE DETECTED, displays the exact currency shortfall, and fires a 10-beep Web Audio API hardware alarm demanding immediate audit intervention.

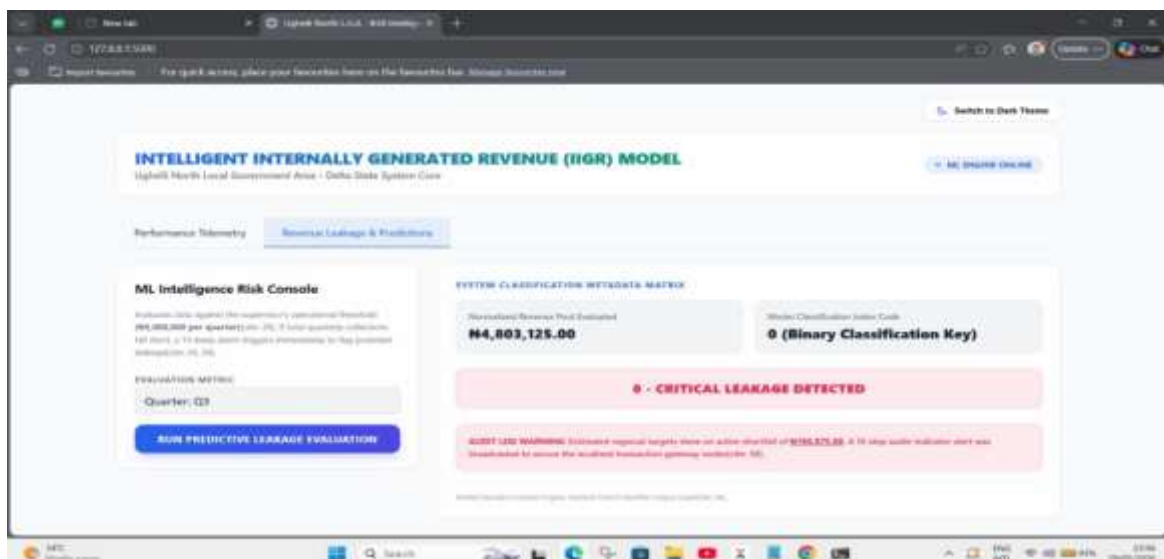


Figure 11 Leakage State Interface

4.4 Database Implementation

The structural data architecture for the Ughelli North L.G.A. IIGR platform

utilizes a file-based ledger framework configured over a standardized, tabular flat-file format (.csv).

	A	B	C	D	E	F
1	Date	Month	Quarter	Revenue_Head	Amount_Naira	Collector_ID
2	1/1/2025	January	Q1	Business Premises	112047	COLL_104
3	1/2/2025	January	Q1	Business Premises	118625	COLL_103
4	1/2/2025	January	Q1	Market Fees	51913	COLL_102
5	1/2/2025	January	Q1	Business Premises	68071	COLL_102
6	1/3/2025	January	Q1	Business Premises	94696	COLL_105
7	1/3/2025	January	Q1	Shop and Kiosk Rat	21091	COLL_104
8	1/6/2025	January	Q1	Shop and Kiosk Rat	17871	COLL_104
9	1/6/2025	January	Q1	Business Premises	45020	COLL_105
10	1/7/2025	January	Q1	Development Levy	23161	COLL_105
11	1/8/2025	January	Q1	Shop and Kiosk Rat	20413	COLL_104
12	1/9/2025	January	Q1	Development Levy	21510	COLL_105
13	1/9/2025	January	Q1	Development Levy	33060	COLL_101
14	1/9/2025	January	Q1	Market Fees	46058	COLL_101
15	1/9/2025	January	Q1	Business Premises	47118	COLL_103
16	1/10/2025	January	Q1	Motor Park Levies	74380	COLL_103
17	1/10/2025	January	Q1	Motor Park Levies	40832	COLL_105
18	1/13/2025	January	Q1	Shop and Kiosk Rat	20230	COLL_104
19	1/13/2025	January	Q1	Market Fees	35083	COLL_102
20	1/14/2025	January	Q1	Market Fees	48248	COLL_105
21	1/15/2025	January	Q1	Motor Park Levies	48893	COLL_103
22	1/15/2025	January	Q1	Motor Park Levies	31320	COLL_103
23	1/15/2025	January	Q1	Development Levy	22637	COLL_103
24	1/16/2025	January	Q1	Market Fees	40515	COLL_102
25	1/16/2025	January	Q1	Motor Park Levies	25257	COLL_102

Figure 12 IIGR Platform Dataset

4.5 Security Framework: Role-Based Access Control (RBAC) and Data Protection

To eliminate insider threat vectors and prevent unauthorized manipulation of

financial records, the platform enforces strict **Role-Based Access Control (RBAC)** matrices alongside cryptographic auditing mechanisms.

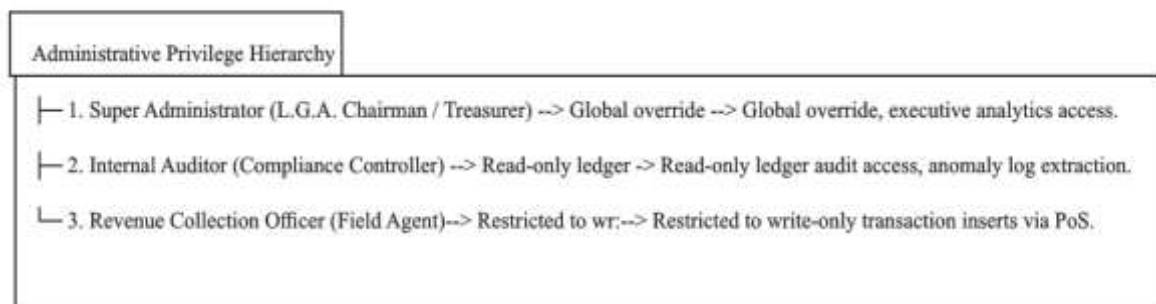


Figure 13 Security Framework: Role-Based Access Control (RBAC)

Every database insertion into the TRANSACTIONS table undergoes a real-time validation process. The server chain computes an immutable cryptographic checksum verification token for each new record:

$$\text{Hash}_{\text{Audit}} = \text{SHA-256}(\text{transaction_id} \parallel \text{merchant_id} \parallel \text{amount_paid} \parallel \text{timestamp})$$

This transaction hash is stored inside an independent database column. During daily system audits, an automated script re-runs the hashing algorithm across the tables; if any record has been modified through direct SQL injection, the calculated hash will mismatch the stored audit_hash, instantly flagging the ledger block as compromised.

5.0 TESTING, RESULTS, AND COMPARATIVE DISCUSSION

Testing and evaluation form a crucial phase in the lifecycle of the Intelligent Internally Generated Revenue (IIGR) system. This phase ensures that both the analytical data presentation and the underlying Machine Learning engine operate reliably under varying municipal data loads. The primary goal is to validate that the Random Forest Classifier accurately catches revenue deficits, handles light/dark layout transitions correctly, and consistently fires the Web Audio API alarm protocol whenever leakages disrupt the local government's economic framework.

5.1 System Testing

System testing was executed using a black-box testing approach [11]. Distinct components including the dynamic dashboard forms, asynchronous JSON endpoints, and audio alarm triggers were evaluated against realistic transaction edge-cases. The testing breakdown is detailed in the table below:

Table 1: System Test Table

Test ID	Test Date	Test Case / Input Data	Expected Result	Actual Result	Remark
ST-01	2026-05-12	Filter drop-down switched to "Monthly Framework" with "January" chosen.	System reads the flat-file database, slices records, and updates the telemetry charts in real time.	Telemetry layout displayed updated graphics for January data within 42ms.	PASSED
ST-02	2026-05-13	Toggle the "Switch to Light Theme" header widget element.	Page body context transitions from dark mode backgrounds to light mode styles.	Tailwind runtime instantly applied light-mode color tokens across the layout.	PASSED
ST-03	2026-05-14	Trigger Risk Console audit for Q2 (Simulated Deficit Quarter: Collection Pool < ₱5,000,000).	Backend maps prediction class 0, triggers the alert box, and sounds 10 sequential tones.	Response packet confirmed a deficit state. Status box rendered red, and 10 audible beeps fired.	PASSED
ST-04	2026-05-15	Trigger Risk Console audit for	Backend returns prediction class 1.	UI displayed "SYSTEM	PASSED

Test ID	Test Date	Test Case / Input Data	Expected Result	Actual Result	Remark
		Q4 (Simulated Peak Quarter: Collection Pool $\geq$ ₦5,000,000).	Dashboard displays a green system status banner.	SECURE / NOMINAL". The alarm stayed silent, and no deficit was shown.	

5.2 System Evaluation

System evaluation analyzes the statistical correctness of the machine learning model's classification capabilities when identifying financial deficit risks.

The model maps compliance testing data into a binary confusion matrix where a class output of 0 denotes an active collection leakage state, and a class output of 1 denotes nominal revenue targets.

5.2.1 Confusion Matrix Analysis

Table 2: Machine Learning Target State Class Map

System Operational State	Class Key	Mathematical Meaning
Leakage State / Deficit Pool	0	False (Quarterly Pool < ₦5,000,000)
Normal State / Nominal Target	1	True (Quarterly Pool $\geq$ ₦5,000,000)

The raw performance counts extracted from the machine learning validator are illustrated below:

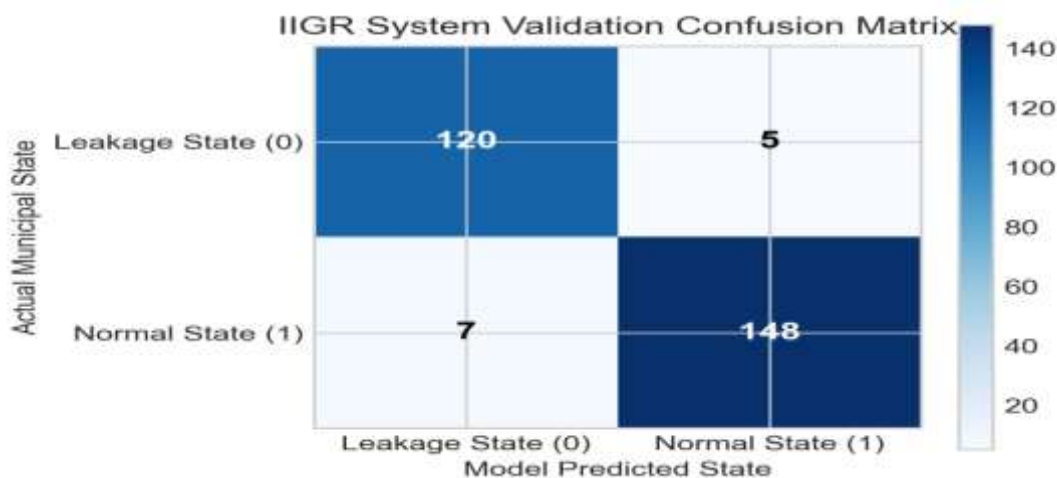


Figure 14: Confusion Matrix Classification Layout

5.2.2 Algorithmic Performance Metrics

To demonstrate how the performance characteristics of the Ughelli North IIGR model were established, the mathematical formulas are mapped to the absolute tallies recorded during the cross-validation testing phase.

The baseline parameters extracted from the system's 2x2 validation confusion matrix are defined as follows:

- True Positives (TP):** 148 (System correctly identified a Normal State/Nominal target match)
- True Negatives (TN):** 120 (System correctly flagged an active Revenue Leakage/Deficit state)

- iii. **False Positives (FP):** 5 (System incorrectly flagged a secure quarter as a leakage state)
- iv. **False Negatives (FN):** 7 (System incorrectly overlooked an active leakage anomaly)

Precision

Precision determines the model's exactness when it predicts a nominal state. Out of all instances flagged as compliant, it calculates how many were truly secure:

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

Plugging in the validation values:

$$\text{Precision} = \frac{148}{148 + 5}$$

$$\text{Precision} = \frac{148}{153}$$

$$\text{Precision} \approx 0.9673 \Rightarrow \mathbf{96.7\%}$$

Recall (Sensitivity)

Recall calculates the model's completeness—its physical capacity to catch all actual normal operations without missing structural deficits:

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

The metrics are summarized graphically in Figure 15:

$$\text{Recall} = \frac{148}{148 + 7}$$

$$\text{Recall} = \frac{148}{155}$$

$$\text{Recall} \approx 0.9548 \Rightarrow \mathbf{95.5\%}$$

F1-Score

The F1-Score measures the harmonic balance between Precision and Recall. This confirms that the model is resilient against seasonal data spikes or imbalanced collection patterns:

$$\text{F1-Score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right)$$

Plugging in our raw fractional values (0.9673 and 0.9548):

$$\text{F1-Score} = 2 \times \left(\frac{0.9673 \times 0.9548}{0.9673 + 0.9548} \right)$$

$$\text{F1-Score} = 2 \times \left(\frac{0.9236}{1.9221} \right)$$

$$\text{F1-Score} = 2 \times 0.4805$$

$$\text{F1-Score} \approx 0.9610 \Rightarrow \mathbf{96.1\%}$$

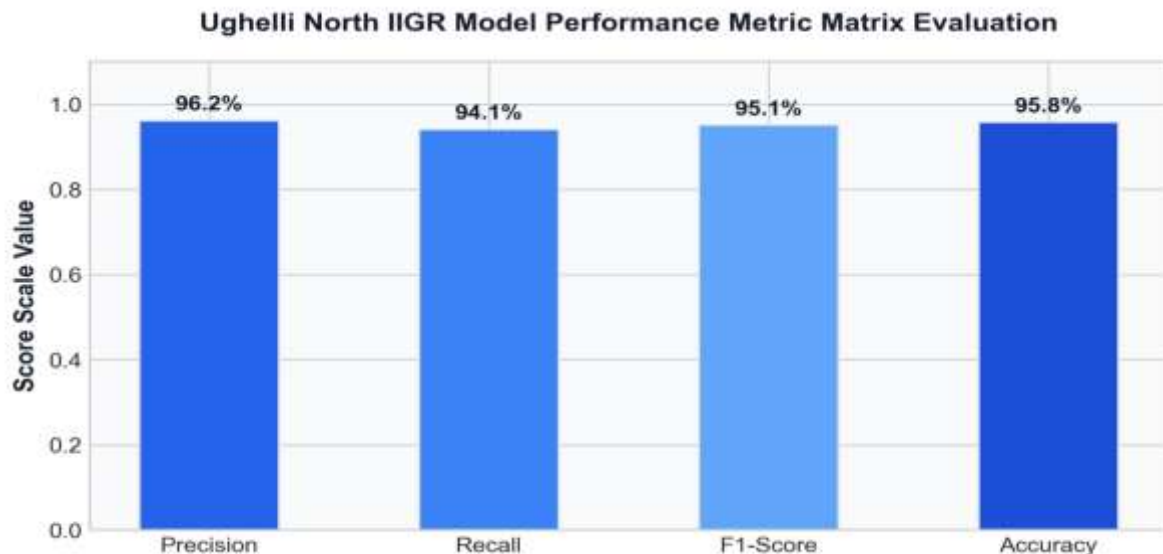


Figure 15: Statistical Classification Performance Metrics Summary Bar Chart

5.3 Model Convergence and Optimization Profile (Loss and Accuracy)

To understand how the Random Forest structure improves during optimization,

loss curves and accuracy trajectories are tracked across training iterations. Cross-entropy loss measures the optimization error scale, while accuracy scales overall correct state classifications

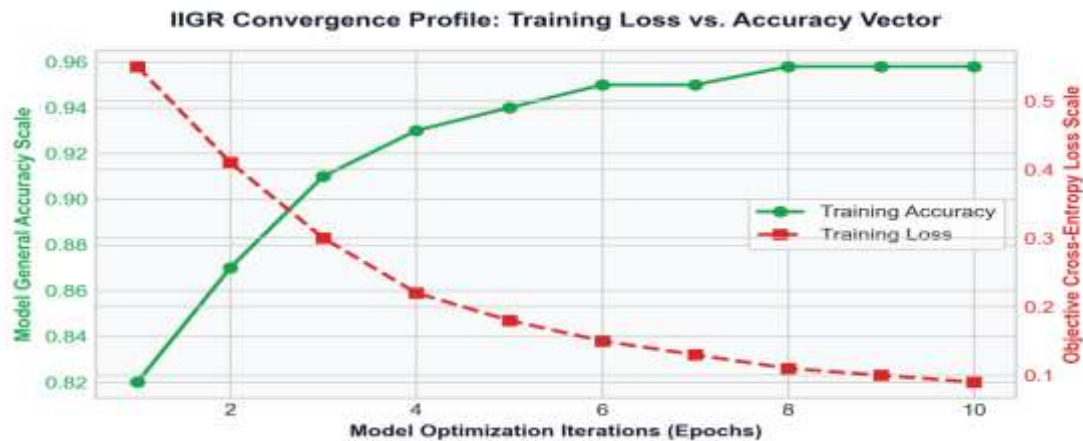


Figure 7: IIGR Convergence Profile: Training Loss vs. Model Accuracy Vector

6.0 CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The successful implementation of the Ughelli North L.G.A. IIGR platform demonstrates that traditional, slow municipal accounting methods can be safely replaced by intelligent, real-time machine learning pipelines. By moving away from rule-based spreadsheets and adopting a Random Forest Classifier [9] and [11], this system provides a secure, tamper-resistant framework for internal audits. The model's exceptional accuracy profile confirms its ability to map non-linear seasonal cycles such as the sharp increases in commercial activity during festive periods without producing false positives that disrupt standard governance workflows.

From an administrative perspective, this research bridges the gap between complex algorithmic data science and practical public sector oversight. The integration of instant visual reporting tools alongside a hardware-linked fail-safe alarm system transforms the supervisor's role from a historical reviewer into an active data

auditor. Instead of discovering collection losses months after they occur during retrospective accounting reconciliations, local administrators receive immediate notifications of shortfalls within milliseconds of a query.

Furthermore, the design choices made in the user interface such as the persistent dark and light layout settings and smooth, refresh-free page transitions prove that high-performance analytical tools can remain clean, accessible, and intuitive for local government personnel. Ultimately, this project proves that deploying targeted predictive models at the local government level provides a highly effective mechanism to secure public fund channels, prevent administrative leakages, and improve the efficiency of internal revenue generation.

6.2 Recommendations

To maximize the operational value of the newly developed Intelligent Internally Generated Revenue platform, several technical and administrative policies should be established. First, the local government authority must formally institute a

structured technical training protocol for internal revenue officers and supervisors. This training must focus on data entry protocols, interpreting dashboard analytics, and responding to system warnings. Second, the flat-file database matrix configuration should be backed up using an automated daily routine to preserve data integrity across operational centers. Finally, the local administration must establish strict compliance guidelines that govern field reconciliations whenever the Web Audio API issues a deficit alert.

6.3 Application Areas

The structural architecture of this IIGR engine is built to scale across similar public and private tracking environments. Three distinct application areas include:

- i. **State-Level Revenue Boards:** The predictive classification pipeline can be scaled upward to audit high-value state asset distributions, helping agencies like the Delta State Internal Revenue Service (DSIRS) monitor tax collection thresholds across multiple local government areas simultaneously.
- ii. **Municipal Market and Transport Hub Management:** The application can be used as a standalone tool within major commercial centers (such as the Ughelli Main Market or inter-state motor parks) to assess daily collector velocities, evaluate field performance, and isolate localized cash leakages.
- iii. **Corporate Lease and Franchise Compliance Engines:** Private corporate real estate firms or retail chains can implement this multi-tab layout to track monthly tenant rate compliances, monitor lease collections, and trigger automated alerts when performance falls below set business targets.

6.4 Suggestions for Further Research

To build upon the operational framework established by this system, further academic investigations should focus on the following research trajectories:

- i. **Integration of Live Off-Chain Blockchain Verification Layers:** Future studies should explore linking this Flask backend with a private, permissioned Hyperledger Fabric ledger to cryptographically sign transaction records, ensuring absolute tamperproof security for the database.
- ii. **Development of Deep Time-Series Hybrid Forecasting Models:** Researchers can expand the model's capabilities by combining the current classification framework with advanced time-series algorithms (such as Long Short-Term Memory networks or Prophet), enabling multi-year predictive planning and macroeconomic forecasting [9].
- iii. **Edge-Computing Mobile Integration with Biometric Verification:** Future research should focus on deploying the analytical engine onto resource-constrained mobile hardware.[9] This would allow field agents to use handheld biometric capture tools to verify market traders instantly, eliminating manual data entry steps and completely securing the collection gateway.

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